Neuromuscular Dynamics and the Vehicle Steering Task

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Summary

This thesis is concerned with driver steering-control with particular reference to the role of the neuromuscular dynamics. The steering torque felt through the steering wheel provides a key feedback signal to the driver. This feedback is used in closed-loop control of the steering system and vehicle. The neuromuscular dynamics must be considered in order that predictions of closed-loop driver behaviour can be made that take account of the steering torque feedback.

Chapter 1 reviews previous work relevant to driver steering control. The review shows little attention has been given to understanding the driver’s neuromuscular system. To address this gap in current knowledge and allow measurements to be made, a driving simulator was developed (Chapter 2). The simulator was commissioned to allow the neuromuscular dynamics to be measured and a novel method for measuring the steering forces produced by each of the driver’s arms was devised.

Chapter 3 reports measurements of the drivers’ muscle activity using electromyography (EMG). It was found that the measured muscle activity could be used to predict driver steering torque; this had not previously been achieved. In Chapter 4 the mechanical properties of drivers’ neuromuscular systems are identified. Parameters describing the neuromuscular system were found to depend on the degree of muscle activity as measured using EMG.

Chapter 5 reports measurements from the driving simulator of steering performance during a double lane change manoeuvre. A model is developed in Chapter 6 to predict the measured driver behaviour. The model builds on previously published driver models, but also incorporates the neuromuscular dynamics identified in Chapter 4. In this way the new driver model can take account of the effect of changes in steering torque feedback. Conclusions and recommendations for further work are given in Chapter 7.
Preface

A PhD research project was carried out between October 2001 and December 2004 aimed at investigating the effect of steering torque feedback on the dynamic response of the driver-vehicle system. The research was funded by the Engineering and Physical Sciences Research Council (EPSRC) through an Industrial CASE award and sponsored by TRW Conekt. Additionally St Catharine’s College gave substantial support. I would like to thank these organisations for their support during the course of my research.

TRW is involved in the supply of steering, braking and other components to vehicle manufacturers. TRW Conekt, a branch of TRW, is involved in the development of new products and technologies such as Electric Power Steering (EPS) and steer-by-wire technology. Gaining a fuller understanding of the driver-vehicle interaction with respect to steering torque feedback is of particular importance in allowing these new steering technologies to be fully exploited. As project sponsors TRW Conekt provided an EPS unit, which has been used to generate torque feedback in a driving simulator commissioned for this project. As part of the EPSRC CASE sponsorship, three months were spent working on site with TRW Conekt. The time was spent modifying the EPS hardware for use in the driving simulator and working on a control interface for EPS tuning.

My thanks and gratitude go to Dr David Cole who supervised and originally proposed this project. His support, encouragement and advice have been invaluable. I would like to thank Dr Jim Farrelly and his colleagues at TRW Conekt for all their input and help throughout the project. I would also like to thank the staff at Cambridge University Engineering Department.

I would like to thank the test subjects, who participated in the study. My thanks also go to my colleagues, Julius Rix, Andrew Odhams, Simon Rutherford, Steve Keen and members of the dynamics and vibrations research group for their interest and helpful discussion of the project. My thanks and gratitude are due to my house mates, friends at St Catharine’s College and especially Ella Hinton, all of whom have given me a great deal of personal support.

This dissertation is my own work and contains nothing that is the outcome of work done in collaboration with others, except as specified in the text and acknowledgements. No part of the work has already been, or is currently being, submitted for any degree, diploma or other qualification. This dissertation contains 50,000 words and 122 figures.

Andrew Pick, December 2004
### Abbreviations

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<thead>
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<th>Abbreviation</th>
<th>Description</th>
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<tbody>
<tr>
<td>A-A</td>
<td>Anti-aliasing</td>
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<tr>
<td>ARX</td>
<td>Auto regressive with exogenous inputs</td>
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<tr>
<td>CAN</td>
<td>Controller area network</td>
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<tr>
<td>CNS</td>
<td>Central nervous system</td>
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<td>CUED</td>
<td>Cambridge University Engineering Department</td>
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<tr>
<td>ECU</td>
<td>Electronic control unit</td>
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<tr>
<td>EMG</td>
<td>Electromyography</td>
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<tr>
<td>EPS</td>
<td>Electric power steering</td>
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<tr>
<td>GIF</td>
<td>Image file used to generate virtual reality display</td>
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<tr>
<td>JPEG</td>
<td>Image file used to generate virtual reality display</td>
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<tr>
<td>LQR</td>
<td>Linear quadratic regulator</td>
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<tr>
<td>MUAP</td>
<td>Motor unit action potential</td>
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<tr>
<td>MPC</td>
<td>Model predictive control</td>
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<tr>
<td>PRBS</td>
<td>Pseudo-random binary sequence</td>
</tr>
<tr>
<td>RARX</td>
<td>Recursive auto regressive with exogenous inputs</td>
</tr>
<tr>
<td>s.d</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>SREMG</td>
<td>Smoothed rectified EMG</td>
</tr>
<tr>
<td>TCP/IP</td>
<td>Transmission control protocol/Internet protocol</td>
</tr>
<tr>
<td>VAF</td>
<td>Variance accounted for by model</td>
</tr>
<tr>
<td>VR</td>
<td>Virtual reality</td>
</tr>
<tr>
<td>XPC</td>
<td>Matlab XPC toolbox</td>
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Notation

\[ a \]
Distance from centre of mass to front axle
Length

\[ A_d, B_d, C_d, D_d \]
Discrete time state space matrices representing yaw/side slip vehicle model

\[ A(q), B(q) \]
Polynomials in ARX model

\[ A_y \]
Vehicle lateral acceleration

\[ b \]
Distance from centre of mass to rear axle
Length

\[ B_{dr} \]
Driver arm damping

\[ B_e \]
EPS controller velocity feedback gain (damping)

\[ B_{eqv} \]
Equivalent damping of load cell, EPS motor and steering wheel

\[ B_{mot} \]
EPS motor and gear damping

\[ B_r \]
Reflex damping

\[ B_{en} \]
EPS torque sensor damping

\[ B_{sw} \]
EPS steering wheel damping

\[ C_f, C_r \]
Tyre cornering stiffness (suffix \( f \) and \( r \) for the front and rear tyre)

\[ C_{MA} \]
Tyre aligning stiffness

\[ C \]
Cost function

\[ C_{a} \]
Cost associated with co-contraction

\[ C \]
Cost function transformation matrix (LQR control)

\[ d \]
Lateral tyre offset otherwise known as scrub

\[ D, E \]
Shift register matrix and vector for previewed road path

\[ D_q, E_q \]
Shift register matrix and vector for driver time delay

\[ E \]
Measure proportional to rate of energy consumption

\[ E_N \]
Normalised measure of rate of energy consumption

\[ \bar{E} \]
Mean level of \( E \)

\[ F_p, F_t, F_c \]
Passive, tendon and contractile forces in three element muscle model

\[ F_{mot} \]
EPS motor friction

\[ F_n \]
Free response array
$F_x, F_y, F_z$  Load cell forces in orthogonal directions

$F_{ylb}, F_{yrb}, F_{zlb}, F_{zrb}$  Left and right tangential hand forces and left and right axial hand forces respectively

$\hat{F}_{yl}, \hat{F}_{yrb}$  EMG based predictions of left and right tangential hand forces respectively

$F_{yl}, F_{yrb}$  Front axle and rear axle equivalent tyre force

$F_{xfl}, F_{yfl}, F_{zfl}$  Longitudinal, lateral and vertical tyre forces (suffix $fl$ and $fr$ refer to the front left and right tyres respectively)

$G(s)$  Transfer function

$G_\alpha$  EPS controller feedback gain proportional to slip angle (generates steering feel)

$G_d$  Driver inverse reference model

$G_n$  Control response scalar

$G_a(s)$  Arm and steering dynamics transfer function

$H_0$  Null hypothesis

$H(s)$  Transfer function

$H_r(s)$  Reflex controller transfer function

$H(\omega)$  Frequency response

$H_{\text{exp}}(\omega)$  Experimentally measured frequency response

$H_{\text{mod}}(\omega)$  Model frequency response

$I_N$  Normalised co-contraction

$I_c$  Mean level of co-contraction

$I_{zz}$  Vehicle yaw inertia

$J$  LQR cost function

$J_{dr}$  Identified inertia $(J_{dr}+J_{lc}+J_{sw})$

$J_{lc}$  Driver arm inertia

$J_{equiv}$  Equivalent inertia of load cell, EPS motor and steering wheel

$J_{mot}$  Load cell inertia

$J_{sw}$  EPS motor and gear inertia

$J_{sw}$  EPS steering wheel inertia

$k_1$ to $k_4$  State gains that make up $K_p$

$k_{p1}$ to $k_{p_n}$  Preview gains that make up $K_p$
\( K(s) \) Transfer function
\( K_a \) Active stiffness
\( K_{dr} \) Driver arm stiffness
\( K_c \) EPS controller angle feedback gain (self centring)
\( K_r \) Reflex stiffness
\( K_{sen} \) EPS Integral torque sensor stiffness
\( K_p \) State variable feedback gains for LQR regulator
\( m \) Vehicle mass

\( M_e, M_s \) Torque about the elbow and shoulder respectively
\( M_{Fx}, M_{Fy}, M_{Fz}, M_{MA} \) Aligning torque about the kingpin due to \( F_x, F_y, F_z \) & \( M_A \) respectively
\( M_x, M_y, M_z \) Load cell moments in orthogonal directions
\( M_I \) Total aligning torque about the kingpin
\( M_A \) Tyre self aligning moment (suffix \( fl \) and \( fr \) refer to the front left and right tyres respectively)
\( M_{+ve} \) EMG based steering torque prediction for muscles that produce positive torques
\( M_{-ve} \) EMG based steering torque prediction for muscles that produce negative torques
\( M_c \) Column steering torque measured from load cell
\( \dot{M}_z \) EMG based steering torque prediction

\( n_k \) Number of sample delays in ARX model
\( n_{gb} \) EPS motor gearbox ratio
\( n_{rsw} \) Road to hand wheel steer angle gain
\( N \) Number of data points

\( N_{rpp} \) Number of road path preview points
\( q_{Ay} \) Weight associated with lateral acceleration
\( q_{Ta} \) Weight associated with torques produced through muscle activation
\( q_y \) Weight associated with lateral position error
\( q_\psi \) Weight associated with attitude angle error
\( Q \) Weight matrix
\( r(s) \) Reference input
\( r_{sw} \)  
Steering wheel radius

\( r_w \)  
Road wheel rolling radius

\( r \)  
Correlation coefficient

\( R \)  
Multiple correlation coefficient

\( \mathbf{R} \)  
Vector describing position of vehicle centre of mass

\( R_{1}, R_{2} \)  
Cost function weighting matrix and scalar

\( s \)  
Laplace variable

\( S_{uu} \)  
Auto spectrum

\( S_{yu} \)  
Cross spectrum

\( T \)  
Sample interval time

\( T_\alpha \)  
Muscle torque generated by activation of alpha motor neurons

\( T_{col} \)  
Torque from EPS integral torque sensor

\( T_{dem} \)  
EPS motor torque demand

\( T_{dr} \)  
Driver torque

\( T_{mot} \)  
EPS motor torque

\( T_{m} \)  
Total muscle torque

\( T_{p} \)  
Preview time constant

\( T_0 \)  
Memory time constant (RARX routine)

\( u(s) \)  
System input

\( \mathbf{u} \)  
System input array

\( v_x, v_y \)  
Longitudinal and lateral vehicle velocity

\( V \)  
Voltage

\( V_d \)  
SREMG voltage from EMG sensor on front portion of deltoid (suffixes \( l \) and \( r \) denote left and right arms respectively)

\( V_p \)  
SREMG voltage from EMG sensor on sternal portion of pectoralis major (suffixes \( l \) and \( r \) denote left and right arms respectively)

\( V_t \)  
SREMG voltage from EMG sensor on triceps long head (suffixes \( l \) and \( r \) denote left and right arms respectively)

\( w(s) \)  
System noise input

\( \mathbf{x} \)  
State vector
$x_L$  Logging state vector
$x$  Longitudinal position
$x_i$  Independent variable in regression analysis
$y$  Lateral position
$y$  Dependent variable in regression analysis
$y(s)$  System output
$y_{pi}$  Road path lateral displacement at point $i$
$y_{ri}$  Previewed road path lateral displacement at point $i$ in driver reference frame
$Y_c(\omega)$  Cross over model controlled element dynamics
$Y_p(\omega)$  Cross over model operator/pilot describing function
$Y_e$  Mean squared path error
$y$  System output vector
$y_p$  Vector of previewed road path lateral displacements
$z$  State vector
$\alpha$  Tyre slip angle (denoted $\alpha_f$ and $\alpha_r$ for the equivalent front and rear tyres in the yaw side slip vehicle model)
$\beta_i$  Regression coefficient relating to $x_i$
$\beta_d$  Regression coefficient for front portion of deltoid (suffixes $l$ and $r$ denote left and right arms respectively)
$\beta_p$  Regression coefficient for sternal portion of pectoralis major (suffixes $l$ and $r$ denote left and right arms respectively)
$\beta_t$  Regression coefficient for triceps long head (suffixes $l$ and $r$ denote left and right arms respectively)
$\delta$  Road wheel steer angle
$\epsilon$  Frequency domain minimisation function
$\gamma$  Damping ratio
$\lambda$  King pin inclination angle
$\nu$  Forgetting factor in RARX routine
$\theta_q$  Castor angle
$\theta_i$  Vector of delayed steer angle inputs arising from driver time delay
\( \theta_{col} \)  Steering column angle
\( \theta_{sw} \)  Steering wheel angle
\( \hat{\theta}_{sw} \)  Optimal steering wheel angle
\( \sigma^2 \)  Variance
\( \tau \)  Time delay
\( \tau_d \)  Driver time delay
\( \tau_r \)  Reflex dynamic time delay
\( \omega \)  Vehicle yaw rate
\( \omega_c \)  Measure of frequency
\( \omega_t \)  Cut off frequency for reflex dynamic
\( \omega_h \)  Resonant frequency
\( \psi \)  Vehicle attitude angle
\( \Psi_e \)  Mean squared path error
\( \psi_p \)  Road path heading angle
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Chapter 1: Introduction

The introduction of Electric Power Steering (EPS) has a number of benefits [1]. Eliminating the pumps, valves and hoses associated with traditional hydraulic systems allows simpler packaging and the reduction in complexity leads to a potentially more reliable system. In traditional systems hydraulic pressure is maintained at all times whether steering torque assist is required or not. By using an electric system, power is only used when torque assist is required and resulting improvements in fuel efficiency of up to 4% are reported [2].

In EPS systems the assist torque is controlled by an Electronic Control Unit (ECU). The ECU can be used to generate varying steering characteristics. This includes not only speed sensitive assist torque, but also the option of applying active torque feedback signals based on the vehicle motion, for example lateral acceleration or yaw rate.

Future developments in steering technology include steer-by-wire systems, where the mechanical connection between the steering wheel and road wheels is eliminated. Instead, the steering wheel angle is measured and sent electrically to actuators at the road wheels. Torque feedback to the driver can be recreated through a smaller actuator at the steering wheel. The technology allows complete freedom over the relationship between steering wheel angle and steering torque.

In terms of the driving process the human acts as a feedback controller with a variety of signals available, Figure 1.1. The role of visual feedback is of obvious importance and has been the subject of considerable research [3-5]. However kinaesthetic (force) and proprioceptive (position) feedback signals are also used. According to Gordon [4] the steering feel and torque feedback were the highest rated cues after vision. Segel [6] investigated the effect of steering torque gradient and damping on drivers’ subjective ratings of handling quality. It was found that low torque gradients made positioning of the steering wheel difficult and drivers were found to be particularly sensitive to the steering damping. Low levels of damping created unfavourable ratings.
Chapter 1: Introduction

Figure 1.1: Driver-vehicle feedback paths.

The importance of steering feel with respect to lane change manoeuvres was noted by Godthelp [5]. In particular, steering torque feedback helps the driver reduce steering variability and locate on centre position more quickly following a manoeuvre. It is also thought that the driver can respond more quickly to kinaesthetic cues than those perceived through vision [7, 8].

Although the importance of steering torque feedback is recognised in published literature, the way the driver uses the torque feedback signal is not widely understood. In order to explore the full potential of new technologies like EPS and steer-by-wire it is necessary to understand the effect of steering torque feedback on the overall closed loop performance of the driver-vehicle system. The aim of the research presented here is to produce a physiologically based, predictive model of driver steering control that takes account of steering torque feedback.

In this chapter, section 1.1 gives a brief review of literature relating to steer-by-wire and electric power steering systems. The mechanisms of steering torque generation and steering dynamics are discussed in section 1.2. Subsequently, in section 1.3, driver models are reviewed. A review of literature relating to the neuromuscular dynamics is given in section 1.4. Finally, the objectives for the PhD research are stated in section 1.5.
1.1 ACTIVE STEERING

The new developments in electric power steering and the continuing research into steer-by-wire technology allow the vehicle to be actively controlled through the steering system. In this section a review of some of the most recent developments in steering technology is given.

McCann [9] simulates yaw-rate torque feedback applied to an EPS system. The feedback improves vehicle stability when driving on wet and icy roads. During an aggressive steering manoeuvre the tendency for an oversteer response is minimised by reducing the driver’s ability to rapidly change the steering angle. Simulation is achieved using Hess’s control theoretic driver model [10]. The simulated vehicle-driver system is shown to have increased stability margins.

Yuhara et al. [7] apply active control based on a reference control model. The reference control model is designed to have faster dynamics than the vehicle. The error between vehicle and model outputs is fed back to the driver as kinaesthetic information (steering torque cue). The effect is to cause the vehicle output to follow the model output. Simulation is carried out using a driver model with second order muscle dynamics. Driver parameters, lead time and gains were established using non-linear optimisation and a cost function designed to minimise path error. In addition proving ground tests were used to validate the results found.

Both Yuhara’s and McCann’s models take no account of the way the driver adapts and responds to the new torque feedback strategy. The muscle and limb dynamics are assumed to be fixed and linear. Without an understanding of the way the driver responds to varying torque feedback, the full potential of this type of steering control may not be achieved. Understanding the way in which the driver responds to varying torque feedback and steering dynamics may provide an insight into steer-by-wire technology too. By using steer-by-wire technology both the steer angle and torque characteristics can be varied.

Hisaoka et al. [11] investigated the effect of varying yaw rate, lateral acceleration and steering torque time constants using a steer-by-wire vehicle with four-wheel steer.
Drivers’ subjective ratings of handling quality were recorded. The most desirable steering torque feedback was found to be highly dependent on the vehicle dynamics. A possible conclusion is that, as the steering torque feedback provides information on the vehicle dynamics, the torque feedback must be tuned to complement the vehicle dynamics.

Kramer and Hackl [12] investigate a system that applies additional steer angle to the road wheels in response to the hand wheel steer angle through a planet gear arrangement. The system is somewhat different to a power steering system because it applies angles rather than torques. By using yaw rate control increased yaw damping is achieved, which again acts to stabilise the vehicle response.

Steer-by-wire systems also have a potential role in improving vehicle stability during braking manoeuvres. Segwa [13] discusses stability improvements during split mu braking (braking on a surface where the coefficient of friction varies between wheels). Present vehicle stability controllers provide yaw moment control through variation of brake and drive forces. Steer-by-wire allows actuation of the road wheel steer angle. In this way both lateral acceleration and yaw control can be achieved independently when combined with four wheel steer-by-wire.

Vehicles with more radical steer-by-wire control systems have been proposed. Yuhara et al. [14] investigate a steering system where the steer angle is linearly proportional to target path angle irrespective of speed. Under these circumstances, the question of what steering torque feedback to provide still remains.
1.2 STEERING DYNAMICS

In order to investigate the role of steering torque feedback an understanding of the source of the torque in conventional vehicles is useful. The literature shows that the vehicle dynamics in isolation are widely understood [15-18]. However the steering torque feedback not only depends on the vehicle dynamics, but also the tyre forces and steering dynamics. In the following section a review of the mechanisms behind generation of steering torque feedback is given and models of steering dynamics are reviewed.

1.2.1 Torque feedback
Steering torque feedback is generated by transmission of tyre forces through the steering geometry. In particular inclination of the kingpin and tyre castor offset generate steering torques that act to self-centre the steering Figure 1.2. Additionally asymmetry in the tyre contact patch leads to significant moments about the centre of the contact patch. The moment generated is known as the tyre self-aligning moment. The components of torque feedback generated from the tyre forces can be calculated and are given by equations 1.1-1.4 [18]. The total self-centring torque about the kingpin axis is given by equation 1.5, while the torque felt by the driver is reduced due the gear ratio of the steering rack.

Figure 1.2: Shows right hand front wheel and positive forces acting on the tyre.
The steering torque feedback components about the kingpin axis created by the tyre forces can be calculated as follows:

**Torque due to lateral forces:**

\[ M_{Fy} = (F_{yfl} + F_{yfr})r_w \tan(\nu) \]  

(1.1)

where:
- \( M_{Fy} \) – Aligning torque about the kingpin due to lateral tyre forces
- \( F_{y} \) – Lateral tyre force
- \( r_w \) – Road wheel rolling radius
- \( \nu \) – Castor angle

(suffix \( fl \) and \( fr \) refer to the front left and right tyres respectively)

**Torque due to longitudinal forces:**

\[ M_{Fx} = (F_{xfr} - F_{xfl})d \]  

(1.2)

where:
- \( M_{Fx} \) – Aligning torque about the kingpin due to longitudinal tyre forces
- \( F_{x} \) – Longitudinal tyre force
- \( d \) – Lateral tyre offset otherwise known as scrub

**Torque due to vertical forces:**

\[ M_{Fz} = (F_{zfr} - F_{zfl})d \sin \nu \cos \delta + (F_{zfr} + F_{zfl})d \sin \lambda \sin \delta \]  

(1.3)

where:
- \( M_{Fz} \) – Aligning torque about the kingpin due to vertical tyre forces
- \( F_{z} \) – Vertical tyre force
- \( \lambda \) - King pin inclination angle
- \( \delta \)– Road wheel steer angle

The tyre self aligning torque is resolved onto the kingpin axis:

\[ M_{MA} = (M_{Afl} + M_{Afr}) \cos(\sqrt{\lambda^2 + \nu^2}) \]  

(1.4)

where:
- \( M_{MA} \) – Aligning torque about the kingpin due to tyre aligning moment
- \( M_A \) – Tyre aligning moment

The total self-centring torque about the kingpin axis is the sum of all the individual components:

\[ M_T = M_{Fy} + M_{Fx} + M_{Fz} + M_{MA} \]  

(1.5)

Other sources of steering torque include driveline torque induced if the drive shafts are not perpendicular to the steer axis. Gyroscopic forces can also generate torques about the steering axis, but only if there is a change in wheel camber.
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For constant speed linear vehicle models a linearised approximation of the self-centring torque can be generated (equation 1.6). Because the model is constant speed the longitudinal tyre forces are neglected and it is assumed that the castor angle, kingpin angle and road wheel steer angle are sufficiently small that small angle approximations can be made. Additionally because the difference between the left and right tyre response is small it is usually assumed that a single tyre generating twice the force and moment can represent the tyre force at the front and rear axles.

\[ M_T = (F_{yfr} + F_{yr})r_u \tan(\nu) + (M_{Af} + M_{Ar}) + (F_{yfr} + F_{yr})d \sin(\lambda)\delta \quad (1.6) \]

1.2.2 Tyre forces

Lateral tyre force \( F_y \) and aligning moment \( M_A \) can be modelled as a linear functions of tyre slip angle (equation 1.7 and 1.8) [18]. The slip angle is the angle between the wheel’s heading vector and velocity vector as shown in Figure 1.3.

![Figure 1.3: Velocity of tyre, slip angle and forces (positive values are shown).](image)

\[ F_y = C\alpha \quad (1.7) \]
\[ M_A = C_{MA}\alpha \quad (1.8) \]

where:

- \( F_y \) – Tyre lateral force (denoted \( F_{yf} \) & \( F_{yr} \) for an equivalent front or rear tyre)
- \( M_A \) – Tyre aligning moment
- \( C \) – Tyre cornering stiffness (denoted \( C_f \) and \( C_r \) for the front and rear tyre)
- \( C_{MA} \) – Tyre aligning stiffness
- \( \alpha \) – Tyre slip angle (denoted \( \alpha_f \) and \( \alpha_r \) for the front and rear tyre)

(Note \( C \) and \( C_{MA} \) are negative because the tyre force acts to resist motion)

In reality the tyre forces and moments are non-linear; the cornering stiffness reduces as slip angles increase and the tyre force saturates at large slip angles. In addition the
tyre force is dependent on the vertical tyre load, $F_z$. Pacejka’s magic formula tyre model [19], as cited by [16] provides a mathematical function that can be used to fit empirical tyre data (equation 1.9). The variations in lateral force and aligning moment with slip angle and vertical tyre force are shown in Figure 1.4. The reduction in tyre aligning moment may be one of the cues the driver uses to establish if the vehicle is close to the limit of tyre adhesion.

$$F_y = D \sin \left( C \tan^{-1} \left\{ B(1 - E)\alpha + E \tan^{-1} (B\alpha) \right\} \right)$$  \hspace{1cm} (1.9)

where:

- $D$ – Peak tyre force
- $C$ – Shape factor
- $BCD$ – Gradient at zero slip angle, $\alpha$
- $E$ – Parameter to determine slip angle at peak tyre force

Differentiating equation 1.9 with respect to the slip angle $\alpha$ and taking the gradient when $\alpha=0$, for an appropriate value of $F_z$, gives the linear tyre stiffness coefficients $C_{\gamma}$ and $C_{\alpha}$ (equation 1.10).

$$\frac{\partial F_y}{\partial \alpha}_{\alpha=0} = BCD$$  \hspace{1cm} (1.10)
Figure 1.4: Typical non-linear tyre properties for lateral forces and aligning moments (evaluated for coefficients given by Genta [16]).
1.2.3 Steering dynamic models

The steering torque feedback acts to excite the steering dynamics, which must be considered if the overall vehicle and steering system response is to be established. Segel [20] models the steering system as quasi-linear with two degrees of freedom and non-linear friction. The second degree of freedom comes from compliance in the steering column, shown in Figure 1.5. By coupling the steering system to a vehicle model, linear analysis of the system shows that unstable oscillations can occur. Such oscillations are classed as shimmy modes. In practice non-linear Coulomb friction helps damp out any oscillations in the steering system.

where:

- $T_{dr}$ - Driver torque
- $\theta_{col}$ - Column angle
- $J_{col}$ - Column inertia
- $B_{col}$ - Column damping
- $K_{col}$ - Column stiffness
- $n_{rsw}$ - Road to hand wheel steer angle gain
- $B_{rk}$ - Rack damping
- $J_{rk}$ - Rack inertia
- $\delta$ - Road wheel steer angle

Figure 1.5: Linearised steering dynamic model.

Pacejka [21] describes an additional mode of steering oscillation generated through gyroscopic effects. This gyroscopic shimmy mode is of particular importance when considering vehicle motion on an undulating road surface [22]. The gyroscopic effects are often cited as the main cause of wheel shimmy. However Segel’s linear analysis shows that instability can still occur even when the gyroscopic effects of the wheels are left unmodelled.
According to Segel, the column inertia has the largest influence on the unstable shimmy motion. Stabilisation can be achieved by reducing the column inertia or increasing the aligning stiffness of the tyre. However, dynamic tyre lag is not considered and may be responsible for further oscillatory modes due to the increased phase lag in generation of tyre forces. By holding the steering wheel the driver changes the dynamics of the system. The interaction between the driver and steering system is not well reported in the literature, but may be a significant aspect of the steering dynamic behaviour.

Because the steering dynamics are coupled to the vehicle dynamics, the steering feel changes with vehicle speed and state. The change in angle-torque characteristics with speed are analysed through simulation by Shimomura [23]. The damping and steering torque gradient with respect to angle are evaluated from plots of steering torque against steering angle in response to a sinusoidal steering input. It is noted that at higher speed the steering torque gradient increases, but the damping reduces. The degree of variation in steering dynamics with vehicle speed could be controlled using a steer-by-wire system. However the effect of such a controller can only be predicted if the interaction between the driver and steering torque feedback is fully understood.

The fundamental reduction in apparent steering damping with increased vehicle speed has implications for the design of speed sensitive EPS systems. The EPS systems described by Kim and Song [24] as well as Yun and Han [25], both apply control proportional to steer angle velocity in order that additional damping is added to the steering system. The need for additional damping can be predicted from Segel’s [20] earlier analysis of steering dynamics. Connecting an electric motor to the steering column increases the effective inertia of the column considerably. Segel’s analysis showed that undesirable oscillations due to an increase in steering inertia could be removed by increasing damping. Additionally, increasing the torque assist gain can induce a second order resonance, which should be damped out [26]. Although additional damping helps suppress unwanted oscillations of the steering system, it also limits the driver’s capability to apply rapid steering inputs. The design trade off here is discussed further by Sharp [27].
Additional difficulties in designing electric power steering control are addressed by Chabaan [2]. In particular there is a compromise between making the steering light by applying high torque gain and maintaining overall stability. Robust control is discussed and in this case achieved through H-infinity control.

Attempts have been made to predict and evaluate the steering feel through objective measures of the vehicle and steering dynamics alone [28] and [8]. However the studies are essentially open loop and attempt to predict vehicle performance by applying simple control inputs like sine sweep steer inputs. The studies do not take account of the way the driver uses the torque and angle feedback or account for the coupling between the neuromuscular system and the steering dynamics. By understanding the way the driver interacts with the steering system a better understanding and prediction of the quality of steering feel might be gained.
1.3 DRIVER MODELS

1.3.1 Human-machine interaction

The basis of human control models specific to the driving task can be traced back to early research on human-machine systems. In understanding human-machine interaction the research focused on compensatory tracking tasks, in particular minimising visually perceived errors by exercising continuous control. This type of compensatory control is exhibited by aircraft pilots aligning a virtual horizon or following a moving target with a gun sight. McRuer [29, 30] showed that the human operator could apply lead/lag compensation to visually perceived errors in order to control compensatory tracking tasks. This type of control forms the basis of the crossover model, Figure 1.6. The principle of the crossover model is that humans adapt their control to provide compensation, \( Y_p(\omega) \), that is dependent on the dynamics of the system to be controlled, \( Y_c(\omega) \).

\[
Y_p(\omega) = K_p \left( \frac{T_L j\omega + 1}{T_I j\omega + 1} \right) e^{-j\omega(\tau + T_I)} \tag{1.11}
\]

where:

- \( Y_c(\omega) \) - Dynamics of the controlled element
- \( K_p \) - Gain term
- \( \left( \frac{T_L j\omega + 1}{T_I j\omega + 1} \right) \) - Simplified equalisation characteristic
- \( \tau \) - Central processing time delay

Figure 1.6: Crossover model loop structure for compensatory tracking tasks.
\[ T_N \] - Delay to represent the neuromuscular system time delay

Compensation includes lead and lag equalisation and a constant gain to ensure closed loop stability. Experiments showed that the open loop transfer function gain dropped off at 20dB/decade in the crossover region (crossover is the point where \( Y_p(\omega)Y_c(\omega) \) has unity gain) for controlled elements with a wide range of dynamics. Good phase margin was also observed. Equalisation is subject to the operator’s neural processing delay, which limits the achievable bandwidth of control. A remnant is also reported that is the portion of the operator’s output that is not linearly coherent with the forcing function.

The crossover model parameters not only describe humans’ control strategy, but can also form the basis of analytical handling quality assessment. Ashkenas and McRuer [31] found that controlled elements requiring no lead or lag equalisation gave the best subjective handling ratings when applied to aircraft control tasks.

1.3.2 Compensatory control

The crossover model can be used to describe the control response of the driver vehicle system when subjected to disturbing forces such as side winds [32, 33]. Using the crossover model to represent this type of control indicates that feedback of vehicle attitude angle is most effective, requiring only gain equalisation. In contrast lateral position control requires large lead equalisation in order to achieve the 20dB/decade attenuation in gain at crossover. Large lead equalisation is thought to place a high mental workload on the driver and increases the expected time delay [33].

Although vehicle control can be achieved through application of a single feedback loop of attitude angle or lateral position, the resulting tracking errors indicate that a multi-loop control structure might be more appropriate. An outer loop using lateral position error and an inner attitude angle loop give well damped and stable control. Again crossover model rules can be applied to these loop closures. The multi-loop structure identified by Weir and McRuer [33] has been used in more recent research [34] and validated through experimental testing and system identification techniques.
Early driver models based on lateral position or attitude angle feedback can be used to represent some aspects of driving, for example responding to side wind and other disturbance forces acting on the vehicle. However the driver’s neural processing delay limits the bandwidth of control and so path following models based on feedback alone are inadequate. For good path following response the driver must look ahead.

1.3.3 Preview control

By previewing the road path ahead the driver is able to anticipate the necessary control input and compensate for the inherent time delay. Preview also allows some degree of path planning [35] within the constraints of the road boundaries. Weir and McRuer [33] consider the case of preview in the context of the crossover model by assuming that the driver looks at some point ahead of the vehicle. The preview information takes the form of a pure lead equalisation term. Including the pure lead in the driver vehicle loop structure eliminates the need for additional equalisation control by the driver. Kondo [36], as cited by [37], uses a simple linear predictive model of the vehicle to evaluate previewed path error. The predicted lateral position is given by equation (1.12) and when used in a feedback loop is essentially responding to attitude angle and lateral position. The preview model of the form shown in equation (1.12) has been successfully used to evaluate anti-lock brake performance on closed-loop driver-vehicle behaviour [38]. However as the preview model does not include torque feedback it cannot be used to evaluate electric power steering performance.

\[ y(t + T_p) = y(t) + T_p v_x \psi(t) \] (1.12)

where:

- \( y(t) \) - Lateral position at time \( t \)
- \( T_p \) - Preview time
- \( v_x \) - Vehicle forward velocity
- \( \psi(t) \) - Attitude angle at time \( t \)

A comprehensive review of preview models is given by Guo and Guan [37]. The idea that the driver acts by previewing the road at a single point ahead of the vehicle is a simplification. In fact the driver can preview the road continuously ahead of the
vehicle to build up a picture of the overall road path [27]. This may improve the driver’s ability to control the vehicle.

MacAdam [39] generates an algorithm for optimal control of linear systems based on previewed information. This algorithm is subsequently used to model the driving process [40]. The driver previews the road path over some interval ahead of the vehicle. The previewed road path is compared to a prediction of the future vehicle path across the preview interval. The prediction is based on the vehicle’s current state and control input, which is assumed to be constant across the preview interval. The control input, in this case steer angle, is chosen to minimise the error between predicted and previewed paths. MacAdam’s model is a special case of model predictive control, as noted by Peng [41].

Although MacAdam’s optimisation algorithm is based on a continuous comparison between previewed road path and predicted vehicle path, the algorithm is more easily implemented in discrete form. A discrete form of the algorithm is used to form CarSim’s driver model (a commercial vehicle model produced by Mechanical Simulation Corporation, www.carsim.com). The algorithm can be simplified to take on a single point preview form if the preview points are weighted using the Dirac delta function [40]. In this form the model shows some characteristics predicted by Weir and McRuer’s crossover model [33]. In particular the open loop gain for the driver and vehicle system drops off at 20dB/decade at crossover. Weir and McRuer suggest preview times in excess of 5s in order to compensate for time lags. However, MacAdam’s comparison to vehicle data [40] had the best fit when the preview time was 1.3s. Hence there is a significant difference in the expected preview times. For MacAdam’s controller, increasing the preview time leads to the driver smoothing the vehicle response, but in the extreme this leads to the driver cutting corners. For Weir and McRuer’s model, excessive preview causes premature initiation of manoeuvres. The effect of preview time is also discussed by Tousi et al. [42]. The effect of reduced visibility is to reduce the preview distance, which can ultimately lead to control instability.

The idea that the driver can act as an optimal controller is built upon by Sharp and Valtetsiotis [43]. Control is achieved using Linear Quadratic Regulator (LQR) control
theory with inclusion of the previewed road path. The solution gives a series of preview gains that are summed together along with the vehicle state feedback to form the optimal steer angle input. The feedback controller optimises control subject to a cost function based on the vehicle path, attitude angle errors, and steer angle control input.

It is not necessary to specify a preview time or distance in Sharp and Valtetsiotis’ LQR controller because the value is inherent in the controller; road path points previewed further ahead are given progressively smaller weightings towards the overall control input. Although the LQR controller is based on a linear vehicle model, by choosing appropriate weightings in the optimisation cost function good control of non-linear vehicles can be achieved. The controller has been developed further by including saturators in the feedback loops to limit the steering angle and improve non-linear control [44].

In fact both Sharp and Valtetsiotis’, and MacAdam’s driver models apply gains to the previewed road path as well as requiring state variable feedback. As stated earlier MacAdam’s model predicts the vehicle path across the preview interval by assuming that the driver applies a constant fixed control input. However the LQR model used by Sharp does not make this assumption and the control response of the two models therefore differs.

The state variable feedback structure used by Sharp and Valtetsiotis and by MacAdam is comparable with the multi loop structure proposed by Weir and McRuer [33]. Because the state variable feedback consists of lateral position and yaw angle as well as their velocity terms the effect is to apply lead compensation to the position and angle signals. The gain weightings placed on the previewed road path represent a learnt, precognitive control action.

In precognitive control the control is open loop and based on previous experience, therefore less importance is placed on the visual feedback. Manoeuvres that are thought to be controlled in some part by precognitive control include lane change manoeuvres where rapid inputs are required with little time for feedback [5]. It is
thought that precognitive control inputs applied by the driver may be the result of an internal model or input-output relation of the vehicle dynamics [35].

Model Predictive Control (MPC) has also been used as the basis of driver models [41, 45]. It is assumed that the model used in the MPC control represents the driver’s internal model of the vehicle dynamics. Various internal model structures are possible, both linear and non-linear. However it is not clear how well these MPC structures actually represent human driving as little experimental validation is reported.

The driver models reviewed above all assume that control is achieved through instantaneous application of the desired steering angle. This is a simplification because the steering angle is generated through actuation of the arm and neuromuscular system, which in turn is coupled to the steering dynamics. The neuromuscular system has been given very little attention with reference to driver steering control. A better understanding of the interaction between steering torque and the neuromuscular system is needed to generate a predictive model of driver steering behaviour that takes account of steering torque feedback.
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1.4 NEUROMUSCULAR SYSTEM

Although very little literature can be found relating the neuromuscular dynamics to the driving task, a large amount of research has been carried out aimed at understanding the properties of the neuromuscular system with respect to controlled movement. Much of the research relates to contrived movements about a single joint where only one degree of freedom is possible. Simple neuromuscular models have been successfully applied to human control of aircraft control sticks [46, 47]. However the application of this knowledge to understanding the driving task is limited. In the following sections the components of the neuromuscular system are explained and models of their function are reviewed.

1.4.1 Mechanical properties of muscles

Muscles are the prime movers of the neuromuscular system and provide force actuation and movement about joints. Each muscle is made up of hundreds of thousands of muscle fibres. The muscle fibres are usually arranged in parallel. Each muscle is controlled by about a hundred large motor neurons whose cell bodies lie in a distinct cluster in the spinal cord; these are known as the alpha motor neurons and they are in direct control of muscle contraction. Each motor neuron is attached to between one hundred and one thousand muscle fibres. The ensemble of muscle fibres and their alpha motor neuron is called a motor unit. Activation of the alpha motor neuron causes subsequent contraction of the muscle fibres in that motor unit [48]. In this way muscles can be controlled via the spinal cord to produce force through contraction.

At a microscopic scale each muscle fibre is made up of many longitudinal elements. The longitudinal elements are made up of repeating cylinders with overlapping thick and thin filaments. These repeating cylinders are responsible for the contractile property of muscles. Under contraction the thick and thin filaments are pulled together to increase overlap through chemical reactions between cross-bridges, Figure 1.7. This is the sliding filament model proposed by Huxley [49] as cited by McMahon [50].
It is widely reported that muscles show non-linear properties. The sliding filament model gives some explanation to the consistently observed phenomenon of muscle stiffening under active contraction [51]. When the muscles are inactive the thick and thin filaments are free to slide over one another and the intrinsic stiffness of the muscle is low and due only to the inherent stiffness of the connecting tissue in the muscle. When muscle contraction is required motor units are activated and there is contraction between the thick and thin filaments preventing sliding. This contraction may cause a localised stiffening of the muscle fibres. As more and more muscle fibres are recruited and become active the muscle as a whole stiffens because the fibres lie in parallel. The stiffening is expected to occur about the muscle’s current operating length rather than about the muscle’s free length due to the sliding mechanism that exists.

Muscles can only generate force in tension. To generate positive and negative torques about joints an opposing pair of muscles is needed. The muscles in the opposing pair are known as the agonist and antagonist muscles. It is possible to co-contract opposing muscles, which increases muscle tension without producing any net torque about the respective limb joint. The co-contraction has the effect of changing the muscle’s operating point, which modulates the mechanical stiffness about the joint. Hogan [52] showed that in this way the stiffness of the joint could be increased and used for stabilisation or control. However the co-contraction has a high associated metabolic energy cost. It is plausible that the driver uses muscle co-contraction in steering control, but there appears to have been no research in this area.
1.4.2 Three-element muscle model

It has been shown by Hill [53] and Wilkie [54] that the mechanical properties of muscles can be represented by a three-element model (Figure 1.8). The model consists of two non-linear springs and a contractile force-producing element. The Parallel Elastic Component (PEC) represents the elasticity of the passive muscle and ligaments, while a Series Elastic Component (SEC) is connected to the Contractile Component (CC). The contractile component is often modelled as a force-producing element in parallel with a viscous damper [55].

Figure 1.8: Three-element muscle model showing parallel, series and contractile components.

Typical length tension properties of the muscle are shown in Figure 1.9, where $F_p$ and $F_t$ are the passive and tendon forces respectively. The force produced by the contractile component, $F_c$, is dependent on muscle length, velocity and the muscle activity, as commanded through the motor neuron. The maximum possible contractile force occurs when the muscle is at its free length (length normally occupied in the body). This can be predicted from Huxley’s sliding filament model, as this is the point of maximum cross bridge overlap. When the muscle is shorter than its free length the thin filaments interfere with each other limiting contractile force generation. At lengths beyond the free length fewer cross bridges overlap. If the muscle is in steady state tension and of constant length the conditions are said to be isometric. Under conditions of isometric contraction the total muscle force produced, $F_t$, is proportional to the firing rate of the alpha motor neuron controlling that muscle [56]. The alpha motor neuron firing rate is a measure of the muscle activation.
Figure 1.9: Typical length tension properties of the muscle under isometric contractions generated from data in Winter [57].

Although the muscle properties are clearly non-linear, experiments have shown that for small movements the non-linear stiffness and damping of muscles can be adequately approximated by linear elements. The three-element muscle model is widely used with linearised components when representing neuromuscular dynamics [46, 58, 59]. However it has also been shown that the muscle dynamics can be adequately modelled by a simple parallel spring and damper, with a mass to represent the limb inertia [51, 60].
1.4.3 Measuring muscle activity

Muscle activity and muscle co-contraction can be measured through the process of Electromyography (EMG). EMG is the process of measuring Motor Unit Action Potentials (MUAP) through placement of electrodes on the skin or by needle into the muscle. The motor unit is the smallest controllable muscle unit consisting of the alpha motor neuron, its junction and muscle fibres that it innervates. When the muscle fibre is innervated a MUAP can be measured. The myoelectric signal measured is the sum of all action potentials. The more motor units that are innervated the greater the signal. The measured signal is not usually used in its raw form but is rectified and filtered to give an envelope representing muscle activity. The rectified and filtered EMG signal has been found to be linearly proportional to the muscle’s isometric force [61]. Some work has been carried out to allow calculation of muscle force from the EMG signal irrespective of the specific type of contraction [62]. The calculation is based around a three-element muscle model. However a large number of parameters is involved, so the method is best suited to analysis of isolated muscle groups.

Paassen [46] incorporates the three-element muscle model structure in an aircraft-pilot roll control model. Linearised parameters were measured for the series and parallel elastic components as well as the damping associated with the contractile element using an active control stick. Normally movement of the arm leads to subsequent reactions and changes in muscle activation. Test subjects were asked to suppress activation of the muscle in order that the passive properties could be measured. As an aid, a measure of the EMG signal from the active muscle groups was displayed to test subjects. The test subjects were asked to minimise this measure. The process of conscious control of motor units through feedback is discussed further in [56]. Subsequently the same experiments were carried out whilst test subjects applied an offset force to the system, thereby increasing the muscle activation level. A change in muscle properties with increased muscle activation and muscle contraction was observed.

Some measurements of EMG activity of muscle groups used in the driving task have been carried out [63]. In the study no attempt was made to correlate the EMG signal with force generated, instead the activity was compared to steering wheel motion. The anterior (front) and middle portions of the deltoid muscle group were found to be
most highly correlated with steer angle. Other active muscle groups were assumed to be used to stabilise the joints in the driver’s limbs. Although it was hypothesised that pushing and pulling of the steering wheel would result in activation of the classic agonist and antagonist muscles, such as the biceps and triceps, no such relation was observed. One explanation might be that identical muscles on the left and right arms form new symmetric agonist and antagonist muscle pairs by reacting through the steering wheel. The symmetric agonist and antagonist muscle pair behaviour was also noted by Magdaleno and McRuer [64] when analysing aircraft rudder pedals.

1.4.4 Sensors and feedback control

A host of sensory information is available for limb positioning and control through reflex action [48]. Sensory information can be obtained from muscles, joints and skin. Although voluntary movement is initiated through the central nervous system, reflex action takes place at a peripheral level without further initiation from higher centres in the brain. Pathways running through the spinal cord allow communication between the peripheral and central systems. The time delay for feedback from the peripheral nervous system is much shorter than that associated with the central nervous system and therefore reflex action plays an important role in limb position control.

At a spinal level there are two main feedback paths for reflex action. One path is via the muscle spindle, which responds to muscle length and velocity. The other path is via the Golgi tendon organs, which are responsible for regulating the overall tension in the muscle.

The muscle spindle lies embedded and parallel with the muscle fibres; as such its stretch is proportional to the stretch in that muscle. The Ia afferents form a feedback path from the muscle spindle to the alpha motor neuron, in the spinal cord, of the same muscle. The Ia afferents excite the alpha motor neuron in response to stretch in the muscle spindle. This leads to an increase in the alpha motor neuron firing rate and contraction of the muscle. The muscle contraction then reduces the stretch in that muscle and the whole process is known as the stretch reflex. The reflex action is also known to reduce muscle activity in the antagonist muscle, which aids feedback control.
The length of the muscle spindle can be controlled through the gamma motor neuron. The spindle length determines the set point at which reflex action is initiated. The gamma motor neuron signal comes from higher centres within the Central Nervous System (CNS). It is widely accepted that the muscle spindle acts like a position servo controller [65] Figure 1.10.

There is strong evidence that the CNS sends alpha motor neurons commands simultaneously with the gamma motor neurons during voluntary movements [48]. Without this simultaneous activation of alpha and gamma pathways the reflex action, through the muscle spindle, would act to inhibit any voluntary contraction of the muscles initiated through the alpha motor neurons. During movement, if the estimate of the required force is correct, control is in effect open loop as there is no error for the muscle spindles to correct. Hence both servo position control and open loop force control are possible.

The Golgi tendon organ is essentially a force sensor that acts to inhibit the agonist muscle but excites the antagonist when under tension. Conversely the spindle is sensitive to changes in length and velocity, exciting the agonist muscle and inhibiting the antagonist when stretched. It is thought that the Golgi tendon organs and their feedback act as a force limiting sensor to prevent damage to muscles under excess tension [65]. However the organs could also play a more active role in muscle force regulation.
1.4.5 Models of the neuromuscular system

Research by Magdaleno and McRuer [64] using aircraft control stick manipulators has shown that the measured frequency response of the combined limb and manipulator can be represented by third order dynamics. When the dynamics of the manipulator are considered, the measured response can be shown to be consistent with the three-element muscle model described in section 1.3.2. Measurements were made during compensatory tracking tasks and estimates for the closed-loop neuromuscular system dynamics were made. However, the frequency response measured is only valid for a small region about an operating point because the muscle dynamics change with length, tension and velocity. Although the linearised dynamics represent the small movements involved in controlling an aircraft control stick, the degree to which the neuromuscular system involved in the vehicle steering task can be linearised is not known.

Magdaleno and McRuer [64] show that the Golgi tendon and spindle feedback can be combined as one reflex feedback path providing lead compensation. The feedback is at a spinal level so the time delay is small and cited as 0.025s (other authors quote larger delays of 0.04s [66] and 0.05s [51]). Additionally feedback of joint angle and position can be received centrally through other proprioceptive and visual stimuli. However the time delays for this central feedback are much greater. The control structure for Magdaleno and McRuer’s neuromuscular model is shown in Figure 1.11.

Models of the neuromuscular system dynamics similar to those identified by Magdaleno and McRuer [64] have been incorporated into models of driver steering control [7, 10]. Other authors have simply approximated the neuromuscular subsystem as either a pure time delay or lag term [67, 68]. In the few examples cited, where neuromuscular dynamics are included, the parameters used are based on those obtained for aircraft pilots controlling side sticks. A review of published literature has found no measurements of the neuromuscular dynamics specific to steering control.
In terms of the driving task, the driver not only has visual feedback of the road path and current steer angle, but also has reflex feedback through the neuromuscular system. The adaptive properties of the neuromuscular system allow adaptation of these feedback paths. Because the reflex pathways in the neuromuscular system are much faster than the response to visual stimulus it is likely that they play a significant role in driver steering control.
1.4.6 Neuromuscular control strategy

In the field of Neurophysiology, much debate arises as to whether limb control is closed loop or open loop. The same question can be asked of the driving task; either the driver previews the road ahead, then generates appropriate neural responses based on an internal model of the system, or the control is purely feedback where the driver responds directly to perceived path errors.

Open loop control requires the human operator to have some kind of internal model or input output relationship of the system being controlled [65]. The operator can then use the inverse of the internal model to establish the control commands necessary to generate the desired system output; the control commands being muscle force (alpha motor neuron command) and expected muscle length (gamma motor neuron command). The internal model is based on past experience and pre-learnt models. As open loop control is based on an internal model it does not explain the human’s ability to perform new tasks, not previously experienced, or offer an explanation to robustness of the system to disturbances.

An alternative strategy is to rely on the visco-elasticity properties, regulated through co-contraction and reflex action, to form a feedback controller. The CNS then specifies a series of points along the required trajectory. The points on the trajectory are specified as a gamma motor neuron command. Feedback control is achieved at a peripheral level by passing messages to and from the spinal cord where the time delay is smaller.

Osu et al. [69] give results that indicate both internal model and feedback control might occur. At the early stages of learning a specified movement a high degree of muscle co-contraction is observed. The co-contraction and associated increase in joint stiffness helps to compensate and reject unknown disturbance forces that may be encountered during the movement, although there is a high metabolic energy cost. As the task becomes familiar, the degree of co-contraction is reduced. The phenomenon is also discussed by Kandel [48] and it is widely thought that co-contraction of antagonist and agonist muscles is a characteristic of unskilled movements, that is, it is observed when people first learn a new motor skill. The degree of muscle co-
contraction during the driving task may provide information on the driver’s control strategy.
1.5 RESEARCH OBJECTIVES

The findings from the literature review into driver-vehicle interaction can be summarised as follows:

- **Active steering:**
  Advances in electric power steering allow active steering, where the EPS motor provides additional torque to control the vehicle dynamics. Some research has been carried out to investigate such controllers. It is clear that without a full understanding of the way the driver responds to steering torque feedback the full benefit of active steering is unlikely to be achieved.

- **Steering dynamics:**
  The dynamics of the mechanical steering system are widely understood. However there seems to be little if any research looking at the interaction between the steering and neuromuscular systems with respect to the driving process.

- **Driver modelling:**
  The first driver models proposed by Weir and McRuer [33], based on the crossover model of manual control, represent some aspects of driver behaviour. The models have been developed further to cover road preview and model the path following capabilities of drivers. However all these models assume the driver control input is steer angle. To understand the way the driver responds to varying torque feedback it is necessary to model the way the driver controls the steering dynamics and include the neuromuscular system.

- **Neuromuscular dynamics:**
  A wide range of research has been carried out relating to the neuromuscular system. Although little of the research is specific to the driver steering task the principles and results obtained provide an insight into the likely control strategies employed by drivers.
Chapter 1: Introduction

The literature review highlights a need to better understand steering torque feedback in the driver-vehicle system and in particular identify the role of the neuromuscular system with respect to driver steering control. Based on the findings of the literature review the following research objectives have been identified to meet this need:

- As driving requires closed loop control, both the vehicle and human driver should be considered when evaluating vehicle performance. Therefore an objective of this work is to set up a driving simulator to allow human in the loop testing.

- The literature review reveals that no measurements of the neuromuscular system dynamics have been made with reference to the driving task. Hence an objective of this work is to measure the properties of the neuromuscular system for inclusion in a model of driver steering control.

- In order that the role of the neuromuscular dynamics in the driver steering task can be better understood the key muscles involved in driver steering control must be identified. Muscle co-contraction may play an important role in driver steering control. Once the muscles involved in driver steering control have been identified it can be established if the driver uses co-contraction as a control strategy.

- The literature review highlights several possible strategies for control of the neuromuscular system. By measuring the neuromuscular system performance during typical driving manoeuvres it may be possible to identify the control strategies used by drivers.

- New developments like EPS and steer-by-wire allow additional freedom over the torque-angle relationship at the steering wheel. To allow these new technologies to be evaluated early in the design process, predictive models of steering control are needed. Hence an objective of this research is to develop a predictive model of driver steering control that takes account of steering torque feedback.

Chapter 2 of this dissertation describes the development of a lab based driving simulator with variable steering torque feedback for human in the loop testing. EMG
testing equipment was developed and has been used to measure the key muscles involved in driver steering control (Chapter 3). Chapter 4 reports measurements made of the neuromuscular system dynamics with respect to the driver steering task. In Chapter 5 driver performance during a double lane change manoeuvre is reported as measured using the newly developed driving simulator. In Chapter 6 methods of modelling driver steering performance are reported and a model of driver steering control is developed that incorporates the neuromuscular dynamics. Chapter 7 gives conclusions and recommendations for future research.
Chapter 2: Driving Simulator and Hardware

2.1 INTRODUCTION

As a tool for investigating the properties of the driver’s neuromuscular system a driving simulator was developed. The simulator consists of a virtual reality display giving a projected image of the road path, torque feedback steering wheel with integral sensors, multi-axis column mounted load cell and vehicle model running in real-time. The components of the simulator are shown schematically in Figure 2.1.

The Electric Power Steering (EPS) hardware, provided by TRW Conekt, provides steer angle and driver torque measurements. These are sent to the vehicle model using a Controller Area Network (CAN) bus. The vehicle model returns a torque demand signal to the EPS hardware to simulate steering feel.
The simulator makes extensive use of Matlab and its toolboxes: Simulink, Real-Time Workshop, xPC Target and Virtual Reality. The vehicle model has been implemented using Simulink. Using the Real-Time Workshop toolbox, the model can be downloaded and compiled in C-code on the xPC Target machine. xPC allows the vehicle model to run in real time from the compiled C-code. Because the target xPC machine is dedicated to running the vehicle model alone and no operating system is required, highly efficient simulations can be made. CAN messages from the EPS hardware are also processed, sent and received by the target computer. Data is logged to the xPC target computer’s memory. The xPC target computer is also capable of logging additional data, for example measurements from the load cell and the outputs from the electromyography (EMG) instrumentation described in Chapter 3.

Co-ordinates for the vehicle position and heading angle are generated on the xPC target computer by the vehicle model. The information is then sent to the host computer, as a TCP/IP message. The host computer generates the vehicle and road path display for projection to the human test subject using the Virtual Reality toolbox.

In this chapter the components of the simulator are described in detail. Section 2.2 describes the EPS hardware and EPS sensor calibration. In Section 2.3 experiments used to identify a model and parameters for the EPS hardware are described. Section 2.4 gives details of the multi-axis load cell and its uses. Section 2.5 describes the vehicle model and section 2.6 gives information on the Virtual Reality display used to project the road path to the driver.
2.2 ELECTRIC POWER STEERING HARDWARE

A modified EPS unit from a small passenger car is used to provide steering torque feedback in the simulator. The unit was provided by TRW Conekt. The torque assist loops, self-centring and vehicle speed maps have been removed from the unit’s ECU, as the details of these are commercially sensitive. The EPS ECU has been reprogrammed, by the manufacturers, to accept torque demand signals and return column angle, velocity and torque sensor signals over a CAN bus. A schematic of the EPS hardware, sensors and controllers is shown in Figure 2.2.

![Figure 2.2: EPS hardware photo and schematic of controllers, signals and sensors. $T_{dem}$ is the demand torque and $T_{mot}$ is the torque generated in motor windings.](image)

The sensor resolutions, as measured from signals transmitted over the CAN bus, are given in Table 2.1.
A motor controller, running at 2 kHz, controls the motor current such that the demand torque is met. This controller has a bandwidth in excess of 500Hz. The remaining sensors operate with the CAN bus at 420Hz. Experiments were carried out to assess the performance of the EPS hardware. The linearity and frequency response of the sensors and the overall system were measured. Results are discussed in the following sections.

2.2.1 Sensor calibration

An inclinometer that measures angles to +/- 0.1deg was used to confirm the calibration of the EPS hardware’s angle sensor. The EPS hardware was mounted so that the steering wheel axis of rotation was in a horizontal plane and the inclinometer was rigidly mounted to the centre of the steering wheel. The steering wheel was rotated through a series of discrete positions, whilst the inclinometer and steer angle sensor readings were logged and compared. The results show good linearity (Figure 2.3).
Once the angle sensor measurements had been confirmed, the angle signal was differentiated and used to confirm the velocity signal scaling. This was also found to be scaled correctly.

Torques were applied to the steering column using a lever arm arrangement and hanging weights to the arm. An angle control loop was used around the EPS unit to ensure that the lever arm remained parallel to the ground. Measurements were taken during loading and unloading of the steering column (Figure 2.4). A best-fit linear regression line was used to fit the measured data points. To correct for the non-unity gradient, the torque sensor signal was subsequently scaled by a factor of $1/1.089$. The small amount of hysteresis (roughly 0.02Nm) in the loading and unloading curves indicates some friction, but its value is negligible.

Figure 2.3: Calibration of EPS hardware angle sensor. (Positive column angle refers to clockwise rotation of the steering wheel.)
Figure 2.4: Calibration of the torque sensor on loading and unloading. Best fit regression line: $y = 1.089x$. (Positive torques measured by the torque sensor act to turn the steering wheel clockwise.)

The column torque sensor has mechanical end stops limiting relative rotation, between steering wheel and steering column, to +/-1.5deg. The end stops govern the saturation point of the sensor. The torque sensor stiffness can be calculated from the measured torque at saturation (+/-7.35Nm) and the angular rotation. Using these values of torque and angular rotation, the sensor stiffness, $K_{sen}$, was calculated to be 281Nm/rad (4.9 Nm/deg).

The motor controller was calibrated for steady state operation using the newly calibrated torque sensor. A slowly varying ramped torque demand signal was sent to the EPS unit with the steering wheel clamped rigidly. The resulting calibration and regression lines are shown in Figure 2.5. The motor demand torque signal was subsequently scaled by a factor of 1/1.37 to give unity gain. The hysteresis in Figure 2.5 indicates the presence of coulomb friction of up to 0.9Nm between the torque sensor and motor. The most likely source of the friction is a helical worm gear and wheel that couples the EPS motor to the steering column.
Figure 2.5: Motor controller calibration with clamped steering column. The negative gradient arises because the torque sensor is designed to measure the torque applied by the driver to the steering wheel rather than the torque applied by the motor to the steering wheel. Positive torque demands, applied by the motor, act to turn the steering column clockwise.
Chapter 2: Driving Simulator and Hardware

2.3 FREQUENCY RESPONSE TESTING OF THE EPS HARDWARE

To ensure stability of the control loops used with the EPS hardware an understanding of the dynamic properties of the hardware is needed. Additionally, if the EPS hardware is used to identify the driver’s neuromuscular system, the dynamics of the EPS hardware must be known in order that the two can be distinguished from one another. The stiffness of the torque sensor and friction in the motor were identified as 281Nm/rad and 0.9Nm respectively as described in section 2.2. This section describes frequency response testing that was carried out to establish the remaining mechanical properties and dynamic response of the EPS unit.

2.3.1 Method and test signal

Frequency response testing was carried out using a pseudo-random binary sequence (PRBS) as the excitation signal. The PRBS signal was sent to the EPS unit as a torque demand. A PRBS signal consists of a random sequence of logic levels, 0 or 1, and can be generated using shift registers [70]. An n-bit PRBS repeats every $2^n-1$ bits, but within the sequence each string of n-bits is unique. Hence the properties of a PRBS signal are similar to those of band-limited white noise. However, white noise has normally distributed amplitude about zero mean, but the PRBS signal has only two levels, 0 or 1. By scaling the logic levels, 0 and 1, the peak amplitude variation in the PRBS signal can be chosen to prevent saturation of the test equipment. In contrast, the peak amplitude for white noise is unlimited.

A 13-bit PRBS with time interval 0.01s was chosen as the excitation signal. The PRBS signal was filtered at 50Hz using a fourth order Butterworth filter to prevent high frequency torque demands being introduced to the EPS hardware. The PRBS signal chosen allows signals as low as 0.015Hz to be generated. Because the PRBS signal is noise like and random the low frequency components do not induce large steering column velocities in the unrestrained steering column. Large velocities should be avoided as they can cause the motor to exceed its speed breakpoint, which creates non-linearity in the system.

Data was collected from the torque sensor and column velocity sensors in response to the PRBS excitation in order that the EPS hardware dynamics could be identified. The
PRBS excitation was repeated four times, the first of the four repeats was discarded as it contains transients relating to the initial conditions. The remaining three repeats of data were ensemble averaged. The data was then windowed, using a Hanning window, and a discrete Fourier transform method was used to generate the auto and cross-spectral estimates. The frequency response was generated using the cross spectral method [71] with every three adjacent spectral estimates averaged.

Various PRBS excitation amplitudes were used. However it was found that the data showed best coherence when the amplitude was +/-6Nm. At this amplitude the signal gave the best signal to noise ratio without causing non-linearity due to saturation of the torque sensor.

2.3.2 Parameter identification and results

Model fits were generated to match the measured frequency responses. The measured frequency response was compared to the model frequency response with the aim of minimising the phasor error function given by equation 2.1. A similar system identification approach was subsequently found to have been used previously by Allison and Sharp [72].

$$\varepsilon = \frac{1}{N} \sum_{\omega} \frac{\text{Re}(H_{\exp}(\omega) - H_{\mod}(\omega))^2 + \text{Im}(H_{\exp}(\omega) - H_{\mod}(\omega))^2}{\text{Re}(H_{\exp}(\omega))^2 + \text{Im}(H_{\exp}(\omega))^2}$$  \hspace{1cm} (2.1)

- $H_{\exp}(\omega)$ - Experimentally measured frequency response
- $H_{\mod}(\omega)$ - Model frequency response
- $N$ - Number of data points

Model parameters were varied until equation 2.1 was minimised. The minimisation was carried out using Matlab’s ‘fminsearch’ function. The function carries out multidimensional unconstrained nonlinear minimization using the simplex method (Nelder and Mead [73]).

When using the simplex method, there is a danger that any identified minimum may only be a local minimum of the function to be minimised. To ensure that a global
minimum was identified various initial search points were tried and the search routine was repeated until the global minimum was found.

2.3.3 Frequency response of EPS hardware

The measured frequency response between torque demand and steering column velocity is shown in Figure 2.6. The primary response is first order indicated by the break frequency of around 0.5Hz followed by a roll-off in magnitude of 20dB/decade. A first order response can be expected if the motor and steering column are modelled as a single rigid body rotating with some viscous damping (1DOF model). A simple first order model was fitted to the measured frequency response (equation 2.2). The denominator term in $s^1$ is the equivalent column inertia, while the term in $s^0$ represents the column damping. The first order model does not take account of the resonance and anti-resonance that occur at around 18Hz.

$$1\text{ DOF model:} \quad \frac{\hat{\theta}_{\text{col}}}{T_{\text{dem}}} = \frac{1}{0.122s + 0.41} \quad (2.2)$$

To take account of the 18Hz resonance a higher order model is needed. A linear transfer function was fitted to the measured frequency response with polynomials in $s^2$ in the numerator and $s^3$ in the denominator. A pure time delay was also included. Parameters were initially fitted by hand to give a rough approximation. The method involved fitting a first order transfer function with break frequency of 0.5Hz, then adding second order terms to the numerator and denominator to create the feature at roughly 18Hz. Finally a pure time delay was added to give appropriate phase lag. The parameters obtained by the rough approximation were subsequently used as the start point for the minimisation routine described in section 2.3.2. The resulting transfer function that gave the best fit to the measured data is given by equation 2.3 and is shown in Figure 2.6. Equation 2.3 gives an excellent fit to the measured data with phasor error, $\epsilon=0.0368$.

$$2\text{ DOF model:} \quad \frac{\hat{\theta}_{\text{col}}}{T_{\text{dem}}} = \frac{12.2s^2 + 90.7s + 1.548 \times 10^5}{1.09s^3 + 37.8s^2 + 1.79 \times 10^4s + 6.30 \times 10^4} e^{-0.01s} \quad (2.3)$$

Although the transfer function given by equation 2.3 gives an excellent fit to the data at the current operating point, if the excitation amplitude changes so does the measured frequency response. To take account of this non-linearity in the EPS hardware (thought to be due to the friction in the steering column) and also generate a
model with physical significance, a mechanical model of the EPS system was generated.

![Frequency response and coherence between torque demand and steering column velocity measured using a PRBS input signal. A linear transfer function, fitted to the frequency response, is also shown.](image)

Figure 2.6: Frequency response and coherence between torque demand and steering column velocity measured using a PRBS input signal. A linear transfer function, fitted to the frequency response, is also shown.

2.3.4 Mechanical model of EPS hardware

A mechanical model was set up in Simulink of the EPS hardware that included coulomb friction. The transfer function identified and given by equation 2.3 is consistent with a system with two degrees of freedom. The model, Figure 2.7, has two damped inertial loads (geared motor and steering wheel) coupled by a spring (the torque sensor) giving two degrees of freedom and is represented by equations 2.4 & 2.5. The coulomb friction is modelled to be on the motor side of the torque sensor. Friction in the steering wheel bearings was found to be negligible in section 2.2.1. The outputs of the model (column angle, column velocity and steering torque) are delayed by 0.01s to represent sensor time delays associated with the signals in the EPS hardware.
The frequency response from torque demand to column velocity, measured under +/- 6Nm PRBS excitation, was used as the basis of the parameter identification procedure. This data was chosen as it showed the best coherence. Values for the torque sensor stiffness, $K_{sen}$, and motor friction, $F_{mot}$, were taken from the static calibration results to simplify the identification task. The motor torque scaled by the gear ratio, $n_{gb}T_{mot}$, can be assumed to be equal to the torque demand, $T_{dem}$, for the frequency range of interest due to the high bandwidth motor controller.

Several runs of the minimisation routine were carried out with different start points to ensure a global minimum was obtained. After successive runs there was little variation in identified parameters or the error function value, $\varepsilon$. The only significant variation was seen in the damping values $B_{sw}$, $B_{mot}$ and $B_{sen}$ indicating some uncertainty in their values. The parameters found to minimise the error function (equation 2.1) are given in Table 2.2.
Table 2.2: Identified parameters for EPS model. Model fit was carried out to minimise phasor error between measured and model steering column velocity data using +/-6Nm PRBS.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Steering wheel inertia</td>
<td>$J_{sw}$</td>
<td>0.0207</td>
</tr>
<tr>
<td>Steering wheel damping</td>
<td>$B_{sw}$</td>
<td>$2.7 \times 10^{-5}$</td>
</tr>
<tr>
<td>Motor and gear inertia</td>
<td>$J_{mot}$</td>
<td>$3.72 \times 10^{-4}$</td>
</tr>
<tr>
<td>Motor and gear damping</td>
<td>$B_{mot}$</td>
<td>$1.5 \times 10^{-5}$</td>
</tr>
<tr>
<td>Torque sensor stiffness</td>
<td>$K_{sen}$</td>
<td>281 (fixed)</td>
</tr>
<tr>
<td>Torque sensor damping</td>
<td>$B_{sen}$</td>
<td>0.22</td>
</tr>
<tr>
<td>Motor coulomb friction</td>
<td>$F_{motn_{gb}}$</td>
<td>0.9 (fixed)</td>
</tr>
<tr>
<td>Motor gearbox ratio</td>
<td>$n_{gb}$</td>
<td>16.5 (fixed)</td>
</tr>
<tr>
<td>Sensor time delay</td>
<td>$\tau$</td>
<td>0.01 (fixed)</td>
</tr>
</tbody>
</table>

The model fit to measured steering velocity is shown in Figure 2.8. The model not only shows good agreement with the measured column velocity, but also with column torque shown in Figure 2.9. At approximately 18Hz a resonance can be seen between the steering wheel and lower column, due to the inherent compliance in the torque sensor. At resonance there is some discrepancy between the experimental and model data. The discrepancy could arise because the torque sensor damping is modelled as viscous. In reality the damping may be due to structural hysteresis in the torque sensor.

The non-linear model fit shown in Figure 2.8 shows some additional discrepancies when compared to the linear model fit in Figure 2.6. This is to be expected as only five parameters were allowed to vary in the non-linear model identification compared to eight parameters for the linear model.
Chapter 2: Driving Simulator and Hardware

Figure 2.8: Model fit to measured steering column velocity with +/-6Nm PRBS excitation.

Figure 2.9: Model fit to measured steering column torque with +/-6Nm PRBS excitation.
The EPS model, with parameters given in Table 2.2, also shows good agreement to the experimental data when the input excitation amplitude is reduced from +/-6Nm to +/-3Nm, although the data has more noise (Figure 2.10).

![Graph of Frequency response between torque demand and steering column velocity.](image)

**Figure 2.10:** Model fit to experimental data with +/-3Nm PRBS excitation.

Having successfully measured and modelled the EPS dynamics, the EPS hardware can be used with confidence as a tool to identify the driver’s dynamics. Identification of the driver dynamics using the EPS hardware is discussed in Chapter 4.
2.4 STEERING COLUMN LOAD CELL

A six-axis load cell that mounts to the steering column has been manufactured within Cambridge University Engineering Department¹ (CUED) (Figure 2.11). The load cell was primarily developed to increase the measurable range of steering torque beyond the nominal +/-8Nm provided by the EPS unit’s integral column torque sensor. However, measuring forces and torques about all six axes allows the individual forces generated by the left and right arms to be estimated. In this section the calibration of the load cell is described along with the method for estimating the individual hand forces applied by each arm.

The load cell is a thin walled “top hat” design with six pairs of strain gauges mounted around its circumference. The six pairs of gauges allow measurement of forces and torques in three orthogonal directions. The load cell output is amplified using an op-amp with gain of 1000. Anti-aliasing filtering was carried out on all six channels measured from the load cell before logging using a second order Butterworth filter with cut off frequency of 80Hz. The filter has a gain of 1.6, which is corrected for in software by post processing the data.

¹ Designed by Dr D J Cole
2.4.1 Load cell calibration

A series of experiments was required to calibrate the load cell. The experiments involved applying forces and torques to the load cell in six unique configurations in order that the calibration matrix could be calculated (Table 2.3). The loading configurations were generated by mounting the load cell in various orientations and hanging weights either directly to the unit or from a lever arm. Loading was limited to 150N for direct forces and 20Nm for moments. The datum for the calibration was chosen as the centre of the mating face between the load cell and steering wheel Figure 2.12.

![Diagram of Load Cell and Orthogonal Axes System](image)

Figure 2.12: Load cell and orthogonal axes system.

Table 2.3: Loading configurations for load cell calibration. x denotes loaded axis in test configuration.

<table>
<thead>
<tr>
<th>Configuration</th>
<th>$F_x$</th>
<th>$F_y$</th>
<th>$F_z$</th>
<th>$M_x$</th>
<th>$M_y$</th>
<th>$M_z$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Config. 1</td>
<td></td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Config. 2</td>
<td>x</td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Config. 3</td>
<td></td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Config. 4</td>
<td>x</td>
<td></td>
<td></td>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Config. 5</td>
<td></td>
<td></td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Config. 6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>
The results from the six loading configurations were combined into a single matrix in order that the calibration matrix $[X]$ could be calculated. Equation 2.6 is over determined, but can be solved to give the least squares best fit to $[X]$. The identified calibration matrix, $[X]$, is appended (section A.1).

$$
[V_1 \ V_2 \ V_3 \ V_4 \ V_5 \ V_6][X] = [F_x \ F_y \ F_z \ M_x \ M_y \ M_z]
$$

where: $[X]$ – six by six calibration matrix
$V_i$ – array containing the voltage output from strain gauge $i$
$F_{x,y,z}$ – array containing forces applied to the load cell in $x,y,z$ directions
$M_{x,y,z}$ – array containing moments applied to the load cell in $x,y,z$ directions

The success of the calibration can be seen in Figure 2.13. The forces and torques applied under all loading configurations are plotted alongside the forces and torques measured from the calibrated load cell. If the calibration is successful all the plotted points should fall on the dotted line shown ($y=x$). It can be seen that there is excellent agreement between the applied torques and forces, and those that were measured by the calibrated load cell.
Figure 2.13: Load cell calibration results showing forces and torques applied to the load cell and measured forces and torques output from the calibrated load cell. The axis datum was taken as the steering wheel mounting face on the load cell and the axes directions are shown in Figure 2.12.
2.4.2 Load cell inertia

The load cell adds additional inertia to the steering column. This additional inertia was not considered in the frequency response testing described in section 2.3 because the load cell was not fitted. Based on the dimensions of the load cell, the inertia was calculated as \( J_{lc} = 0.051 \text{kgm}^2 \) including the cover. For dynamic calculations it should be noted that the inertia of the load cell on the steering wheel side of the strain gauges is 0.03kgm\(^2\), while the inertia on the column side is 0.021 kgm\(^2\).

2.4.3 Calculating forces applied by drivers arms

The calibrated load cell can be used to estimate the axial and tangential forces applied individually by the driver’s left and right arms to the steering wheel (Equations 2.7-2.8) as shown in Figure 2.14. In this way the degree to which each arm contributes to the overall steering torque can be estimated. (Hand forces \( F_{xl} \) and \( F_{xr} \) cannot be determined individually because both forces fall along the same line of action.)

![Figure 2.14: Steering hub, co-ordinate system, and hand forces.](image)

\[
F_{yr} = \frac{1}{2}(F_y - \frac{M_z}{r_{sw}}) \quad F_{yl} = \frac{1}{2}(F_y + \frac{M_z}{r_{sw}}) \tag{2.7}
\]

\[
F_{yr} = \frac{1}{2}(F_z + \frac{M_y}{r_{sw}}) \quad F_{yl} = \frac{1}{2}(F_z - \frac{M_y}{r_{sw}}) \tag{2.8}
\]
In equations 2.7 and 2.8 it is assumed that at the point of contact, where the hand meets the steering wheel, no torque is applied. This assumption is necessary to ensure that the problem is statically determinate. When only one hand is on the steering wheel the steering forces and torques applied by that hand are fully determinate. In the fully determinate case (only the right hand), the axial and tangential steering forces were measured. The measurements were compared with estimates of the axial tangential hand forces calculated using equations (2.7 and 2.8). The estimated steering forces and measured steering forces are shown in Figure 2.15 whilst a test subject was asked to apply a ramped steering torque to a fixed steering wheel. There is good agreement between the estimated steering forces and measured steering forces, although small errors arise suggesting that small torques are applied at the point of contact between the hand and the steering wheel. The tangential hand force estimate is of primary interest because it generates steering torque and the estimate shows excellent agreement with the measured value.

Figure 2.15: Comparison between estimated hand force, calculated using equations 2.7 and 2.8, and measured hand force for the statically determinate case with only the right hand on the steering wheel.
Figure 2.15 shows that significant axial hand forces were generated despite the fact that the test subject was only consciously applying a ramped steering torque. One explanation might be that as the axial force is normal to the steering wheel it generates friction used to prevent the hands slipping whilst steering torques are applied. The relationship between axial forces and steering torques has been investigated further in conjunction with measurements of muscle activity using electromyography (EMG) instrumentation. The results are discussed in Chapter 3.
2.5 VEHICLE MODEL

A simple two degree of freedom yaw/side slip vehicle model was used in the simulator. Although initially more complex models were generated with roll dynamics and non-linear tyre models [74] it was later decided that the linear yaw/side slip model was sufficient. Additionally, by using a simple vehicle model the driver’s control strategy may be more easily extracted.

2.5.1 Yaw/side slip vehicle model

The two degree of freedom yaw/side slip model is often called the bicycle model because it is assumed that the four vehicle tyres can be represented as two combined front and rear tyres. It is convenient to use a vehicle fixed co-ordinate system see Figure 2.16.

![Figure 2.16: Yaw/side slip vehicle model.](image)

The tyres are modelled as linear gains with force proportional to tyre slip angle ($\alpha_f$ and $\alpha_r$):

\[
F_{yf} = C_f \alpha_f \quad (2.9) \quad \text{where: } \alpha_f = \frac{v_y + a \omega}{v_x} - \delta \quad (2.10)
\]

\[
F_{yr} = C r \alpha_r \quad (2.11) \quad \text{where: } \alpha_r = \frac{v_y - b \omega}{v_x} \quad (2.12)
\]

Figure 2.17 shows the relationship between the ground fixed vehicle position, heading angle (integral of yaw rate, $\omega$) and vehicle fixed reference frame.
In order to generate the equations of motion for the vehicle the absolute acceleration of the vehicle is required, referenced to the vehicle fixed axes system. The absolute velocity is given by equation 2.13.

\[
\dot{\mathbf{R}} = v_x \mathbf{i} + v_y \mathbf{j} \tag{2.13}
\]

Differentiating equation 2.13 with respect to time and taking account of the rotating axis system gives absolute acceleration (equation 2.15).

\[
\ddot{\mathbf{R}} = \dot{v}_x \mathbf{i} + \dot{v}_y \mathbf{j} + \ddot{v}_x \mathbf{i} + \ddot{v}_y \mathbf{j} \tag{2.14}
\]

where: \( \frac{d\mathbf{i}}{dt} = \omega_k \Lambda \mathbf{i} = \omega \mathbf{j} \) and \( \frac{d\mathbf{j}}{dt} = \omega_k \Lambda \mathbf{j} = -\omega \mathbf{i} \)

\[
\ddot{\mathbf{R}} = (\dot{v}_x - v_x \omega) \mathbf{i} + (\dot{v}_y + v_y \omega) \mathbf{j} \tag{2.15}
\]

The vehicle velocity can be evaluated in directions along the ground fixed axis using equations 2.16 and 2.17.

\[
\dot{x} = v_x \cos \psi - v_y \sin \psi \tag{2.16}
\]

\[
\dot{y} = v_x \sin \psi + v_y \cos \psi \tag{2.17}
\]
In the vehicle simulator the vehicle trajectory \((x,y)\), in the ground fixed axis system, is calculated by integrating equations 2.16 and 2.17.

To linearise the equations of motion, it is assumed that \(v_x\) is constant and that angles are small. The tyre forces (equations 2.9-2.12) are then resolved with the absolute acceleration in the \(j\) direction and moments are taken about the centre of mass giving the vehicle model equations of motion (equation 2.18). Parameters for the vehicle model are given in Table 2.4.

\[
\begin{bmatrix}
\dot{v}_y \\
\dot{\omega} \\
\dot{\psi} \\
\end{bmatrix} = 
\begin{bmatrix}
\frac{(C_f + C_r)}{v_x m} & \frac{(a C_f - b C_r)}{v_x m} - v_x & 0 & 0 \\
\frac{v_x m}{(a C_r - b C_f)} & \frac{v_x m}{(a^2 C_f + b^2 C_r)} & 0 & 0 \\
\frac{v_x I_{zz}}{1} & \frac{v_x I_{zz}}{1} & 0 & 0 \\
0 & 1 & 0 & 0 \\
\end{bmatrix}
\begin{bmatrix}
v_y \\
\omega \\
\psi \\
\end{bmatrix} + 
\begin{bmatrix}
-\frac{C_f}{m n_{rsw}} \\
-\frac{a C_f}{I_{zz} n_{rsw}} \\
0 \\
0 \\
\end{bmatrix}
\theta_{sw}
\tag{2.18}
\]

where: \(\theta_{sw}\) – Steering wheel angle \((\theta_{sw} = n_{rsw} \delta)\)

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Name</th>
<th>Value</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>(I_{zz})</td>
<td>Yaw inertia</td>
<td>2550</td>
<td>kgm(^2)</td>
</tr>
<tr>
<td>(M)</td>
<td>Vehicle mass</td>
<td>1673</td>
<td>kg</td>
</tr>
<tr>
<td>(b)</td>
<td>Distance from centre of mass to rear axle</td>
<td>1.73</td>
<td>m</td>
</tr>
<tr>
<td>(a)</td>
<td>Distance from centre of mass to rear axle</td>
<td>0.913</td>
<td>m</td>
</tr>
<tr>
<td>(C_f)</td>
<td>Front axle cornering stiffness</td>
<td>-2*88310</td>
<td>N/rad</td>
</tr>
<tr>
<td>(C_r)</td>
<td>Rear axle cornering stiffness</td>
<td>-2*64076</td>
<td>N/rad</td>
</tr>
<tr>
<td>(n_{rsw})</td>
<td>Road wheel to steering wheel gear ratio</td>
<td>16</td>
<td></td>
</tr>
</tbody>
</table>
2.5.2 Generating steering feel

Realistic steering feel can be generated in response to the driver’s input by sending appropriate torque demand signals to the EPS motor. The torque demand signal is generated as a function of the steering column angular velocity, steering wheel angle and front tyre slip angle (equation 2.10), Figure 2.18. The steer angle gain $K_e$ generates self-centring feel equivalent to that generated by king pin inclination. The steer velocity gain $B_e$ adds additional damping to the system. $G_\alpha$ generates torque feedback proportional to tyre slip angle, which arises from castor offset and tyre aligning moments in the true vehicle. Suitable values for the parameters shown in Figure 2.18 can be calculated using equation 1.6 and published parameters, for example those given by Genta [16].

![Figure 2.18: Signals used to generate steering torque feedback.](image-url)
2.6 VIRTUAL REALITY DISPLAY

Matlab’s Virtual Reality toolbox was used to generate the visual display of the road path to the driver. The graphical display was generated by using repeated JPEG and GIF images to form the road path and surrounding scenery, Figure 2.19. By using a ceiling mounted projector the image was displayed on a screen positioned 2.5m in front of the driver giving a projected screen size of 2.4m by 1.8m. A screen resolution of 1024x768 pixels was used.

A high performance graphics card was used and a resulting frame rate of 50Hz was achieved, giving an associated time delay of around 20-40ms between frame updates. The transport delay associated with TCP/IP data communication between the host and target PC was found to be negligibly small. A delay of one or two samples, at the xPC Target computer clock speed (1kHz), was measured. The overall time delay of the simulator was not found to cause problems and is comparable with the delays reported in commercial simulators of around 60ms [75, 76].

Figure 2.19: Simulator graphical display showing lane change generated from repeated JPEG and GIF images.
2.7 CONCLUSIONS

This chapter describes the components of a driving simulator that has been developed to allow the role of the driver’s neuromuscular system in the vehicle steering task to be investigated. The subsequent chapters give results measured using the hardware described here.

Although the EPS hardware was a production unit, its use here in generating steering torque feedback is novel and has warranted careful calibration and measurements of its sensors and performance. In Chapter 4, the steering hardware is used in isolation from the simulator. By applying torques through the motor with the driver’s arms on the steering wheel, the EPS unit can be used as a dynamic shaker to excite the driver’s arm dynamics. With the EPS unit used in this way the mechanical properties of the EPS unit, identified in this chapter, are needed in order that the mechanical properties of the driver’s arms can be separately identified.

The steering column load cell allows measurements of the steering forces and estimation of the forces generated by each of the driver’s arms individually. A review of published literature has revealed that no measurements of this type have previously been made. Extensive use of the load cell was made throughout the experiments described in later chapters.
Chapter 3: Electromyography

3.1 INTRODUCTION

The output of the driver’s neuromuscular system can be measured in terms of the applied forces and steering wheel angle. However if an understanding of the driver’s control process is to be gained measurements of signals within the driver’s control system are also of interest. Electromyography (EMG) provides a non-intrusive way of measuring muscle activity. EMG uses the phenomenon that contracting muscles generate impulses of electrical activity. By measuring these impulses the state of muscle contraction can be established. In studies aimed at understanding human motor control muscle activity is often measured using EMG [64, 69, 77].

Under isometric conditions (static condition where the muscle length remains constant) it is widely reported that muscle force is proportional to the mean rectified EMG signal [61]. This chapter describes experiments carried out to establish if this proportional relationship can be extended to forces applied to the steering wheel.

Muscle tissue is only able to produce force by contraction. Hence two muscles are required, positioned to oppose each other as an agonist/antagonist muscle pair, in order that both positive and negative forces can be generated. Co-contraction between opposing muscles has been shown to increase muscle stiffness due to the non-linear visco-elastic properties of muscles [52]. However this muscle co-contraction leads to an increase in metabolic energy consumption. By measuring EMG signals from key muscles any co-contraction in opposing muscles can be seen. Using EMG to measure muscle co-contraction during the driving task may provide information on the driver’s control strategy.

In order that muscle activity involved in driver steering control can be measured, it is necessary to determine the key muscles involved in generating steering torque. A review of published literature has only revealed one study relating EMG to the driver steering control task [63]. The results showed strong activity in the deltoid muscles
Chapter 3: Electromyography

associated with steering wheel rotation. However as steering torque was not measured a quantitative relationship with muscle activity remains unknown.

A simple model of the steering wheel and right arm is shown in Figure 3.1. It is assumed that the steering wheel is held in the on centre position and that the projected steering axis passes through the wrist and shoulder joints. $M_s$ represents the total muscle torque generated about the shoulder joint acting on the upper arm and reacted through the driver’s body. $M_e$ represents the total muscle torque generated about the elbow joint acting on the upper arm forearm (positive $M_e$ acts to open the elbow joint). $F_{yr}$ and $F_{zr}$ are the tangential and axial forces applied by the right hand to the steering wheel. By using this model the relationship between joint torques ($M_e$ and $M_s$) and hand forces ($F_{yr}$ and $F_{zr}$) can be established.

![Figure 3.1: Planar view of the right arm showing joint torques and steering forces.](image)

The shoulder, elbow and wrist joints are modelled as pin joints. Additionally it is assumed that no muscle torque is generated across the wrist, because the muscles and moment arms are small here. By assuming static equilibrium of forces and moments two equations can be generated, equations 3.1 and 3.2, for moments about the upper arm and forearm respectively in terms of the unknown forces $F_{yr}$ and $F_{zr}$:

\[ M_e + M_s - \frac{a}{2} F_{yr} - b F_{zr} = 0 \]  
\[ b F_{zr} - M_e - \frac{a}{2} F_{yr} = 0 \]
Solving these equations simultaneously gives:

\[ F_{yr} = \frac{1}{a} M_s \]  

(3.3)

\[ F_{zr} = \frac{1}{2} \frac{M_z}{b} + \frac{M_z}{b} \]  

(3.4)

Equation (3.3) shows that only muscle torque generated about the shoulder can act to generate tangential steering force. Hence it is the muscles of the shoulder that are likely to be of primary importance in generating steering torques when the steering wheel is held on centre (Figure 3.1).

Using information from literature on Kinesiology [78], the muscles involved in steering control can be hypothesised. Steering motion can be described anatomically as forward elevation of the arm, which creates positive tangential steering forces \( F_{yr} \), and downwards depression of the arm and shoulder to generate negative tangential steering forces (Figure 3.2).

Muscles involved in forward elevation of the arm and shoulder are the front deltoid muscle and clavicular portion of the pectoralis major muscle. Muscles involved in downward depression of the arm and shoulder are the sternal portion of the pectoralis major, latissimus dorsi, teres major and possibly the rear deltoid and long head of the triceps brachii [78]. Jonsson and Jonsson’s study [63] of muscle activity in the driver steering task showed very little significant activity in the latissimus dorsi or teres
major and hence these muscles are not considered further here. The remaining muscles become the primary candidates for investigation and their locations are indicated (Figure 3.3).

In order to establish the key muscles involved in the steering task and generate meaningful EMG measurements a set of experiments was carried out. EMG measurements were taken from eight muscles in the arm and shoulder whilst a test subject applied forces to the steering wheel with the right arm alone. Muscles investigated included the, front, mid and rear portions of the deltoid. Additionally measurements were taken from the clavicular (connected to the collar bone) and sternal (connected to the breast bone) portions of the pectoralis major. The triceps and biceps muscles were also measured as they are bi-articulate, spanning both the elbow and shoulder joint. EMG sensors were placed on the triceps’ lateral head and long head, and on the bulk of the muscle of the biceps.

The tangential steering forces, $F_{yr}$ and $F_{yl}$, generate steering torques and are of primary interest. However, the six-axis load cell (described in Chapter 2) also allows axial hand forces to be individually measured. As both the axial and tangential hand forces seem to be intimately related, due to the geometry of the driver’s arm (Figure 3.1), both were measured and analysed in the following experiments.
The remainder of this chapter describes EMG measurements related to the driving task. A description of the EMG measurement instrumentation is given in section 3.2. Initially measurements were taken for the right arm alone, using the EMG instrumentation, to establish the muscles involved in generating steering torque. Section 3.3 gives EMG and steering forces measured under a range of conditions. Section 3.4 describes a regression analysis used to establish a relationship between steering forces and muscle activity. The results indicate the key muscles involved in generating steering forces.

Having established the most suitable muscles for measurement with the EMG instrumentation, measurements were taken from eight test subjects. In these experiments measurements were taken from both left and right arms. The results are given in section 3.5. The eight test subjects also participated in the experiments described in Chapters 4 and 5, where EMG signals were also measured. As measurements were all taken in the same session for each test subject, the results given in this chapter can be used in conjunction with results from later chapters.
3.2 EMG HARDWARE AND METHOD

3.2.1 EMG instrumentation

Eight channels of EMG instrumentation were developed within CUED\(^2\). Winter [57] gives an excellent description of EMG measurement methods, which was used when developing this EMG instrumentation. The instrumentation developed consists of an EMG amplifier and optical isolator Figure 3.4. The EMG amplifier has high gain and input impedance and is used to measure the small voltages across the skin electrodes. The optical isolator is used to isolate the test subject from the mains data logging equipment. Equipment directly connected to the test subject was battery powered. The optical isolator converts the amplified EMG voltage to a frequency modulated optical signal. Using optic fibre, the optical signal is passed to a frequency to voltage converter where the signal is filtered and logged.

The optical isolator gives a linear response provided that the input signal lies in the range of –1V to +1V. It was found that setting the EMG amplifier gain to 500 met this constraint. The EMG signals reported in this work are the outputs from the EMG sensor instrumentation. If the actual potential difference between the electrodes on a muscle is required the reported EMG measurements should be divided by 500.

![Figure 3.4: EMG measurement instrumentation.](image)

3.2.2 EMG instrumentation frequency response

The frequency response of all eight EMG measurement channels was measured to confirm the correct functioning of the instrumentation. In order that the roll-off in the anti-aliasing filters could be seen a high logging frequency of 10kHz was used (in normal operation the logging frequency is 1kHz). A white noise test signal was

\(^2\) Designed by Dr D J Cole
generated with noise power $1 \times 10^{-5} \text{V}^2/\text{Hz}$. This gave a signal with RMS level of around 0.3V. The test signal voltage was scaled using an operational amplifier with gain 0.002 (Figure 3.5). This gave a signal of similar magnitude to that measurable from muscles by the EMG electrodes.

![Figure 3.5: Test circuit for EMG measurement instrumentation with operational amplifier.](image_url)

The frequency response and coherence between the input white noise signal and the measured output from the EMG instrumentation was calculated (Figure 3.6). A unity gain is expected in the measured frequency response resulting from the combined gain of the operational amplifier (gain of 1/500) and the EMG amplifier (gain of 500). A unity gain can be seen from 10-150Hz which encompasses the frequency range where EMG activity is most prominent (50-150Hz) [62]. The effect of the anti-aliasing filters can be seen as a roll-off at break frequency of 300Hz. Additionally a high-pass filter was used with cut off frequency below 1Hz to remove the steady state offset voltage inherent in the optical isolator. The coherence across the whole frequency range is good apart from the inevitable noise that occurs at mains frequency of 50Hz. The 50Hz noise was not found to be significant in later experiments and may have been introduced by the mains powered op-amp used to generate the small test voltages.
3.2.3 Processing the raw EMG signal

The measured EMG signal is the sum of the motor unit action potentials. When the muscle fibre is innervated the impulse-like action potential can be measured. As muscles generate larger forces, more muscle fibres are innervated. Hence in its raw form the measured EMG signal, or sum of the motor unit action potentials, is noise like. The signal is rectified then smoothed by low-pass filtering in order to generate a Smoothed Rectified EMG (SREMG) signal (Figure 3.7). It is this smoothed rectified signal that is proportional to muscle force under isometric conditions [61]. It is also usual to high-pass filter the raw signal to remove any artefacts introduced as the sensor leads move. High-pass filtering also removes some of the low frequency components picked up as the human heart beats. In the following experiments the raw signal was high-pass filtered at 20Hz, rectified, then low-pass filtered at 5Hz. Filtering of the data set was carried out in forward and reverse directions to prevent any change in phase.
Chapter 3: Electromyography

Figure 3.7: Signal processing of the raw EMG signal to give a smooth rectified envelope of mean activity. The smoothing is achieved using a 5Hz low-pass filter.

3.2.4 Electrode placement

Silver / silver chloride self adhesive electrodes were used with inter electrode spacing of approximately 20mm. The skin was prepared by wiping with a medical anti-septic swab, then shaving any hair in the region and finally using an abrasive pad to remove any dead skin. Preparing the skin in this way gave good electrical contact between the skin and the electrodes.

Surface EMG measurements were made of eight muscles on the right arm and shoulder as shown in Figure 3.3. The electrodes were positioned by contracting the relevant muscles and placing the electrodes on the bulk of the contracted muscle.

The biceps can be contracted by pulling axially on the steering wheel. The triceps contract whilst pushing axially on the steering wheel. The positions of the muscles with sensors in place can be seen in Figure 3.8.
The deltoids wrap around the top of the shoulder. All three muscles can be felt to contract when the driver pushes upwards on the steering wheel against a resistance.

The pectoralis major is a large fan shaped muscle across the chest. Because the muscle twists on itself the clavicular and sternal portions can perform different functions. The clavicular portion can be contracted by pushing upwards on the steering wheel, whilst the sternal portion can be felt to contract by pulling downwards on the steering wheel. Careful placing of the sensors on the pectoral is required to prevent cross talk between the clavicular and sternal portions. The pairs of electrodes were placed as far apart as possible whilst still over the contracted muscle.
3.3 EMG AND STEERING FORCES FOR THE RIGHT ARM

3.3.1 Experimental procedure

An initial experiment was carried out to establish the role of various muscles of the right arm in the steering task. The steering wheel was held with the right hand alone in order that the forces and moments generated were fully determinate using the six-axis load cell. All eight channels of EMG instrumentation were used to measure muscles of the right arm and shoulder of one test subject. The test subject was a right-handed male, aged 22, 1.8m tall and of slim build (For full details see Appendix, Table A2, test subject F). The muscles measured are listed in Table 3.1 and the locations can be seen in Figure 3.3.

Table 3.1: Muscles measured in the right arm using EMG.

<table>
<thead>
<tr>
<th>Measurement Channel</th>
<th>Muscle</th>
</tr>
</thead>
<tbody>
<tr>
<td>EMG 1</td>
<td>Deltoid front</td>
</tr>
<tr>
<td>EMG 2</td>
<td>Deltoid middle</td>
</tr>
<tr>
<td>EMG 3</td>
<td>Deltoid rear</td>
</tr>
<tr>
<td>EMG 4</td>
<td>Clavicular portion of pectoralis major</td>
</tr>
<tr>
<td>EMG 5</td>
<td>Sternal portion of pectoralis major</td>
</tr>
<tr>
<td>EMG 6</td>
<td>Biceps</td>
</tr>
<tr>
<td>EMG 7</td>
<td>Triceps long head</td>
</tr>
<tr>
<td>EMG 8</td>
<td>Triceps lateral head</td>
</tr>
</tbody>
</table>

A target steering force was generated that slowly varied using a linear ramp function. A graph was displayed to the test subject showing the target signal along with the measured steering force. Test subjects were asked to follow the target signal by applying either axial or tangential forces to the steering wheel. The steering wheel was either fixed rigidly, in order that the measurements could be made under isometric conditions, or allowed to rotate providing a “spring” resisting force proportional to steering angle with rate 0.1Nm/deg. The test conditions are summarised in Table 3.2.
Table 3.2: Test conditions under which EMG was measured.

<table>
<thead>
<tr>
<th>Steer angle range/ deg</th>
<th>Test condition</th>
<th>Target force/ N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Steer angle fixed 0deg</td>
<td>Isometric</td>
<td>$F_{y r} = -60N$ to $+60N$</td>
</tr>
<tr>
<td>Steer angle fixed 0deg</td>
<td>Isometric</td>
<td>$F_{zr} = -120N$ to $120N$</td>
</tr>
<tr>
<td>-90 to 90deg (approx)</td>
<td>Spring rate 0.1Nm/deg</td>
<td>$F_{y r} = -50N$ to $+50N$</td>
</tr>
</tbody>
</table>

3.3.2 Measured muscle activity for the right arm

Muscle activity was measured whilst tangential steering forces were applied to the steering wheel under isometric conditions. The measured forces, applied at the point of contact between the hand and steering wheel, are shown along with the corresponding muscle activity in Figure 3.9. Although torques applied at the point of contact between the hand and steering wheel were also measured, these were small and have been omitted from the figure for clarity.

Figure 3.9 shows activity in all three portions of the deltoid and clavicular portion of the pectoral during application of positive tangential forces (for the right hand pushing upwards on the steering wheel). However, the most significant activity appears to be in the mid and front portions of the deltoid. When the tangential steering force is negative, significant activity can be seen in the sternal portion of the pectoral and triceps long head. Small electrical pulses (approx 50mV) from the heart can be seen in the EMG signal measured at the pectoral. Although some activity can be seen in both the biceps and triceps lateral head, its magnitude is small.

The results are consistent with those obtained by Jonsson and Jonsson [63], who found that the front- and mid-deltoids were the prime movers in generating positive tangential steering forces. The anatomical description [78] of the motion involved in generating positive tangential steering forces (forward elevation of the arm and shoulder accompanied by flexion of the upper arm) predicts that the front deltid will be of key importance, which is consistent with the measured results.

Jonsson and Jonsson’s results give no clear indication as to the muscles involved in generating negative tangential steering forces. The results measured here show the
sternal portion of the pectoral and triceps long head as the prime movers, again this is consistent with the anatomically based prediction.

The muscle activity measured during application of axial and tangential forces is shown in Figure 3.10. When the axial force is positive activity can be seen in both the triceps lateral and long head, but when the axial force is negative activity is seen in the biceps.

The measurements were also made under conditions where the steering wheel was able to rotate against a spring-like resistance. The muscle activity using a fixed steering wheel and the spring rotating steering wheel can be compared using Figure 3.9 and Figure 3.11. A common feature of both sets of results is that strong activity in the front and mid deltoid is seen when the tangential steering forces are positive. When the tangential steering forces are negative, corresponding activity is still seen in the sternal portion of the pectoral and long head of the triceps. Figure 3.11 also shows significant activity in the biceps characterised by the large amplitude SREMG signal of around 0.4V. The origin of this activity is not clear, but could arise from the biceps stabilising the elbow joint or result from a change in the mechanical advantage of the muscle with respect to the arm.
Figure 3.9: SREMG showing muscle activity when tangential steering forces are applied.
Figure 3.10: SREMG showing muscle activity when axial steering forces are applied.
Figure 3.11: SREMG showing muscle activity when tangential steering forces are applied with spring rotating steering wheel giving resistance of 5.7Nm/rad (0.1Nm/deg).
3.4 REGRESSION ANALYSIS

In order to establish a quantitative relationship between muscle activity and steering forces a multiple regression analysis was carried out. This gives a least squares best fit between measured steering forces and SREMG voltage. The multiple regression model is a linear model given by equation 3.5 [79].

\[ y(n) = \beta_0 + \beta_1 x_1(n) + \beta_2 x_2(n) + \ldots + \beta_p x_p(n) + w(n) \] (3.5)

where:

- \( y \) – Dependent measured response variable
- \( x \) – Independent variable

\( \beta_0, \beta_1, \beta_2, \ldots, \beta_p \) are the constant regression coefficients and \( w(n) \) is the random disturbance that is minimised for all \( n \) data points in a least squares sense. Using the regression coefficients the predicted response is given by equation 3.6.

\[ \hat{y}(n) = \beta_0 + \beta_1 x_1(n) + \beta_2 x_2(n) + \ldots + \beta_p x_p(n) \] (3.6)

where:

- \( \hat{y} \) - Predicted response variable using the regression model

A measure of the quality of the fit is given by the multiple correlation coefficient squared, \( R^2 \), (equation 3.7). \( R^2 \) should be interpreted as the proportion of the total variability accounted for by the regression model.

\[ R^2 = 1 - \frac{\sum(y(n) - \hat{y}(n))^2}{\sum(y(n) - \bar{y})^2} \] (3.7)

where:

- \( \bar{y} \) - Sample mean of the dependent variable

The multiple correlation coefficient squared has a range from zero to one. \( R^2 = 1 \) indicates an exact fit to the measured response. If there is no correlation between the independent and dependent variables \( R^2 = 0 \) and the best fit is obtained with \( \beta_0 \) equal to the sample mean. If \( R^2 \) is calculated for a set of comparison data using a previously
identified regression model and the mean value of the signal has changed significantly negative values for $R^2$ can be obtained.

3.4.1 Regression analysis procedure

A good spread of data is required across a variety of loading conditions to allow the regression analysis to be carried out. The aim was to distinguish those muscles that generate axial forces on the steering wheel from those that are responsible for generating tangential steering forces and steering torque.

To ensure that a good spread of data was measured, a method was used whereby the applied forces were displayed to the test subject. The applied axial and tangential steering forces were displayed simultaneously as an $x$-$y$ plot with moving cursor. The moving cursor left a trace on the screen. Applying tangential forces to the steering wheel caused the cursor to move left and right along the $x$-axis, whilst positive and negative axial forces moved the cursor up and down the $y$-axis respectively. The test subjects were asked to evenly fill all quadrants of the $x$-$y$ plot by slowly and smoothly applying forces to the steering wheel Figure 3.12. With a small amount of practice test subjects were easily able to perform the task. Because a good distribution of both axial and tangential forces was measured sufficient data was obtained to carry out the regression analysis.

![Figure 3.12: Plot showing typical distribution of forces applied by test subject during 50s test.](image-url)
When carrying out regression analysis, if any number of the independent \( x \) variables are highly correlated with each other then the problem of multicollinearity of the data may arise [79]. In this circumstance, although the regression model may have a good fit to the measured data, the actual regression coefficients between the two correlated signals become meaningless and the model’s predictive performance is poor. Essentially one of the two correlated independent variables used in the regression analysis is redundant. For the measured EMG data, some of the muscles may act together and therefore the EMG measurements may be correlated. An indication of the correlation between EMG signals is given by the correlation coefficients squared (equation 3.8), Table 3.3. Squared correlation coefficients close to one indicate significant correlation. Correlation is seen between the sternal portion of the pectorals and triceps long head and also the front and mid portions of the deltoids.

\[
r^2 = \frac{\left( \sum (x_i(n) - \bar{x}_i)(x_j(n) - \bar{x}_j) \right)^2}{\sum (x_i(n) - \bar{x}_i)^2 \sum (x_j(n) - \bar{x}_j)^2}
\]

(3.8)

<table>
<thead>
<tr>
<th></th>
<th>Deltoid front</th>
<th>Deltoid mid</th>
<th>Deltoid rear</th>
<th>Pectoral (clavicular)</th>
<th>Pectoral (sternal)</th>
<th>Biceps</th>
<th>Triceps (lat head)</th>
<th>Triceps (long head)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deltoid front</td>
<td>1.000</td>
<td>0.881</td>
<td>0.537</td>
<td>0.466</td>
<td>0.066</td>
<td>0.405</td>
<td>0.001</td>
<td>0.137</td>
</tr>
<tr>
<td>Deltoid mid</td>
<td>1.000</td>
<td>0.667</td>
<td>0.592</td>
<td>0.061</td>
<td>0.445</td>
<td>0.004</td>
<td>0.132</td>
<td></td>
</tr>
<tr>
<td>Deltoid rear</td>
<td>1.000</td>
<td>0.588</td>
<td>0.054</td>
<td>0.381</td>
<td>0.244</td>
<td>0.022</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pectoral (clavicular)</td>
<td>1.000</td>
<td>0.014</td>
<td>0.669</td>
<td>0.048</td>
<td>0.008</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pectoral (sternal)</td>
<td></td>
<td></td>
<td>1.000</td>
<td>0.001</td>
<td>0.375</td>
<td>0.790</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Biceps</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.000</td>
<td>0.024</td>
</tr>
<tr>
<td>Triceps (lat head)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.506</td>
</tr>
<tr>
<td>Triceps (long head)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.000</td>
</tr>
</tbody>
</table>
3.4.2 Regression analysis between tangential hand forces and SREMG

When predicting steering forces it may not be necessary to use all eight channels of EMG data. If a particular muscle does not contribute to the steering force of interest then the measurement from the muscle need not be included in the regression analysis. For the eight channels of EMG measured there are 255 combinations of regression models that can be generated. An exhaustive search was carried out to establish how the number of channels used in the regression analysis affects the quality of the model fit. The multiple correlation coefficients squared for all 255 model variants are plotted along with the number of EMG channels used in each model (Figure 3.13).

![Variance account for versus number of parameters in regression model](image)

Figure 3.13: Multiple correlation coefficients squared, $R^2$, for regression analysis between tangential steering force and SREMG for various muscles. Coefficients for all 255 possible combinations of regression model are shown.

It can be seen that the majority of the measured variance can be accounted for by using a regression model with just two EMG parameters included. All combinations of regression models formed from any two of the measured EMG channels are shown in Table 3.4 along with the multiple correlation coefficient squared, as measured for that model. In order to assess the predictive performance of the identified regression
models, multiple correlation coefficients squared were also calculated using a new set of comparison data that had not been used previously in the regression analysis (Table 3.5).

Table 3.4: Multiple correlation coefficient squared, $R^2$, for all combinations of two-muscle regression models.

<table>
<thead>
<tr>
<th></th>
<th>Deltoid front</th>
<th>Deltoid mid</th>
<th>Deltoid rear</th>
<th>Pectoral (clavicular)</th>
<th>Pectoral (sternal)</th>
<th>Biceps</th>
<th>Triceps (lat head)</th>
<th>Triceps (long head)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deltoid front</td>
<td>-</td>
<td>0.797</td>
<td>0.733</td>
<td>0.729</td>
<td>0.850</td>
<td>0.728</td>
<td>0.733</td>
<td>0.838</td>
</tr>
<tr>
<td>Deltoid mid</td>
<td>-</td>
<td>0.869</td>
<td>0.843</td>
<td>0.917</td>
<td>0.807</td>
<td>0.822</td>
<td>0.900</td>
<td></td>
</tr>
<tr>
<td>Deltoid rear</td>
<td>-</td>
<td>0.354</td>
<td>0.832</td>
<td>0.367</td>
<td>0.526</td>
<td>0.843</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pectoral (clavicular)</td>
<td>-</td>
<td>0.689</td>
<td>0.310</td>
<td>0.350</td>
<td>0.633</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pectoral (sternal)</td>
<td>-</td>
<td>0.591</td>
<td>0.402</td>
<td>0.395</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Biceps</td>
<td>-</td>
<td>0.296</td>
<td>0.577</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-</td>
</tr>
<tr>
<td>Triceps (lat head)</td>
<td>-</td>
<td>0.624</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Triceps (long head)</td>
<td>-</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 3.5: Multiple correlation coefficient squared, $R^2$, for all combinations of two-muscle regression models calculated using comparison data.

<table>
<thead>
<tr>
<th></th>
<th>Deltoid front</th>
<th>Deltoid mid</th>
<th>Deltoid rear</th>
<th>Pectoral (clavicular)</th>
<th>Pectoral (sternal)</th>
<th>Biceps</th>
<th>Triceps (lat head)</th>
<th>Triceps (long head)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deltoid front</td>
<td>-</td>
<td>0.777</td>
<td>0.656</td>
<td>0.644</td>
<td>0.748</td>
<td>0.674</td>
<td>0.659</td>
<td>0.782</td>
</tr>
<tr>
<td>Deltoid mid</td>
<td>-</td>
<td>-</td>
<td>0.817</td>
<td>0.615</td>
<td>0.842</td>
<td>0.809</td>
<td>0.783</td>
<td>0.871</td>
</tr>
<tr>
<td>Deltoid rear</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.353</td>
<td>0.681</td>
<td>0.128</td>
<td>0.481</td>
<td>0.830</td>
</tr>
<tr>
<td>Pectoral (clavicular)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.592</td>
<td>0.215</td>
<td>0.380</td>
<td>0.677</td>
<td></td>
</tr>
<tr>
<td>Pectoral (sternal)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.411</td>
<td>0.153</td>
<td>0.397</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Biceps</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.013</td>
<td>0.522</td>
</tr>
<tr>
<td>Triceps (lat head)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.487</td>
<td></td>
</tr>
<tr>
<td>Triceps (long head)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

Based on the results shown in Table 3.4 the best-fit two-muscle model is generated using the sternal portion of the pectoral and the mid portion of the deltoid. In this configuration a correlation coefficient squared of 0.917 was obtained. The model also shows good predictive performance, as confirmed by the multiple correlation coefficient squared of 0.842 shown in Table 3.5. The resulting model fit is shown in Figure 3.14 and regression parameters given in Table 3.6. The offset, $\beta_0$, is in part due to the weight of the arm, but also any background noise in the signals. The multiple regression coefficients in Table 3.4 also indicate that models including the triceps long head or front deltoid may also be appropriate and give good fits.
Figure 3.14: Tangential steering force prediction using measured EMG from mid deltoid and sternal portion of pectoral and regression parameters in Table 3.6.

Table 3.6: Regression coefficients used to predict tangential hand force.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Regression coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deltoid (mid), $\beta_1$</td>
<td>0.247 N/mV</td>
</tr>
<tr>
<td>Pectoralis Major (sternal), $\beta_2$</td>
<td>-0.462 N/mV</td>
</tr>
<tr>
<td>Offset, $\beta_0$</td>
<td>-11.2 N</td>
</tr>
</tbody>
</table>

3.4.3 Regression analysis between axial hand forces and SREMG

The regression analysis was also carried out to investigate the muscles involved in generating axial steering forces, $F_z$, in the right arm. Figure 3.15 shows the results of an exhaustive search using all 255 regression model combinations that can be formed from the eight measured channels of EMG. The multiple correlation coefficient squared is shown. It can be seen that none of the combinations of EMG measurements give $R^2$ values much above 0.6. Hence, around 40% of the variance is still unaccounted for, which indicates that other muscles that have not been measured may play a prominent role in generating axial steering forces.
Figure 3.15 shows that $R^2$ is not significantly improved by increasing the number of EMG channels used in the regression analysis beyond four. The best-fit model for a given number of EMG channels is summarised in Table 3.7. It can be seen that the triceps lateral head and biceps model form the prominent agonist/antagonist muscle pair and adding information from the pectoral and deltoid improves the fit.

Figure 3.15: Multiple correlation coefficient squared for regression analysis between axial steering force and SREMG for various muscles. Coefficients for all 255 possible combinations of regression model are shown.

Table 3.7: Models giving best multiple correlation coefficient squared.

<table>
<thead>
<tr>
<th>Number of channels</th>
<th>Channels used</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Triceps lateral head</td>
<td>0.41</td>
</tr>
<tr>
<td>2</td>
<td>Triceps lateral head, biceps</td>
<td>0.52</td>
</tr>
<tr>
<td>3</td>
<td>Triceps lateral head, biceps, mid deltoid</td>
<td>0.59</td>
</tr>
<tr>
<td>4</td>
<td>Triceps lateral head, biceps, mid deltoid, sternal portion of pectoral</td>
<td>0.61</td>
</tr>
</tbody>
</table>
The model fit to the measured data, generated using the four muscle model consisting of the triceps lateral head, biceps, mid-deltoid and sternal portion of pectoral, is shown in Figure 3.16 based on the parameters in Table 3.8. It can be seen that the un-modelled error occurs whenever the axial force is negative. A possible candidate muscle that generates this un-modelled component of force is the brachialis [78]. The brachialis is a flexor of the elbow joint (closes the angle between the upper arm and forearm) and as such generates negative torques about the elbow and a negative axial force at the steering wheel according to equation 3.4. Unfortunately this muscle lays under the biceps and is not measurable using surface EMG.

Table 3.8: Regression coefficients used to predict axial hand force.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Regression coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deltoid (mid), $\beta_1$</td>
<td>0.086 N/mV</td>
</tr>
<tr>
<td>Pectoralis Major (sternal), $\beta_2$</td>
<td>-0.275 N/mV</td>
</tr>
<tr>
<td>Biceps, $\beta_3$</td>
<td>-0.213 N/mV</td>
</tr>
<tr>
<td>Triceps (lateral head), $\beta_4$</td>
<td>1.662 N/mV</td>
</tr>
<tr>
<td>Offset, $\beta_0$</td>
<td>-10.7N</td>
</tr>
</tbody>
</table>

Figure 3.16: Axial steering force prediction using measured EMG from mid deltoid, sternal portion of pectoral, biceps and triceps lateral head.
3.4.4 Summary of regression analysis results for right arm

The regression coefficients in Table 3.6 and Table 3.8 indicate the relative roles of various muscles in generating forces at the steering wheel. As predicted by equation 3.3, muscles of the shoulder are primarily responsible for generating tangential steering forces. The mid-deltoid has a positive regression coefficient and generates positive tangential steering forces, whilst the sternal portion of the pectoral generates negative tangential steering forces.

Equation 3.4 indicates that both the muscles of the shoulder and the elbow will be involved in generating axial forces on the steering wheel. This is confirmed by the regression coefficients found in Table 3.8 for muscles of the elbow and shoulder. The results are as expected with the biceps being flexors of the elbow (closing the angle) whilst the triceps are the extensors (opening the angle). (The Brachialis may also generate axial force, as it is a flexor of the elbow joint.)
3.5 PREDICTING STEERING TORQUE

Sections 3.3 and 3.4 confirm that EMG measurements can be used to predict the tangential steering forces applied by a single arm. Additionally the significant muscles have been identified through regression analysis. Based on these results further experiments were carried out to establish the relationship between steering torque and the muscle activity with both hands on the steering wheel. In total eight test subjects participated (a description of the test subjects is given in the Appendix, Table A2).

For each test subject the measurements were made in conjunction with the experiments carried out and described in Chapters 4 and 5 in a continuous session. Measurements were taken at the beginning and end of each test session using the method described here. The two sets of data were used to confirm that the relationship between the measured EMG voltages and the steering forces remained constant throughout the test period. Data measured at the beginning of the test session was used in the regression analysis and is labelled as the analysis data, whilst data measured at the end of the test session is labelled the comparison data.

3.5.1 Experimental procedure

Measurements of muscle activity were taken from both arms whilst test subjects applied steering forces to the steering wheel under isometric conditions. Test subjects held the steering wheel symmetrically with hands roughly in the “quarter to three” position with the arms slightly bent at the elbows. The steering wheel was raked so that a projected line along the steering axis was parallel to a line through the shoulder and wrist joint (as shown in Figure 3.1).

Because only eight channels of EMG instrumentation were available the most significant muscles in generating steering torque had to be selected based on the results given in sections 3.3 and 3.4. The eight channels of EMG instrumentation were distributed with four channels on each of the left and right arms. EMG sensors were placed on the front-deltoid (alternatively the mid-deltoid could have been measured, however it was hard to consistently place the sensors to avoid unwanted signal from the rear-deltoid), sternal portion of the pectoralis major and triceps longitudinal head
as well as the biceps. EMG of the biceps was measured as the biceps had shown significant activity under dynamic measurements (Figure 3.11).

A target steering torque signal was generated that slowly varied with range –20Nm to 20Nm using a linear ramp function. As in the experiments measuring the right arm alone, a graph of the target signal was displayed along with the measured steering torque in real time. Test subjects were asked to follow the target signal by applying torques to the steering wheel.

3.5.2 Steering torque prediction using EMG

The measured EMG signals and steering forces were used in a regression analysis. When generating steering torque there is a correlation between muscle activity in the left and right arms. Hence, carrying out regression analysis between steering torque and the EMG activity in the left and right arms directly and simultaneously leads to ill conditioning. With both left and right arms on the steering wheel, the strain gauged steering hub can be used to estimate the tangential steering force applied by each hand. The method is discussed in Chapter 2, section 2.4.2. By using the steering hub in this way, regression analysis between the left hand steering force and left arm EMG activity can be carried out in isolation from the regression between the right hand steering forces and right arm EMG activity. The resultant steering torque can then be calculated from the tangential hand forces and steering wheel radius (equation 3.9) and problems of co-linearity and ill conditioning are avoided.

\[
M_z = r_{sw} (F_{yl} - F_{yr})
\]

(3.9)

where: \( r_{sw} \) – Steering wheel radius (175mm)

Initially the regression analysis was carried out using EMG data measured from the sternal portion of the pectoralis major, front deltoid, triceps long head and biceps as the independent variables \( x_1, x_2, x_3 \) and \( x_4 \). The signals were regressed with the tangential hand forces as described by equation 3.5.

The regression coefficient associated with biceps EMG showed significant variation in magnitude and sign between test subjects. Additionally there was no significant
degradation in the quality of the fit, in terms of the multiple correlation coefficient squared, when the bicep signal was omitted from the regression analysis. Hence measurements from the biceps were not included in the regression analysis and the resulting regression models for predicting left and right tangential hand forces are given by equations 3.10 and 3.11.

\[
\hat{F}_{yl} = \beta_0 + \beta_{pl}V_{pl} + \beta_{dl}V_{dl} + \beta_{vl}V_{vl} \\
\hat{F}_{yr} = \beta_0 + \beta_{pr}V_{pr} + \beta_{dr}V_{dr} + \beta_{vr}V_{rv} \tag{3.10}
\]

where: suffixes \(l\) and \(r\) denote signals from the left and right arms respectively.

- \(\hat{F}_y\) - EMG based tangential steering force estimate (N)
- \(\beta_0\) - Constant coefficient (N)
- \(\beta_{pl}\) - Regression coefficient for sternal portion of pectoralis major (N/mV)
- \(\beta_{dl}\) - Regression coefficient for front portion of deltid (N/mV)
- \(\beta_{vl}\) - Regression coefficient for triceps long head (N/mV)
- \(V_{pl}\) - SREMG voltage from sensor on sternal portion of pectoralis major (mV)
- \(V_{dl}\) - SREMG voltage from sensor on front portion of deltid (mV)
- \(V_{vl}\) - SREMG voltage from sensor on triceps long head (mV)

The regression coefficients for each arm were calculated using the analysis data measured at the beginning of each session of experiments for each test subject. The results for the right and left arms are shown in Table 3.9 and Table 3.10 respectively. The multiple correlation coefficient squared is shown, calculated using the analysis data. The multiple correlation coefficient squared was also calculated for the comparison data (measured at the end of each test session) using the regression parameters identified from the analysis data.

Multiple correlation coefficients squared of around 0.9 were obtained for both the analysis and comparison data. The high correlation coefficients not only indicate a good fit to the measured data, but also confirm that the relationship between EMG and steering forces remained sufficiently constant throughout the test session.
### Table 3.9: Calculated regression coefficients and multiple correlation coefficient squared for the right arm.

<table>
<thead>
<tr>
<th></th>
<th>$\beta_{pr}$</th>
<th>$\beta_{dr}$</th>
<th>$\beta_{tr}$</th>
<th>$\beta_0$</th>
<th>$R^2_{analysis}$</th>
<th>$R^2_{comparison}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject A</td>
<td>-1.929</td>
<td>0.500</td>
<td>-1.295</td>
<td>-11.18</td>
<td>0.920</td>
<td>0.883</td>
</tr>
<tr>
<td>Subject B</td>
<td>-0.412</td>
<td>0.238</td>
<td>-1.802</td>
<td>-13.78</td>
<td>0.873</td>
<td>0.912</td>
</tr>
<tr>
<td>Subject C</td>
<td>-0.396</td>
<td>0.697</td>
<td>-1.027</td>
<td>-5.33</td>
<td>0.911</td>
<td>0.884</td>
</tr>
<tr>
<td>Subject D</td>
<td>-0.742</td>
<td>0.346</td>
<td>-1.202</td>
<td>17.78$^3$</td>
<td>0.779</td>
<td>0.604</td>
</tr>
<tr>
<td>Subject E</td>
<td>-0.323</td>
<td>0.830</td>
<td>-1.813</td>
<td>-17.39</td>
<td>0.931</td>
<td>0.930</td>
</tr>
<tr>
<td>Subject F</td>
<td>-0.476</td>
<td>0.563</td>
<td>-0.429</td>
<td>-14.19</td>
<td>0.927</td>
<td>0.906</td>
</tr>
<tr>
<td>Subject G</td>
<td>-0.497</td>
<td>0.437</td>
<td>-1.754</td>
<td>-10.77</td>
<td>0.935</td>
<td>0.887</td>
</tr>
<tr>
<td>Subject H</td>
<td>-0.318</td>
<td>0.519</td>
<td>-1.163</td>
<td>-15.66</td>
<td>0.951</td>
<td>0.933</td>
</tr>
</tbody>
</table>

The regression coefficients given in Table 3.9 and Table 3.10 were used to estimate the right and left hand tangential steering forces. The tangential steering force

---

$^3$ For the female test subject D, parameter $\beta_0$ was found to be positive. The parameter compensates for steady state noise in the EMG sensors and the weight of the subject's arm. Because of physiological differences between males and females it was more difficult to accurately position the EMG sensors over subject D’s pectoral.
estimates were then used to predict steering torque using equation 3.12 and the multiple correlation coefficients squared calculated for both the analysis and comparison data Table 3.11.

\[
\hat{M}_z = r_{sw}(\hat{F}_{zl} - \hat{F}_{yr})
\]  

(3.12)

It is surprising that \(R^2\) (calculated for steering torque prediction) given in Table 3.11 is even closer to one compared to the individual \(R^2\) values (calculated for each hand force prediction) in Table 3.9 and Table 3.10. Presumably an effect of calculating the steering torque from the predicted hand forces is to average out some of the noise.

The multiple correlation coefficients squared indicate excellent agreement between the torque prediction, calculated using regression coefficients and SREMG data, and the true steering torque. A typical plot showing the model fit to measured data is shown in Figure 3.17 at the beginning and end of the test session. It can be seen that the model shows excellent agreement at the start and the end of the session.

Table 3.11: Multiple correlation coefficients squared, \(R^2\), calculated for steering torque prediction using regression coefficients and SREMG data.

<table>
<thead>
<tr>
<th>Test Subject</th>
<th>(R^2) (analysis data)</th>
<th>(R^2) (comparison data)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject A</td>
<td>0.963</td>
<td>0.934</td>
</tr>
<tr>
<td>Subject B</td>
<td>0.956</td>
<td>0.951</td>
</tr>
<tr>
<td>Subject C</td>
<td>0.955</td>
<td>0.952</td>
</tr>
<tr>
<td>Subject D</td>
<td>0.903</td>
<td>0.823</td>
</tr>
<tr>
<td>Subject E</td>
<td>0.974</td>
<td>0.970</td>
</tr>
<tr>
<td>Subject F</td>
<td>0.967</td>
<td>0.950</td>
</tr>
<tr>
<td>Subject G</td>
<td>0.970</td>
<td>0.960</td>
</tr>
<tr>
<td>Subject H</td>
<td>0.974</td>
<td>0.968</td>
</tr>
</tbody>
</table>
The question arises as to whether the simple proportional relationship between SREM and force is valid under the dynamic conditions experienced during realistic driving action. There are two main reasons why the relationship might break down. The first reason is change in the geometrical relationship between muscles and joints with steering angle. If the steering angles are sufficiently small then the geometry changes will be small and the relationship between EMG and steering forces should still hold. The second reason is that muscle force generation is a rate dependent process. Under dynamic conditions Winter [57] notes that a linear relationship can still be seen between force and SREM. However the force generally lags the SREM signal by 40-100ms. The lag is usually modelled as a series of first order lags [62].

Using the CUED driving simulator, test subjects performed a number of double lane change manoeuvres; the experiments are discussed in full detail in Chapter 5. However the measured data can be used to some extent to investigate the validity of
EMG based steering torque prediction method under dynamic conditions. Figure 3.18 shows a typical measurement of the EMG based steering torque prediction alongside the measured steering torque. As expected there is a lag between muscle activity and measured force, however there is still good agreement between the two measures despite the dynamic conditions.

Figure 3.18: EMG based steering torque prediction measured during simulated double lane change manoeuvre. Data measured for test subject H in car 3 showing run 9.
3.5.3 Co-contraction between opposing muscles

The results from the regression analysis above show that the role of various muscles in generating steering torque has been identified and quantified. The muscles analysed can be categorised into those that generate positive torque at the steering wheel and those that generate negative torque (Table 3.12) by observing the sign of the regression coefficients.

Table 3.12: Role of muscles of the arm and shoulder in generating steering torques.

<table>
<thead>
<tr>
<th>Muscles producing +ve steering torque</th>
<th>Muscles producing -ve steering torque</th>
</tr>
</thead>
<tbody>
<tr>
<td>LH Deltoid (front)</td>
<td>RH Deltoid (front)</td>
</tr>
<tr>
<td>RH Pectoral (sternal)</td>
<td>LH Pectoral (sternal)</td>
</tr>
<tr>
<td>RH Triceps long head</td>
<td>LH Triceps long head</td>
</tr>
</tbody>
</table>

By categorising the muscles in this way, any co-contraction in opposing groups of muscles can be identified by comparing the activity in the positive torque producing muscles and the negative torque producing muscles (Figure 3.19). For Figure 3.19 little co-contraction is seen other than the inevitable constant activity in both groups of muscles necessary to partially support the weight of the arm.
In order that the degree of muscle co-contraction can be quantified a measure of the degree of muscle co-contraction, $I_c$, has been devised according to equation (3.13). The measure gives the amount of the lost torque through co-contraction of opposing muscles by comparing activity in the positive and negative torque producing muscles with the overall EMG based steering torque estimates.
\[ I_c(t) = (M_{+ve}(t) - M_{-ve}(t)) - |\hat{M}_z(t)| \quad (3.13) \]

where:

\[ M_{+ve}(t) = r_{sw}(\beta_{dl} V_{dl}(t) - \beta_{pr} V_{pr}(t) - \beta_{pl} V_{pl}(t)) \]

\[ M_{-ve}(t) = r_{sw}(\beta_{pl} V_{pl}(t) + \beta_{dl} V_{dl}(t) - \beta_{dr} V_{dr}(t)) \]

\[ \hat{M}_z(t) = r_{sw}(\beta_{dl} V_{dl}(t) + \beta_{pl} V_{pl}(t) + \beta_{dr} V_{dr}(t) - \beta_{pr} V_{pr}(t) - \beta_{tr} V_{tr}(t)) \]

- \( M_{+ve} \) - EMG based torque prediction for muscles that produce positive torques
- \( M_{-ve} \) - EMG based torque prediction for muscles that produce negative torques
- \( \hat{M}_z \) - EMG based steering torque prediction

As an example, the components of equation 3.13 are shown in Figure 3.20, which shows typical levels of co-contraction during a double lane change manoeuvre measured from the simulator. It can be seen that during this dynamic manoeuvre, considerable co-contraction arises. One explanation for the co-contraction is that the inherent muscle stiffening associated with co-contraction allows the driver to increase their control bandwidth. The measurement of co-contraction during lane change manoeuvres is discussed further in Chapter 5.

The method described above provides a quantitative measure of co-contraction between opposing muscles. As discussed by Osu et al [69] other methods of establishing co-contraction, for example adding up the raw SREMG signal, are inferior because the resulting measure has no physical significance. The measure is used in subsequent analysis in Chapters 4 and 5.
Figure 3.20: Muscle co-contraction for EMG activity measured during a simulated double lane change manoeuvre. Run 5 in test car 3 for test subject H.
3.6 CONCLUSIONS

a) A review of the published literature revealed very little existing knowledge relating muscle activity to the driving task.

b) Electromyography was used as a measure of driver muscle activity and to identify key muscles involved in generating steering forces.

c) Regression analysis of the EMG data measured from the right arm of one test subject was used to determine the key muscles involved in generating steering forces.

d) Using the identified regression parameters and measured SREMG from key muscles, tangential steering forces were successfully predicted under isometric conditions. Prediction of axial steering forces was less successful as a significant muscle (the brachialis) was inaccessible to the surface electrodes.

e) The method was extended and measurements were taken from the left and right arms of eight test subjects. Using regression analysis a model that predicts steering torque from the SREMG, measured from these test subjects, was generated. The model showed excellent agreement with the measured steering torque under isometric conditions.

f) The method of steering torque prediction from the SREMG signal also shows reasonable agreement with the measured steering torque under dynamic conditions.

g) The results allow co-contraction in opposing muscles to be identified and quantified. Muscle co-contraction is thought to be a potential control strategy employed by drivers.

h) The methods of predicting steering torque from EMG signals and determining muscle co-contraction are used in subsequent chapters as tools for analysis of the driver’s steering control strategy.
Chapter 4: Limb Dynamic Identification

4.1 INTRODUCTION

As discussed in Chapter 1, the neuromuscular system plays an important role in driver steering control. Some more recently published work has recognised the importance of the neuromuscular system in driver steering control [7, 10, 35]. However, a review of published literature has revealed no measurements of the neuromuscular dynamics specific to the driver steering task. This chapter investigates various methods for identifying the neuromuscular dynamics with respect to the driver steering task. By using the EPS hardware as a dynamic shaker and applying random torques to the driver and steering system the driver’s neuromuscular dynamics have been identified.

A substantial body of research has been carried out aimed at investigating and identifying the properties of the neuromuscular system. Much of the work has looked at control about a single joint, for example the ankle [66, 80-82] or elbow [51, 58, 60]. In these studies movements are usually constrained to have one degree of freedom and a agonist/antagonist muscle pair can be identified as the prime movers. The neuromuscular system involved in driver steering control is more complex potentially involving: wrist, elbow and shoulder joints; and associated muscles in both arms. The question arises as to whether neuromuscular properties identified for simple contrived one degree of freedom control tasks can also be used to describe driver steering control.

Neuromuscular identification routines described in the literature can be broadly classified as parametric or non-parametric, as highlighted by Perreault [83]. Non-parametric methods include frequency response analysis [64, 77], and ensemble methods aimed at identifying an impulse response function, for example [80]. It is necessary to assume that any ensemble of measurements is time invariant. The advantage of non-parametric methods is that no a priori knowledge of the system’s structure is needed. Once a non-parametric model or response has been measured, an appropriate parametric model with physical significance can be established.
If the system structure is already known, or can be assumed with confidence, parametric models can be fitted to the measured data. Zhang and Rymer [51] fit a model including intrinsic and reflex dynamics using a double integral filter which allows least squares identification of remaining parameters. Alternatively discrete time methods can be used; the autoregressive moving average model, as used by Bennett [60], allows identification of time varying models and parameters.

The stretch reflex provides a feedback path from the muscle spindle via the spinal cord and back to the muscle to allow closed loop control of the muscle’s length (Chapter 1, Figure 1.10). Much debate arises over the role of this reflex action within the neuromuscular system. The source of the debate is a difficulty in separating intrinsic mechanical responses of the limb and muscles from those generated by reflex feedback. Although stretch reflex characteristics can be observed by measuring EMG activity, the challenge of relating this to a mechanical response still remains.

For simple movements about the ankle the effects of reflex action have been extracted using a parallel cascade method [81, 84]. The method used generates impulse response functions for intrinsic and reflex pathways separately. The method makes use of the time delay in the reflex action (in this case measured at > 40ms). Because no reflex action should be seen initially in the impulse response, the initial components of the impulse response can be attributed to intrinsic components. In Chapter 3, the key muscles involved in steering control were identified as the sternal portion of the pectoralis major and the front deltid. As these are muscles of the shoulder, which are in closer proximity to the spinal cord, the time delay for reflex action is expected to be much shorter than those measured at the ankle or elbow joints. This potentially limits the applicability of a parallel cascade method.

Hogan [52] proposes that the time delays associated with reflex feedback limit posture maintaining performance due to stability constraints. Instead it is proposed that posture is controlled by co-contracting opposing muscles. Under conditions of co-contraction no net torque is generated, but the change in the muscle operating point results in an increase in the intrinsic stiffness of the muscle (see section 1.4.1).
This chapter describes a series of experiments along with results that identify properties of the driver’s neuromuscular dynamics. Section 4.2 describes the methods used, section 4.3 highlights problems associated with closed loop identification, 4.4 gives results from an indirect method of identification, 4.5 describes a simulation of the direct identification method, 4.6 gives results from the direct method and 4.7 describes a method of identifying the neuromuscular dynamics recursively. Finally, sections 4.8 and 4.9 discuss identification of the reflex dynamics. The results are summarised and conclusions are given in section 4.10.
4.2 METHODS

4.2.1 Experimental procedure

Eight subjects, with ages 21 to 32 years and no known neuromuscular anomalies were recruited on a voluntary basis (a description of the participants is given in the Appendix, Table A2). The test subjects also participated in the experiments described in Chapters 3 and 5, and for each test subject the experiments were carried out in a single session. The test subjects gave informed consent to participate in the study.

The response of the driver’s neuromuscular system to steering torque disturbance was investigated, using the EPS hardware as a dynamic shaker. Random torque disturbance signals were applied in the form of a Pseudo Random Binary Sequence (PRBS) to the EPS motor. The PRBS signal essentially provides band-limited white noise and its properties have been discussed in Chapter 2, section 2.3.1. Test subjects held the steering wheel on centre while the disturbance signal was applied. The resulting measured steering torques and angles were used to identify the dynamic properties of the neuromuscular system. EMG measurements were taken to establish the degree of muscle activity. EMG sensors were attached on both the left and right arms to the: biceps, triceps long head, front deltoid and sternal portion of the pectoralis major. A relationship between test subject’s EMG activity and steering torque was established in Chapter 3. This relationship is used in the analysis of the results in this chapter.

The test subjects were seated comfortably, with the seat adjusted so that the arms were slightly bent at the elbow (approximately 100 deg between forearm and upper arm) and the hands were placed in the “quarter to three” position. The steering wheel was raked so that a projected line along the steering axis was parallel to a line through the shoulder and wrist joint.

Test subjects were instructed to hold the steering wheel under various conditions in order that variations in the dynamic properties of the neuromuscular system with muscle activation could be investigated. To measure the properties of the neuromuscular system with the muscles relaxed, test subjects were asked to hold the steering wheel with just enough force to prevent their hands from slipping as the
wheel moved. Alternatively test subjects were asked to tense and hold the wheel firmly on centre, thereby co-contracting the arm muscles.

The properties of the neuromuscular system were also measured with the muscles under pretension. In this case, static offset torques were applied to the EPS motor in addition to the random disturbance. The test subjects had to resist the static component of torque, but otherwise remain as relaxed as possible. The subjects were given a minimum of 90s rest between tests to minimise any effects of muscle fatigue. The test conditions used are summarised in Table 4.1.

<table>
<thead>
<tr>
<th>Static torque offset/ Nm</th>
<th>PRBS amplitude/ Nm</th>
<th>PRBS time interval/s</th>
<th>Driver muscle state</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 +/-4</td>
<td>0.01</td>
<td>relaxed</td>
<td></td>
</tr>
<tr>
<td>0 +/-8</td>
<td>0.01</td>
<td>relaxed</td>
<td></td>
</tr>
<tr>
<td>0 +/-4</td>
<td>0.01</td>
<td>tensed</td>
<td></td>
</tr>
<tr>
<td>-2,-4,-6,-8,-10 +/-4</td>
<td>0.005</td>
<td>pretension</td>
<td></td>
</tr>
</tbody>
</table>

4.2.2 Torque disturbance signal

An 11 bit PRBS signal was used to generate a torque disturbance in order that the neuromuscular dynamics could be identified. The signal was sent to the EPS motor as a torque demand. A time interval of 0.01s was initially chosen for the PRBS signal resulting in a sequence length of 20.47s. The sequence length gives a minimum excitation frequency of approximately 0.05Hz and allows the low frequency response of the neuromuscular system to be measured. To prevent muscle fatigue, when test subjects were asked to oppose a static torque offset, the excitation time interval was set to 0.005s. Reducing the time interval reduces the sequence length to 10.235s. A trade off in reducing the sequence length is a reduction in resolvable frequency following Fourier analysis.
The PRBS signal is periodic and the measured responses to repeated sequences were ensemble averaged to improve the signal to noise level. PRBS signals with time intervals of 0.01s were repeated four times and signals with time intervals of 0.005s were repeated six times. The measured response to the first run of the sequence was discarded as it contains transients, so the 0.01s sequence contains three runs averaged while the 0.005s sequence contains five runs averaged.

In all experiments the torque disturbance signal was low-pass filtered at 50Hz, using a fourth order Butterworth filter, before being sent to the EPS motor. This ensures that the torque demand signal frequency content does not exceed the motor controller bandwidth. The measured column torque signal showed attenuation at certain frequencies (arising from the dynamic response of the driver’s arms and steering system) when compared to the motor torque demand (Figure 4.1 (a)). The attenuation leads to poor coherence between input and output signals. The coherence is improved by amplifying the excitation at certain frequencies. Equation 4.1 describes a notch amplifier, which was designed to increase the signal power at the attenuated frequencies. The frequency, $\omega_a$, was nominally set at 1.5Hz (9.42rad/s), whilst the damping ratio was set to $\gamma=0.625$; this gives an amplification factor of 2 at 1.5Hz. The amplifier frequency response can be seen in Figure 4.2 and the effect on the torque demand and column torque is shown in Figure 4.1.

Notch amplifier: 

$$H(s) = \frac{(s + 2\omega_a) \left(s + \omega_a/2\right)}{s^2 + 2\gamma\omega_a + \omega_a^2}$$

(4.1)
Figure 4.1: Effect of notch amplifier on attenuation in column torque signal. (a) response before amplification. (b) response after amplification.

Figure 4.2: Notch amplifier frequency response. The notch amplifier is used to pre-filter the PRBS torque demand signal.
The effect of perturbation signal bandwidth is discussed by Zhang and Rymer [51] and Kearney et al. [81]. It was found that reflex action was found to be most prominent when the torque disturbance bandwidth ranged from 0-10Hz for ankle and elbow joints. In the experiments reported here, the bandwidth achievable was limited by the performance of the EPS hardware. As can be seen in Figure 4.1, the torque excitation rolls off beyond 10Hz. This is due to compliance in the EPS unit’s integral column torque sensor.

4.2.3 Signal measurement and processing

Eight channels of EMG data were logged. Additionally all six channels from the six axis load cell were logged. Signals were measured and logged at 1kHz with anti-alias filtering applied (as discussed in Chapter 2 and Chapter 3). Motor torque demand \( T_{\text{mot}} \), steering column torque \( T_{\text{sen}} \), steering column velocity \( \dot{\theta}_{\text{col}} \) and steering column angle \( \theta_{\text{col}} \) were logged directly from the EPS hardware.

As discussed in Chapter 3, the EMG data was post processed by high-pass filtering at 20Hz, then rectifying and low-pass filtering at 5Hz to give a smoothed and rectified signal. The filtering was performed on the data series in forwards and reverse directions to eliminate any phase lag.

Frequency responses for the measured data were calculated as follows:

1. Average: Because the PRBS excitation was periodic, successive repeats of the measured data could be ensemble averaged. This reduces the effect of random noise on the signal.
2. Remove mean: Any linear trends were removed from each signal to ensure the signal had zero mean. This removes the steady state torque offset and any drift in the steer angle position.
3. Hanning window: The averaged data was windowed to ensure periodicity.
4. Discrete Fourier transform: The discrete Fourier transform of the data was found and spectral estimates for the cross spectrum and auto spectrum were calculated.
5. Average spectral estimates: Adjacent spectral estimates were averaged in groups of 3 to reduce variance. A trade off in this averaging is a reduction in the measurement bandwidth.

6. Calculate frequency response: The frequency response was calculated from auto and cross spectrums using the cross spectral method (equation 4.2); a description of the method is given by Newland [71].

Frequency response: \[ H(\omega) = \frac{S_{yu}}{S_{uu}} \] (4.2)

where: 
- \( S_{yu} \) - Cross spectrum between \( \theta_{col} \) and \( T_{dem} \)
- \( S_{uu} \) - Auto spectrum for \( T_{dem} \)

4.2.4 Frequency domain identification routine
Model fits were generated to match measured frequency responses. The measured frequency response was compared to the model frequency response with the aim of minimising the phasor error function given by equation 4.3.

Model parameters were varied until equation 4.3 was minimised. The minimisation was carried out using Matlab’s ‘fminsearch’ function. The function carries out multidimensional unconstrained nonlinear minimization using the simplex method (Nelder and Mead [73]).

\[ \varepsilon = \frac{1}{N} \sum_{\omega} \frac{\text{Re}(H_{\text{exp}}(\omega) - H_{\text{mod}}(\omega))^2 + \text{Im}(H_{\text{exp}}(\omega) - H_{\text{mod}}(\omega))^2}{\text{Re}(H_{\text{exp}}(\omega))^2 + \text{Im}(H_{\text{exp}}(\omega))^2} \] (4.3)

where:
- \( H_{\text{exp}}(\omega) \) - Experimentally measured frequency response
- \( H_{\text{mod}}(\omega) \) - Model frequency response
- \( N \) - Number of data points

When using the simplex method, there is a danger that any identified minimum may only be a local minimum of the function to be minimised. To ensure that a global minimum was identified various initial search points were tried. In general, the method was robust and when fitting simple models a unique minimum was identified.
The quality of the fit of an identified model can also be assessed by calculating the proportion of Variance Accounted For (VAF) by the model [51, 81]. This requires simulating the system output in the time domain using the identified model. The VAF can then be calculated from the measured and model data (Equation 4.4).

\[
VAF = \left(1 - \frac{\sigma^2_e}{\sigma^2_s}\right)
\]

(4.4)

where:

\[
\sigma^2_e = \frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i - y_i)^2 - \text{Simulation error variance}
\]

\[
\sigma^2_s = \frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y})^2 - \text{Measured signal variance}
\]

\[
y - \text{Measured signal}
\]

\[
\hat{y} - \text{Model prediction}
\]

When identifying mechanical models, since the arm is physically attached to the steering wheel and in turn to the load cell the identified inertia, \(J\), is the total inertia for the arm and these attachments (equation 4.5). The inertia of the steering wheel and load cell has been calculated separately and was given in section 2.4.2. If the inertia of the arm alone is required the inertia of the steering wheel and load cell should be subtracted from the identified values.

\[
J = J_{dr} + J_{lc} + J_{sw}
\]

(4.5)

where:

\[
J - \text{Identified total inertia}
\]

\[
J_{dr} - \text{Arm inertia}
\]

\[
J_{lc} - \text{Load cell inertia (0.03kgm}^2\text{)}
\]

\[
J_{sw} - \text{Steering wheel inertia (0.02kgm}^2\text{)}
\]
4.3 CLOSED LOOP IDENTIFICATION

There is a dynamic coupling between the EPS hardware and the neuromuscular dynamics; the interface being the compliant torque sensor. The signal flow diagram, Figure 4.3, shows the dynamic coupling and equivalent feedback loops. A direct way of identifying the neuromuscular dynamics would be to calculate the frequency response between the torque sensor signal $T_{sen}$ and the column angle $\theta_{sw}$. However the feedback loops create a number of problems that will be discussed in this section.

![Figure 4.3: Dynamic coupling between EPS system and neuromuscular system.](image)

By considering a more general form of a feedback control system (Figure 4.4), the effect of the feedback loop on system identification can established.

![Figure 4.4: Feedback system where the system of interest, $G(s)$, is unknown and the subject of identification.](image)

A direct way of identifying the system of interest ($G(s)$) is to measure the signals $u(s)$ and $y(s)$ and calculate the frequency response between the signals. This is known as the direct method (Equations 4.6 & 4.7).

Output equation:

$$y(s) = G(s)u(s) + w(s) \quad (4.6)$$
Provided \( u(s) \gg w(s) \) (i.e the signal to noise level is good), the system of interest can be identified using the direct method (equation 4.7).

\[
\frac{S_{yy}}{S_{uu}} = \frac{y(s)}{u(s)} = G(s)
\]  

(4.7)

where: \( S_{uu} \) – Auto spectrum of input signal  
\( S_{yu} \) – Cross spectrum between output and input signals

By analysing the signal flow in Figure 4.4, it can be shown that the measured input signal, \( u(s) \), consists of the following components:

\[
u(s) = \frac{K(s)r(s)}{1 + K(s)G(s)H(s)} - \frac{K(s)H(s)w(s)}{1 + K(s)G(s)H(s)}
\]  

(4.8)

Problems arise when \( r(s) << H(s)w(s) \) and as \( G(s) \to 0 \). In this case:

\[
y(s) \approx w(s) \quad \text{and} \quad u(s) = -K(s)H(s)w(s)
\]  

(4.9)

Under the conditions given in equation 4.9, calculating a transfer function using the direct method yields equation 4.10, the inverse regulator dynamics.

\[
\frac{y(s)}{u(s)} = -\frac{1}{K(s)H(s)}
\]  

(4.10)

Hence, at frequencies when the input signal \( r(s) \) is small, the noise \( w(s) \) is large and the system response \( G(s) \) is small, the inverse regulator dynamics are identified rather than the system of interest \( G(s) \). The problem is discussed further in [85, 86]. For the problem of identifying the neuromuscular dynamics (Figure 4.3) the neuromuscular system is the system of interest, \( G(s) \), and the motor and torque sensor form the feedback regulator, \( K(s)H(s) \).
An alternative method is to extract a transfer function for the system of interest using signals measured outside the feedback loops ($r(s)$ and $y(s)$ in Figure 4.4). This is known as the indirect method. Equation 4.11 gives the closed loop transfer function for Figure 4.4. The transfer function can be found using spectral analysis, which helps to remove any uncorrelated noise $w(s)$.

\[
\frac{y(s)}{r(s)} = \frac{K(s)G(s)}{1 + K(s)G(s)H(s)} \tag{4.11}
\]

Rearranging equation (4.11) gives the transfer function for the system of interest:

\[
G(s) = \frac{\frac{y(s)}{r(s)}}{K(s) \left(1 - H(s) \frac{y(s)}{r(s)}\right)} \tag{4.12}
\]

Hence the system of interest $G(s)$ can be identified using the indirect method, provided $H(s)$ and $K(s)$ are known.

An alternative method of indirect system identification is to fit a parametric model to equation 4.11 using parameter variation. The known parameters for $K(s)$ and $H(s)$ are held constant whilst parameters for the unknown system $G(s)$ are varied until the best fit to equation 4.11 is found. In the following section indirect identification is achieved through parameter variation.
4.4 INDIRECT-METHOD IDENTIFICATION RESULTS

To avoid the problems associated with closed loop identification, discussed in section 4.3, the indirect method of identification was initially used to identify the neuromuscular dynamics. The motor torque demand signal \( T_{dem} \) was used along with the column angle signal \( \theta_{col} \) because the two signals are not connected by any feedback loops. It is convenient to use the column angle signal \( \theta_{col} \) because the signal is output directly from the EPS hardware; the steering wheel angle signal \( \theta_{sw} \) can be calculated, but is subtly different to \( \theta_{col} \) due to compliance in the column at the integral torque sensor. The frequency response between the torque demand \( T_{dem} \) and column angle \( \theta_{col} \) signals was calculated using the cross-spectral method equation (4.2).

The measured frequency response (equation 4.11) gives the combined response for both the neuromuscular dynamics and the EPS hardware. A typical frequency response, measured for test subject A, is shown in Figure 4.5. Good coherence is seen from 0-30Hz indicating that a linear transfer function can be fitted to the data over this range. Transfer functions were fitted to all the data sets using polynomials of the Laplace variable \( s \). A transfer function with order \( s^2 \) in the numerator, \( s^4 \) in the denominator and with a time delay to represent sensor delays gave the best fit (equation 4.13). Attempts were made to fit higher order models, however it was found that there was no improvement in the model fit; the additional terms in the numerator and denominator simply cancelled each other out.

\[
\frac{\theta_{col}(\omega)}{T_{dem}(\omega)} = \frac{15.7(s^2 + 33.1s + 1180)}{(s + 61.7)(s + 56)(s^2 + 4.2s + 12)}e^{-0.012s}
\]  

(4.13)
The structure of the transfer function (equation 4.13) fitted to the data is consistent with a two degree of freedom model of the driver and EPS system Figure 4.6. The two degrees of freedom are column angle, $\theta_{col}$, and steering wheel angle, $\theta_{sw}$, and arise because of compliance at the integral torque sensor, $K_{sen}$, in an otherwise rigid steering column. The driver adds additional inertia, $J_{dr}$, damping, $B_{dr}$, and a restraining stiffness, $K_{dr}$, to the steering wheel. Additional parameters are the inertia of the motor, $J_{mot}$, inertia of the steering wheel, $J_{sw}$, and viscous damping terms $B_{mot}$ and $B_{sw}$ to represent friction in the motor and steering wheel bearings respectively. $B_{sen}$ is a viscous term used to represent any damping in the torque sensor. The torque generated by the motor is assumed to match the demand torque, $T_{dem}$, due to the high bandwidth motor torque controller.
Chapter 4: Limb Dynamic Identification

Figure 4.6: Lumped parameter model of the driver’s arm and steering dynamics.

The equations of motion for the model of the driver’s arms and EPS hardware are:

\[
J_{\text{mot}} \ddot{\theta}_{\text{col}} + B_{\text{mot}} \dot{\theta}_{\text{col}} + B_{\text{sen}} (\dot{\theta}_{\text{col}} - \dot{\theta}_{sw}) + K_{\text{sen}} (\theta_{\text{col}} - \theta_{sw}) = T_{\text{dem}}
\]

\[
(J) \ddot{\theta}_{sw} + (B_{sw} + B_{dr}) \dot{\theta}_{sw} + B_{sen} (\dot{\theta}_{sw} - \dot{\theta}_{col}) + K_{\text{sen}} (\theta_{sw} - \theta_{col}) + K_{dr} \theta_{sw} = 0
\]

where: \( J = J_{dr} + J_{sw} + J_{lc} \)

By rearranging equation 4.14 and taking Laplace transforms the physical significance of the fitted transfer function can be seen (equation 4.15). As expected the model order is \( s^2 \) in the numerator and \( s^4 \) in the denominator. A time delay \( \tau = 0.012s \) is included to represent sensor delays.

\[
\frac{\theta_{\text{col}}(s)}{T_{\text{dem}}(s)} = \frac{a_1 s^2 + a_2 s + a_3}{a_4 s^4 + a_5 s^3 + a_6 s^2 + a_7 s + a_8} e^{-s\tau}
\]

where:

\( a_1 = J \)

\( a_2 = B_{dr} + B_{sen} \)

\( a_3 = K_{\text{sen}} + K_{dr} \)

\( a_4 = J * J_{\text{mot}} \)

\( a_5 = B_{\text{mot}} * J + B_{\text{sen}} * J + J_{\text{mot}} * (B_{dr} + B_{\text{sen}}) \)

\( a_6 = (J_{\text{mot}} * K_{\text{sen}} + B_{\text{mot}} * B_{\text{dr}} + B_{\text{mot}} * B_{\text{sen}} + K_{\text{sen}} * J + B_{\text{sen}} * B_{\text{dr}} + J_{\text{mot}} * K_{\text{dr}}) \)

\( a_7 = (B_{\text{mot}} * K_{\text{sen}} + B_{\text{sen}} * B_{\text{dr}} + B_{\text{sen}} * K_{\text{dr}} + B_{\text{mot}} * K_{\text{dr}}) \)

\( a_8 = K_{\text{sen}} * K_{\text{dr}} \)

Having established a suitable structure for modelling the EPS and driver’s arm dynamics, parameter identification was carried out. Because the EPS system parameters are known (identified in Chapter 2, Table 2.2), only the unknown neuromuscular parameters for the neuromuscular system remain. The frequency domain fitting procedure described by equation 4.3 was used. The EPS parameters
were set as constants, whilst values for $J$, $B_{dr}$ and $K_{dr}$ were varied until the best fit was found. In order to obtain a good fit to the measured data it was also necessary to include a damping parameter between the steering wheel and lower column, $B_{sen}$. The identification carried out in Chapter 2 indicated that $B_{sen}$ was small and negligible. However, the EPS system contains some non-linear elements, for example friction at the worm gear. Fitting $B_{sen}$ allows an extra degree of freedom in the search routine, and it is thought that $B_{sen}$ essentially provides a linear describing function for the non-linear elements.

The frequency response was also measured with the driver’s arms in the tensed state (Figure 4.7). Using the indirect method, values for the inertia, damping and stiffness were identified for comparison with the values identified for the relaxed muscles, Table 4.2 and Table 4.3.

![Frequency response from motor torque demand to steering column angle](image)

**Figure 4.7:** Indirect fit to measured data (subject A). Driver muscle state stiffened. PRBS amplitude +/-4Nm.
Table 4.2: Neuromuscular dynamic properties identified using the indirect method for relaxed muscle state. Data fitted over $N=200$ spectral estimates (upto 30Hz). PRBS amplitude +/- 4Nm.

<table>
<thead>
<tr>
<th>Subject</th>
<th>$\varepsilon$</th>
<th>$J$/kgm$^2$</th>
<th>$B_{dr}$/Nms/rad</th>
<th>$K_{dr}$/Nm/rad</th>
<th>$B_{sen}$/Nms/rad</th>
<th>VAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.041</td>
<td>0.117</td>
<td>0.91</td>
<td>3.66</td>
<td>3.54</td>
<td>0.84</td>
</tr>
<tr>
<td>B</td>
<td>0.039</td>
<td>0.153</td>
<td>0.89</td>
<td>3.97</td>
<td>3.55</td>
<td>0.90</td>
</tr>
<tr>
<td>C</td>
<td>0.041</td>
<td>0.158</td>
<td>0.85</td>
<td>4.91</td>
<td>3.41</td>
<td>0.89</td>
</tr>
<tr>
<td>D</td>
<td>0.060</td>
<td>0.128</td>
<td>1.22</td>
<td>2.96</td>
<td>4.67</td>
<td>0.65</td>
</tr>
<tr>
<td>E</td>
<td>0.041</td>
<td>0.181</td>
<td>1.04</td>
<td>3.05</td>
<td>3.77</td>
<td>0.83</td>
</tr>
<tr>
<td>F</td>
<td>0.051</td>
<td>0.145</td>
<td>0.77</td>
<td>3.76</td>
<td>3.09</td>
<td>0.89</td>
</tr>
<tr>
<td>G</td>
<td>0.036</td>
<td>0.158</td>
<td>1.24</td>
<td>4.93</td>
<td>3.68</td>
<td>0.79</td>
</tr>
<tr>
<td>H</td>
<td>0.044</td>
<td>0.141</td>
<td>1.01</td>
<td>3.63</td>
<td>3.48</td>
<td>0.83</td>
</tr>
</tbody>
</table>

By comparing the results in Table 4.2 and Table 4.3 it can be seen that there is a considerable increase in arm stiffness in the tensed muscle state. This confirms the expectation that muscle co-contraction leads to an increase in the intrinsic stiffness of the muscle.

In general the variance accounted for (VAF) is lower for the models identified with the arms in the tensed state. An explanation for this is that the increase in arm stiffness following tensing of the muscles reduces the amplitude of steering wheel
rotations, reducing the signal to noise ratio. A negative value is seen for the VAF for test subject B in Table 4.3 and the frequency fit shows a large error indicated by $\epsilon > 1$. In this case, an appropriate model has not been identified and the result for subject B should be disregarded.

It is expected that the identified inertia, $J$, will remain constant following tensing of the muscles. With the exception of test subjects C and D the variation in inertia is small.

The accuracy of a neuromuscular model identified using the indirect method depends on the accuracy of the parameters used to describe the EPS system. Any errors in the EPS model will lead to errors in the identified neuromuscular system. In particular non-linearity in the EPS system may lead to uncertainty in the identified neuromuscular system. Significant non-linearity exists in the EPS system at the worm gear as discussed in the system identification carried out in Chapter 2.

The indirect method gives a good indication of appropriate model structures for the neuromuscular system. However a direct method where parameters are fitted directly to the frequency response of the measured data may give more reliable estimates of parameters representing the neuromuscular system.
4.5 DIRECT-METHOD SIMULATION RESULTS

The indirect method, described in the previous section, confirms that a simple second order model represents the key features of the neuromuscular system. In addition, initial estimates for parameter values for the neuromuscular system model were found. The direct method may give better estimates of the neuromuscular parameters, as the method does not rely on the dynamics of the EPS system being known.

Figure 4.8 shows a block diagram representation of the neuromuscular system when coupled to and excited by the EPS motor. The feedback loops around the neuromuscular system are shown. As discussed in section 4.3 some uncertainty arises when using the direct method for system identification within a feedback loop. In order to confirm the effect of these feedback loops, a simulation was performed to determine if known neuromuscular dynamic properties could be correctly identified in the presence of measurement noise using a direct identification method. Typical parameter values, estimated using the indirect method, were used to simulate the neuromuscular system.

Using the direct method, the neuromuscular system dynamics were calculated from the frequency response between the torque sensor signal ($T_{sen}$) and the steering wheel angle ($\theta_{sw}$). At frequencies where the output from the neuromuscular system is small, the measurement noise $w_{3}$ becomes significant and the measured frequency response is corrupted by the feedback path dynamics.
Chapter 4: Limb Dynamic Identification

The system shown in Figure 4.8, with known neuromuscular dynamics, was simulated. The measurement noise ($w_3$) was generated using Matlab Simulink’s white noise block with random seed number, sample frequency of 1kHz and noise power of $w_3=1\times10^{-6}\text{rad}^2/\text{Hz}$ ($w_1$ and $w_2$ were set equal to 0). The known neuromuscular system frequency response is shown in Figure 4.9, along with the response calculated using the direct method (equation 4.16). It can be seen that the frequency response from the direct identification method only matches the true system response up to 10Hz. Above 10Hz the coherence is poor and the response is corrupted by the feedback dynamics as predicted in section 4.3.

$$H(\omega) = \frac{S_{yu}(\omega)}{S_{uu}(\omega)} \approx \frac{1}{|J(j\omega)|^2 + B_{dr}(j\omega) + K_{dr}} \quad (4.16)$$

where: $S_{yu}$ - Cross spectrum between $\theta_{sw}$ and $T_{sen}$

$S_{uu}$ - Auto spectrum for $T_{sen}$

![Simulated frequency response from column torque to steering wheel angle](image)

Figure 4.9: Simulated arm dynamic identification using direct method.
4.6 DIRECT-METHOD IDENTIFICATION RESULTS

The indirect identification method described in section 4.4 confirms a mass, spring and damper may be a suitable structure for the neuromuscular model. Additionally the simulation carried out in section 4.5 confirms that identification by the direct method can be carried out on the low frequency response (<10Hz) when the measurement noise is not significant. Hence a mass, spring and damper model, representing the neuromuscular system, can be fitted to the measured frequency response between column torque and steering wheel angle (equation 4.16).

4.6.1 Identified arm dynamics for relaxed and tensed muscles

The measured frequency response in Figure 4.10 is consistent with the direct method simulation results Figure 4.9, indicating that the direct method is valid. Figure 4.10 and Figure 4.11 show a typical frequency response of the driver’s arms with the muscles relaxed and tensed respectively. The resonant frequency ($\omega_n$), seen in the frequency response, increases when the arm muscles are in the stiffened state, the maximum frequency observed across all subjects was 5Hz. The low frequency response data (0-1Hz) represents compliance in the driver’s arms ($1/K_{dr}$), whilst the resonant frequency and phase change give information on the arm inertia and damping.

Provided identification is carried out up to and marginally beyond the resonant frequency the neuromuscular dynamics can be extracted. The frequency response at higher frequencies is corrupted by noise and feedback path dynamics. Fitting models to the higher frequency components in the frequency response may result in the feedback path dynamics being identified rather than the neuromuscular system which is the system of interest. Hence fitting was carried out on the first 40 points in the measured frequency response spectrum limiting the frequency to 5.8Hz.

Table 4.4 and Table 4.5 give the identified arm dynamics, for test subjects A-H, with muscles in a relaxed and tensed state respectively. It can be seen that the models identified give a good fit to the measured data as characterised by the VAF.
Figure 4.12 shows a typical model fit to measured data along with the power spectrum of the remnant. The model response is shown for an additional 30s of data measured at the end of a run. This data had not previously been used in the identification routine; it therefore gives a reliable indication of the success of the model fit. It can be seen that the noise has power spectral density of $10^{-4}$ to $10^{-6}$ rad$^2$/Hz between 1Hz and 10Hz. This is of similar magnitude to the noise used when simulating the direct identification routine (section 4.5).

Table 4.4: Neuromuscular dynamic properties identified using the direct method for relaxed muscle state. Data fitted over $N=40$ spectral estimates (upto 5.8Hz). PRBS amplitude +/-4Nm.

<table>
<thead>
<tr>
<th>Subject</th>
<th>$\varepsilon$</th>
<th>$\frac{J}{kgm^2}$</th>
<th>$B_{dr}$/Nms/rad</th>
<th>$K_{dr}$/Nm/rad</th>
<th>$\omega_n$/Hz</th>
<th>VAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.116</td>
<td>0.098</td>
<td>0.55</td>
<td>3.69</td>
<td>0.98</td>
<td>0.84</td>
</tr>
<tr>
<td>B</td>
<td>0.114</td>
<td>0.130</td>
<td>0.35</td>
<td>4.17</td>
<td>0.90</td>
<td>0.91</td>
</tr>
<tr>
<td>C</td>
<td>0.083</td>
<td>0.122</td>
<td>0.43</td>
<td>4.76</td>
<td>0.99</td>
<td>0.89</td>
</tr>
<tr>
<td>D</td>
<td>0.088</td>
<td>0.087</td>
<td>0.63</td>
<td>2.84</td>
<td>0.91</td>
<td>0.67</td>
</tr>
<tr>
<td>E</td>
<td>0.128</td>
<td>0.144</td>
<td>0.60</td>
<td>3.42</td>
<td>0.78</td>
<td>0.79</td>
</tr>
<tr>
<td>F</td>
<td>0.072</td>
<td>0.106</td>
<td>0.48</td>
<td>3.45</td>
<td>0.91</td>
<td>0.86</td>
</tr>
<tr>
<td>G</td>
<td>0.105</td>
<td>0.121</td>
<td>0.78</td>
<td>4.62</td>
<td>0.98</td>
<td>0.80</td>
</tr>
<tr>
<td>H</td>
<td>0.071</td>
<td>0.103</td>
<td>0.65</td>
<td>3.46</td>
<td>0.92</td>
<td>0.84</td>
</tr>
</tbody>
</table>

Table 4.5: Neuromuscular dynamic properties identified using the direct method for stiffened muscle state. Data fitted over $N=40$ spectral estimates (upto 5.8Hz). PRBS amplitude +/-4Nm.

<table>
<thead>
<tr>
<th>Subject</th>
<th>$\varepsilon$</th>
<th>$\frac{J}{kgm^2}$</th>
<th>$B_{dr}$/Nms/rad</th>
<th>$K_{dr}$/Nm/rad</th>
<th>$\omega_n$/Hz</th>
<th>VAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.112</td>
<td>0.088</td>
<td>1.01</td>
<td>20.26</td>
<td>2.42</td>
<td>0.81</td>
</tr>
<tr>
<td>B</td>
<td>0.358</td>
<td>0.126</td>
<td>1.08</td>
<td>75.95</td>
<td>3.91</td>
<td>0.77</td>
</tr>
<tr>
<td>C</td>
<td>0.120</td>
<td>0.074</td>
<td>1.42</td>
<td>80.10</td>
<td>5.24</td>
<td>0.84</td>
</tr>
<tr>
<td>D</td>
<td>0.184</td>
<td>0.101</td>
<td>0.62</td>
<td>44.47</td>
<td>3.34</td>
<td>0.83</td>
</tr>
<tr>
<td>E</td>
<td>0.130</td>
<td>0.131</td>
<td>1.35</td>
<td>69.68</td>
<td>3.67</td>
<td>0.63</td>
</tr>
<tr>
<td>F</td>
<td>0.215</td>
<td>0.110</td>
<td>0.87</td>
<td>81.98</td>
<td>4.35</td>
<td>0.69</td>
</tr>
<tr>
<td>G</td>
<td>0.168</td>
<td>0.092</td>
<td>1.08</td>
<td>56.44</td>
<td>3.93</td>
<td>0.81</td>
</tr>
<tr>
<td>H</td>
<td>0.088</td>
<td>0.090</td>
<td>0.97</td>
<td>33.74</td>
<td>3.08</td>
<td>0.86</td>
</tr>
</tbody>
</table>
Figure 4.10: Direct fit to measured data (subject C). Driver muscle state relaxed. PRBS amplitude +/-4Nm.

Figure 4.11: Direct fit to measured data (subject C). Driver muscle state stiffened. PRBS amplitude +/-4Nm.
The identified limb dynamics are sensitive to the estimated limb inertia. Although arm stiffness and damping are expected to vary as muscle stiffness increases, there is no physiological reason for variation in arm inertia. However small variations in the inertia may be seen if the driver moves their arms on the steering wheel. In order that the results were consistent, when carrying out further identifications of arm damping and stiffness, arm inertia values were set as constants for each test subject according
Chapter 4: Limb Dynamic Identification

to the results given in Table 4.4\(^4\); an added advantage is that this approach simplifies the identification routine. Table 4.6 shows the identified limb dynamic properties for the stiffened muscle when the inertia values are fixed to those given in Table 4.4.

Table 4.6: Neuromuscular dynamic properties identified using the direct method for stiffened muscle state. Inertia values fixed to match those in Table 4.4. Data fitted over N=40 spectral estimates (upto 5.8Hz). PRBS amplitude +/-4Nm.

<table>
<thead>
<tr>
<th>Subject</th>
<th>$\varepsilon$</th>
<th>$J$ / kgm$^2$</th>
<th>$B_{dr}$ / Nms/rad</th>
<th>$K_{dr}$ / Nm/rad</th>
<th>VAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.117</td>
<td>0.098</td>
<td>0.98</td>
<td>22.26</td>
<td>0.81</td>
</tr>
<tr>
<td>B</td>
<td>0.358</td>
<td>0.130</td>
<td>1.08</td>
<td>78.63</td>
<td>0.77</td>
</tr>
<tr>
<td>C</td>
<td>0.184</td>
<td>0.122</td>
<td>1.55</td>
<td>97.3</td>
<td>0.76</td>
</tr>
<tr>
<td>D</td>
<td>0.200</td>
<td>0.087</td>
<td>0.63</td>
<td>38.11</td>
<td>0.86</td>
</tr>
<tr>
<td>E</td>
<td>0.134</td>
<td>0.144</td>
<td>1.36</td>
<td>75.72</td>
<td>0.61</td>
</tr>
<tr>
<td>F</td>
<td>0.216</td>
<td>0.106</td>
<td>0.87</td>
<td>79.59</td>
<td>0.69</td>
</tr>
<tr>
<td>G</td>
<td>0.200</td>
<td>0.121</td>
<td>1.13</td>
<td>71.83</td>
<td>0.76</td>
</tr>
<tr>
<td>H</td>
<td>0.097</td>
<td>0.103</td>
<td>0.98</td>
<td>37.98</td>
<td>0.83</td>
</tr>
</tbody>
</table>

Models for the arm inertia, damping and stiffness have been identified using both the direct method and indirect method. In general, the VAF in the case of the direct method is higher than that for the indirect method. For this reason the direct method is preferred. Additionally the models identified using the direct method show less variation in the arm inertia, which is expected to remain roughly constant.

### 4.6.2 Relationship between muscle co-contraction, limb stiffness and damping

By using the measure of muscle co-contraction described in Chapter 3, section 3.5.3, the relationship between the identified limb stiffness and damping, and muscle co-contraction was established. The mean level of muscle co-contraction was calculated for measurements taken from test subjects with muscles in the relaxed and stiffened states according to equation 3.13 (Table 4.7).

The mean change in co-contraction was then plotted against the mean change in stiffness and damping, evaluated from Table 4.4 and Table 4.5, as shown in Figure

\(^4\) Zhang and Rymer [51] also report that inertia was set as constant to simplify the identification and give consistent results.
4.13 and Figure 4.14 respectively. A simple linear regression line was fitted to the data to establish any trend. It can be seen that there is a strong correlation between arm stiffness and muscle co-contraction with $R^2$ value of 0.85. However, the correlation between arm damping and co-contraction is poor. From the results it can be concluded that the intrinsic muscle stiffness can be modulated through muscle co-contraction as predicted by Hogan [52].

Table 4.7: Mean muscle co-contraction measured for the relaxed and stiffened state.

<table>
<thead>
<tr>
<th>Subject</th>
<th>Mean co-contraction (relaxed state)/ Nm</th>
<th>Mean co-contraction (stiffened state)/ Nm</th>
<th>Change in co-contraction/ Nm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject A</td>
<td>13.9</td>
<td>15.0</td>
<td>1.1</td>
</tr>
<tr>
<td>Subject B</td>
<td>2.0</td>
<td>27.4</td>
<td>25.4</td>
</tr>
<tr>
<td>Subject C</td>
<td>1.5</td>
<td>20.1</td>
<td>18.6</td>
</tr>
<tr>
<td>Subject D</td>
<td>12.1</td>
<td>22.8</td>
<td>10.7</td>
</tr>
<tr>
<td>Subject E</td>
<td>5.4</td>
<td>24.8</td>
<td>19.4</td>
</tr>
<tr>
<td>Subject F</td>
<td>7.7</td>
<td>42.9</td>
<td>35.2</td>
</tr>
<tr>
<td>Subject G</td>
<td>5.7</td>
<td>19.4</td>
<td>13.7</td>
</tr>
<tr>
<td>Subject H</td>
<td>4.3</td>
<td>6.6</td>
<td>2.3</td>
</tr>
</tbody>
</table>
Figure 4.13: Variation in arm stiffness with muscle co-contraction.

Figure 4.14: Variation in arm damping with muscle co-contraction.
4.6.3 Effect of excitation amplitude

In order to establish any change in neuromuscular dynamics with amplitude of torque excitation, a +/-8Nm PRBS signal was used to excite the limb dynamics. Parameters identified from the measured frequency response, in the presence of the +/-8Nm torque disturbance (Table 4.8 and Table 4.9), can be compared to the results measured in section 4.6.1 with +/-4Nm torque disturbance (Table 4.5 and Table 4.6).

The identified values for damping and stiffness appear to show little change when the torque disturbance amplitude increases from +/-4Nm to +/-8Nm, in comparison to the variation seen between test subjects. In the case of +/-4Nm signal with relaxed arms, the mean damping and stiffness values (averaged for all subjects) were calculated as $B_{dr}=0.55\text{Nmrad/s}$ and $K_{dr}=3.8\text{Nm/rad}$ respectively. For the +/-8Nm signal values were calculated as $B_{dr}=0.61\text{Nmrad/s}$ and $K_{dr}=2.9\text{Nm/rad}$. The larger torque disturbance causes larger angular displacements. It can therefore be concluded that the system can be linearised independent of the amplitude of angular displacement within the range tested.

Table 4.8: Neuromuscular dynamic properties identified using the direct method for relaxed muscle state. Data fitted over $N=40$ spectral estimates (upto 5.8Hz). PRBS amplitude +/-8Nm.

<table>
<thead>
<tr>
<th>Subject</th>
<th>$\varepsilon$</th>
<th>$J/\text{kgm}^2$</th>
<th>$B_{dr}/\text{Nms/rad}$</th>
<th>$K_{dr}/\text{Nm/rad}$</th>
<th>VAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.130</td>
<td>0.098</td>
<td>0.620</td>
<td>4.18</td>
<td>0.84</td>
</tr>
<tr>
<td>B</td>
<td>0.156</td>
<td>0.130</td>
<td>0.486</td>
<td>2.39</td>
<td>0.80</td>
</tr>
<tr>
<td>C</td>
<td>0.133</td>
<td>0.122</td>
<td>0.442</td>
<td>4.64</td>
<td>0.83</td>
</tr>
<tr>
<td>D</td>
<td>0.113</td>
<td>0.087</td>
<td>0.610</td>
<td>0.77</td>
<td>0.78</td>
</tr>
<tr>
<td>E</td>
<td>0.228</td>
<td>0.144</td>
<td>1.030</td>
<td>3.13</td>
<td>0.75</td>
</tr>
<tr>
<td>F</td>
<td>0.094</td>
<td>0.106</td>
<td>0.459</td>
<td>3.18</td>
<td>0.86</td>
</tr>
<tr>
<td>G</td>
<td>0.199</td>
<td>0.121</td>
<td>0.824</td>
<td>2.86</td>
<td>0.65</td>
</tr>
<tr>
<td>H</td>
<td>0.118</td>
<td>0.103</td>
<td>0.461</td>
<td>2.22</td>
<td>0.80</td>
</tr>
</tbody>
</table>
Table 4.9: Neuromuscular dynamic properties identified using the direct method for stiffened muscle state. Data fitted over \( N = 40 \) spectral estimates (upto 5.8Hz). PRBS amplitude \( \pm 8 \text{Nm} \).

<table>
<thead>
<tr>
<th>Subject</th>
<th>( \varepsilon )</th>
<th>( J )/ kgm(^2)</th>
<th>( B_{dr} )/ Nms/rad</th>
<th>( K_{dr} )/ Nm/rad</th>
<th>VAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.094</td>
<td>0.098</td>
<td>1.039</td>
<td>27.98</td>
<td>0.84</td>
</tr>
<tr>
<td>B</td>
<td>0.335</td>
<td>0.130</td>
<td>0.813</td>
<td>84.22</td>
<td>0.72</td>
</tr>
<tr>
<td>C</td>
<td>0.178</td>
<td>0.122</td>
<td>1.605</td>
<td>90.31</td>
<td>0.79</td>
</tr>
<tr>
<td>D</td>
<td>0.120</td>
<td>0.087</td>
<td>0.773</td>
<td>36.73</td>
<td>0.82</td>
</tr>
<tr>
<td>E</td>
<td>0.117</td>
<td>0.144</td>
<td>1.610</td>
<td>58.52</td>
<td>0.75</td>
</tr>
<tr>
<td>F</td>
<td>0.122</td>
<td>0.106</td>
<td>1.150</td>
<td>53.24</td>
<td>0.78</td>
</tr>
<tr>
<td>G</td>
<td>0.223</td>
<td>0.121</td>
<td>1.471</td>
<td>73.10</td>
<td>0.69</td>
</tr>
<tr>
<td>H</td>
<td>0.110</td>
<td>0.103</td>
<td>0.902</td>
<td>27.28</td>
<td>0.78</td>
</tr>
</tbody>
</table>

4.6.4 Identified arm dynamics with offset torque

The properties of the neuromuscular system were also measured with the muscles under pretension. A static offset torque was applied to the EPS motor in addition to the PRBS torque disturbance. The direct identification method was used and arm inertia values for each test subject were taken from Table 4.4 and fixed as constants.

The full identification results for the arm dynamics with offset torque are presented in tabular form in the appendix, section A.3. Because the length of the PRBS signal time interval was set at 0.005s (to reduce the sequence length and prevent muscle fatigue), a lower frequency resolution was achieved than in previous experiments. To get consistently good fits to the measured data in the frequency domain it was necessary to only fit the data up to 4Hz. This also gave the best fit in terms of VAF. The dominant dynamics were all found to have natural frequencies below 4Hz.

The key feature of interest is the variation in arm stiffness and damping with respect to torque offset. The variation in stiffness and damping, measured for each subject, is shown in Figure 4.15 and Figure 4.16 respectively. A linear regression line is also fitted to the data each side of the origin.
Figure 4.15: Variation in arm stiffness identified for 8 test subjects when neuromuscular dynamics are subject to an offset torque. PRBS amplitude +/-4Nm.
Chapter 4: Limb Dynamic Identification

Figure 4.16: Variation in arm damping identified for 8 test subjects when neuromuscular dynamics are subject to an offset torque. PRBS amplitude +/-4Nm.

The identified values for arm stiffness and damping were averaged for all test subjects. A regression line was fitted to the averaged values with respect to the torque offset (Figure 4.17). There is a clear linear trend in the identified stiffness showing an increase with torque offset. A similar trend can be seen in the damping, although the results are less conclusive. The results are consistent with those published by Zhang and Rymer [51] for the elbow joint; linear increases in stiffness and damping were also identified.
Figure 4.17: Variation in damping and stiffness averaged for all test subjects identified in the presence of a torque offset. PRBS amplitude +/-4Nm.
4.7 RECURSIVE IDENTIFICATION

If the structure of the neuromuscular model is known then parametric identification routines can be carried out. The results from the previous sections give strong evidence that for the driver steering task a single degree of freedom model represents the driver’s arm dynamics at any given operating point sufficiently. Furthermore, the stiffness and damping of the driver’s arms have been shown to vary considerably with muscle activation. Hence it may be appropriate to use a time varying parametric identification method to model and identify the neuromuscular system. Bennett et al. [60], use a recursive least squares method to fit a time varying second order model to constrained elbow movements.

4.7.1 Recursive identification method

The performance of the recursive method was investigated using the measured data described previously. Models identified using a recursive least squares method were compared with those identified in the frequency domain using the direct method.

The Matlab function ‘RARX’ was used to recursively identify parameters for an ARX model (Auto regressive with exogenous inputs). The function performs recursive identification using a least squares method and returns parameter estimates at each time step. The full method is widely understood and documented [86, 87]. To speed up the recursive identification, data was resampled at 100Hz having firstly low-pass filtered to prevent aliasing. A forgetting factor, \( \lambda = 0.995 \) was used. This means that data of age \( T_0 = 1/(1-\lambda) \) samples is given a weighting of \( \approx 36\% \) when identifying current values of system parameters. Parameter \( T_0 \) can be considered to be a memory time constant and in this case has a value of about 2s.

The forgetting factor was varied to see if shorter values of \( T_0 \) could be used and changes in the system dynamics tracked more rapidly. However, it was found that when \( T_0 \) was less than 2s considerable noise and instability was experienced in the identification routine. In particular negative values for damping stiffness and inertia were obtained. As a result the forgetting factor was set at \( \lambda = 0.995 \) limiting \( T_0 \) to 2s.
A linear difference equation is required by the recursive identification routine to represent the system of interest’s dynamics. An Euler approximation (equation 4.17) can be used to convert continuous time models to the linear difference equation (equation 4.18).

\[
\text{Euler approximation: } \frac{1}{s} = \frac{T}{q - 1} \quad (4.17)
\]

where: 
- \( q \) – Forward shift operator
- \( T \) – Sample time

**Linear difference equation:**

\[
A(q)y(t) = B(q)u(t - n_kT) + w(t) \quad (4.18)
\]

\( n_k \) is the number of sample delays between input and output, \( w(t) \) is the noise and \( A(q) \) and \( B(q) \) are polynomials:

\[
A(q) = 1 + a_1q^{-1} + \ldots + a_{na}q^{-na} \quad (4.19)
\]

\[
B(q) = b_1 + b_2q^{-1} + \ldots + b_{nb}q^{-nb} \quad (4.20)
\]

By substitution using equation 4.17, the linear difference equation representing the continuous model of neuromuscular dynamics (equation 4.16) is given by:

\[
a_1 = \frac{B_{dr}T - 2J}{J} \quad (4.21)
\]

\[
a_2 = \frac{J + K_{dr}T^2 - B_{dr}T}{J} \quad (4.22)
\]

\[
b_1 = \frac{T^2}{J} \quad (4.23)
\]

\( n_k = 2 \) \quad (4.24)
Once parameters $a_1$, $a_2$ and $b_1$ have been found equations 4.21-4.24 can be rearranged to give the neuromuscular dynamic properties $J$, $B_{dr}$ and $K_{dr}$.

The measured data must be band pass filtered to allow identification. This prevents the recursive routine simply identifying the high frequency noise. The low-pass filter removes high frequency noise and the high-pass filter removes any torque or angular offsets and gives the signal zero mean.

For both high- and low-pass filters, a fourth order Butterworth filter was used. High-pass filtering was carried out at 0.5Hz. The relaxed limb data was low-pass filtered at 6Hz while the tensed limb data was low-pass filtered at 10Hz to reflect the frequency content of the dominant dynamics. Initial search points of [0.12 0.5 5] and [0.12 1 45] (corresponding to $[J\ B_{dr}\ K_{dr}]$) were used for the relaxed and stiffened muscle states respectively based on the results in section 4.6.1.

4.7.2 Recursive identification results

Figure 4.18 shows typical values for the arm inertia, stiffness and damping identified recursively. It can be seen that initially the recursive identification routine takes approximately 10s to settle to a steady state value. Following this initial phase the dynamics remain essentially time invariant.

Mean values have been calculated for the neuromuscular parameters identified recursively for all test subjects (Table 4.10 and Table 4.11). The values can be compared to those identified using the direct method and described in section 4.6.1 (Table 4.4 and Table 4.5). With the arms in the relaxed state good agreement is seen between the recursively identified parameters, mean damping stiffness and inertia, and the values calculated using the direct method. The recursive method gives a slightly higher VAF than the direct method, this might be expected as the recursive method allows time variation of parameters. With the arms in the tensed state the VAF is lower and the variation between parameters identified using the direct method and recursively is greater. However a clear trend is still present indicating an increase in arm stiffness following tensing and co-contraction of muscles.
The standard deviation (s.d), given for each of the recursively identified parameters, allows the degree of time invariance of the parameters to be established. As the standard deviation for the recursively identified parameters is small, when compared to the mean, it can be assumed that the test subjects maintained a constant muscle state throughout the duration of each individual test.

![Variation of neuromuscular dynamics identified by fitting RARX model](image)

Figure 4.18: Neuromuscular dynamics as identified using recursive identification for test subject G.
Table 4.10: Neuromuscular dynamic properties identified recursively for relaxed muscle state. PRBS amplitude +/-4Nm.

<table>
<thead>
<tr>
<th>Subject</th>
<th>mean J/ $^2$ kgm</th>
<th>s.d J/ $^2$ kgm</th>
<th>mean B$_{dr}$/ Nms/rad</th>
<th>s.d B$_{dr}$/ Nms/rad</th>
<th>mean K$_{dr}$/ Nm/rad</th>
<th>s.d K$_{dr}$/ Nm/rad</th>
<th>VAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject A</td>
<td>0.106</td>
<td>0.007</td>
<td>0.52</td>
<td>0.08</td>
<td>3.95</td>
<td>0.64</td>
<td>0.92</td>
</tr>
<tr>
<td>Subject B</td>
<td>0.133</td>
<td>0.004</td>
<td>0.47</td>
<td>0.07</td>
<td>4.43</td>
<td>0.55</td>
<td>0.91</td>
</tr>
<tr>
<td>Subject C</td>
<td>0.126</td>
<td>0.004</td>
<td>0.49</td>
<td>0.07</td>
<td>5.00</td>
<td>0.67</td>
<td>0.93</td>
</tr>
<tr>
<td>Subject D</td>
<td>0.104</td>
<td>0.014</td>
<td>0.62</td>
<td>0.09</td>
<td>3.28</td>
<td>1.47</td>
<td>0.79</td>
</tr>
<tr>
<td>Subject E</td>
<td>0.157</td>
<td>0.011</td>
<td>0.69</td>
<td>0.16</td>
<td>4.08</td>
<td>0.84</td>
<td>0.84</td>
</tr>
<tr>
<td>Subject F</td>
<td>0.113</td>
<td>0.005</td>
<td>0.52</td>
<td>0.10</td>
<td>3.77</td>
<td>0.64</td>
<td>0.90</td>
</tr>
<tr>
<td>Subject G</td>
<td>0.131</td>
<td>0.007</td>
<td>0.87</td>
<td>0.14</td>
<td>5.37</td>
<td>1.38</td>
<td>0.83</td>
</tr>
<tr>
<td>Subject H</td>
<td>0.116</td>
<td>0.033</td>
<td>0.66</td>
<td>0.16</td>
<td>4.39</td>
<td>2.24</td>
<td>0.89</td>
</tr>
</tbody>
</table>

Table 4.11: Neuromuscular dynamic properties identified recursively for tensed muscle state. PRBS amplitude +/-4Nm.

<table>
<thead>
<tr>
<th>Subject</th>
<th>mean J/ $^2$ kgm</th>
<th>s.d J/ $^2$ kgm</th>
<th>mean B$_{dr}$/ Nms/rad</th>
<th>s.d B$_{dr}$/ Nms/rad</th>
<th>mean K$_{dr}$/ Nm/rad</th>
<th>s.d K$_{dr}$/ Nm/rad</th>
<th>VAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject A</td>
<td>0.139</td>
<td>0.020</td>
<td>1.20</td>
<td>0.16</td>
<td>27.03</td>
<td>7.19</td>
<td>0.79</td>
</tr>
<tr>
<td>Subject B</td>
<td>0.201</td>
<td>0.028</td>
<td>1.55</td>
<td>0.26</td>
<td>76.81</td>
<td>10.84</td>
<td>0.30</td>
</tr>
<tr>
<td>Subject C</td>
<td>0.157</td>
<td>0.041</td>
<td>2.23</td>
<td>0.25</td>
<td>83.79</td>
<td>11.61</td>
<td>0.60</td>
</tr>
<tr>
<td>Subject D</td>
<td>0.143</td>
<td>0.016</td>
<td>1.23</td>
<td>0.14</td>
<td>39.28</td>
<td>4.20</td>
<td>0.68</td>
</tr>
<tr>
<td>Subject E</td>
<td>0.238</td>
<td>0.069</td>
<td>2.31</td>
<td>0.45</td>
<td>71.82</td>
<td>13.43</td>
<td>0.64</td>
</tr>
<tr>
<td>Subject F</td>
<td>0.188</td>
<td>0.028</td>
<td>1.57</td>
<td>0.18</td>
<td>78.45</td>
<td>7.83</td>
<td>0.18</td>
</tr>
<tr>
<td>Subject G</td>
<td>0.135</td>
<td>0.024</td>
<td>1.85</td>
<td>0.24</td>
<td>58.68</td>
<td>6.86</td>
<td>0.68</td>
</tr>
<tr>
<td>Subject H</td>
<td>0.135</td>
<td>0.018</td>
<td>1.38</td>
<td>0.18</td>
<td>33.69</td>
<td>3.86</td>
<td>0.77</td>
</tr>
</tbody>
</table>

4.7.3 Recursive identification conclusions

Having established a suitable structure for the neuromuscular system dynamics in sections 4.4 and 4.6, it has now been shown that the neuromuscular dynamics can also be identified recursively.

The recursive identification procedure might provide a useful method of tracking changes in drivers’ neuromuscular dynamics during typical driving manoeuvres. The method would involve sending a small broad-band random torque disturbance to the steering wheel while drivers performed manoeuvres on the simulator. If the manoeuvres require only low frequency torque inputs from the driver, the components can later be removed from the measured data by high-pass filtering. The remaining higher frequency components in the measured steering torque and steer angle would then represent the input and output from the neuromuscular system and could be used in the recursive identification routine.

Recursive tracking of the neuromuscular dynamics was considered for the lane change manoeuvres described in Chapter 5. However as the manoeuvre requires high frequency inputs, it is difficult to separate the driver’s conscious control torque from the intrinsic neuromuscular response. Furthermore, as the lane change is completed within 2-4s short forgetting factor time constants, $T_0$, are needed if the changes in the neuromuscular dynamics are to be identified. It has been found that forgetting factor time constants of less than 2s induced instability in the identification routine.

The recursive method may be more suitable for tracking slow changes in the neuromuscular dynamics; for example tracking changes with respect to lane width or radius of curvature in steady state manoeuvres. The recursive method warrants further investigation in future research work.
4.8 IDENTIFYING REFLEX DYNAMICS

In the previous sections an identification approach has been taken whereby the inertia, stiffness and damping for components of the driver’s neuromuscular system are lumped together. Many published reports describing the neuromuscular system take the same approach, for example [60]. However it is thought that a significant component of the neuromuscular system behaviour arises from reflex action. Reflex action provides closed loop feedback control of the neuromuscular system via the spinal cord and muscle spindles. The reflex loops are thought to provide some limb velocity and position feedback control, but are subject to a time delay. Attempts were made to determine if a neuromuscular model which separately accounts for delayed reflex action gives a better fit to the measured data than the lumped parameter approach. The frequency domain identification method, described in section 4.2.4, was used.

Figure 4.19: Neuromuscular system model with reflex path included

![Neuromuscular system model with reflex path included](image)

Figure 4.19 shows a second order representation of the neuromuscular dynamics with a delayed reflex path included. Parameters $B_r$ and $K_r$ represent the reflex damping and reflex stiffness respectively. The model structure is essentially a linear equivalent to that proposed by Zhang and Rymer [51]. A transfer function for the system can be generated (equation 4.25). If either the reflex time delay, $\tau$, is equal to zero or both the reflex constants, $B_r$ and $K_r$, are both zero, then equation 4.25 has an identical structure to the simple second order model previously fitted to the measured data (equation 4.16). The frequency response for a purely intrinsic model is shown together with an equivalent reflex regulated model for comparison Figure 4.20. The resonance for the reflex model shows less damping at 1Hz, but otherwise the features are very similar and become difficult to distinguish from noisy data.
\[
\frac{\theta_{sw}(s)}{T_{acr}(s)} = \frac{1}{J s^2 + B_{dr} + K_{drr} + (B_r s + K_r) e^{-s\tau}}
\]  

(4.25)

The frequency response of the neuromuscular model (equation 4.25) was calculated analytically by setting \( s=j\omega \) giving a complex frequency vector containing magnitude and phase information. The model frequency response was subsequently compared to the measured frequency response and parameter variation carried out to minimise phasor error using equation 4.3.

![Predicted frequency response for neuromuscular system](image)

Figure 4.20: Comparison of the dynamic response for an intrinsic neuromuscular model and a reflex neuromuscular model: Intrinsic model= 1/(0.12s^2 + 0.5s + 5) and Reflex model = 1/(0.12s^2+e^{-0.05s}(0.5s+5))

Initial attempts were made to fit the reflex regulated model by allowing variation of model parameters \( B_{dr}, K_{dr}, K_r, B_r \) and \( \tau \). Iterations of the search routine using various start points showed that the best fit to the measured data was not unique. To constrain the search routine and ensure a unique solution was found, the reflex time delay was set to a constant value. A time delay of 0.05s was used, consistent with published data for the elbow joint \([51, 82, 88]\). The resulting identified parameters for test subject A measured in the presence of various levels of torque offset are shown in
Table 4.12. The model fit characterised by the normalised error (equation 4.3) shows no improvement when compared to the purely intrinsic model fit given in the Appendix, Table A3.1. Furthermore, Table 4.12 shows the stiffness and damping appear to be inconsistently identified as either reflex or intrinsic. The identification procedure was repeated with the time delay set at values from 0.06 to 0.02s, however no reduction in model error was found.

<table>
<thead>
<tr>
<th>Torque offset/ Nm</th>
<th>Error ε</th>
<th>Inertia J/ kgm²</th>
<th>Intrinsic Damping B_d/ Nmrad/s</th>
<th>Intrinsic Stiffness K_d/ Nm/rad</th>
<th>Reflex damping B_r/ Nmrad/s</th>
<th>Reflex stiffness K_r/ Nm/rad</th>
<th>Delay τ/ s</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.064</td>
<td>0.098</td>
<td>0.907</td>
<td>0</td>
<td>0.274</td>
<td>11.67</td>
<td>0.05</td>
</tr>
<tr>
<td>4</td>
<td>0.048</td>
<td>0.098</td>
<td>0.623</td>
<td>12.99</td>
<td>0</td>
<td>0</td>
<td>0.05</td>
</tr>
<tr>
<td>6</td>
<td>0.036</td>
<td>0.098</td>
<td>0.647</td>
<td>14.82</td>
<td>0.006</td>
<td>0</td>
<td>0.05</td>
</tr>
<tr>
<td>8</td>
<td>0.164</td>
<td>0.098</td>
<td>1.514</td>
<td>11.78</td>
<td>0</td>
<td>6.85</td>
<td>0.05</td>
</tr>
<tr>
<td>10</td>
<td>0.124</td>
<td>0.098</td>
<td>0.998</td>
<td>22.74</td>
<td>0</td>
<td>4.71</td>
<td>0.05</td>
</tr>
<tr>
<td>-2</td>
<td>0.074</td>
<td>0.098</td>
<td>0.801</td>
<td>7.90</td>
<td>0</td>
<td>2.66</td>
<td>0.05</td>
</tr>
<tr>
<td>-4</td>
<td>0.055</td>
<td>0.098</td>
<td>0.739</td>
<td>12.64</td>
<td>0</td>
<td>0</td>
<td>0.05</td>
</tr>
<tr>
<td>-6</td>
<td>0.133</td>
<td>0.098</td>
<td>1.187</td>
<td>18.88</td>
<td>0</td>
<td>0</td>
<td>0.05</td>
</tr>
<tr>
<td>-8</td>
<td>0.124</td>
<td>0.098</td>
<td>1.205</td>
<td>21.81</td>
<td>0</td>
<td>0</td>
<td>0.05</td>
</tr>
<tr>
<td>-10</td>
<td>0.094</td>
<td>0.098</td>
<td>1.146</td>
<td>16.22</td>
<td>0.039</td>
<td>0</td>
<td>0.05</td>
</tr>
</tbody>
</table>

The frequency response of a neuromuscular model containing intrinsic components is only subtly different to a model that contains reflex components. Any difference, which would allow the identification of reflex components, appears to be masked by noise in the data. A further limitation is that the direct method of system identification is only applicable to the low frequency data. If the reflex time delay is small, prominent features in the frequency response that allow identification of the reflex action are beyond the range of the identification routine.
4.9 IDENTIFYING REFLEX DYNAMICS USING EMG

Section 4.8 showed that using frequency response methods to identify reflex action from steering torque and angle signals alone was inconclusive. However, the measured EMG data along with measured steering wheel motion data can be used to infer muscle activity due to the stretch reflex.

EMG measurements were made during the shaker tests described in section 4.2.1. Test subjects were instructed not to voluntarily resist the motion of the steering system during the tests. Therefore any measured variation in muscle activity can be attributed to some form of involuntary reflex action.

Figure 4.21 shows a typical plot of the right hand deltoid EMG signal versus measured signals from the steering hardware (steer angle, steering wheel velocity and steering column torque). The data is normalised by removing linear trends and dividing each signal by the maximum absolute value measured in that signal. The data was measured in the presence of a +/-4Nm PRBS torque disturbance whilst a steady state static torque of 4Nm was applied. Comparison between normalised steering velocity and normalised EMG shows strong correlation. However, this correlation is not seen between the steering angle signal or the column torque signal. The results suggest that the function of the reflex activity is to provide additional damping. In order to investigate this finding further regression analysis was carried out.
Figure 4.21: Normalised EMG from RH deltoid for test subject A. Data measured in the presence of a +/-4Nm PRBS torque disturbance with +4Nm torque offset. 5 repeats of the PRBS signal have been ensemble averaged.

4.9.1 Regression analysis of EMG data to establish reflex activity

Regression analysis was carried out, to investigate the correlation between steering column velocity and angle versus measured EMG activity. Rather than using the EMG signals in their raw form the EMG based torque prediction described in Chapter 3 (equation 3.12) was used. This relates the EMG signal measured at the muscles to the steering torque produced by those muscles. EMG Coefficients specific to each individual test subject were used as shown in Table 3.9 and Table 3.10. The regression analysis fits a linear function between the measured steering column velocity and EMG based torque prediction (equation 4.26). The regression parameters $\beta_1$ and $\beta_2$ are equivalent to the reflex damping and reflex stiffness parameters $B_r$ and $K_r$ respectively.

$$\hat{M}_z(t) = \beta_1[\dot{\theta}_w(t)] + \beta_2[\theta_w(t)] + \beta_0 + w(t)$$

where:

$\hat{M}_z$ - EMG based steering torque prediction
\( \beta_1 \) – Regression coefficient relating to steering wheel velocity and is equivalent to the reflex damping \( B_r \) (Nms/rad)

\( \beta_2 \) – Regression coefficient relating to steering wheel angle and is equivalent to the reflex stiffness \( K_r \) (Nm/rad)

\( \beta_0 \) - Constant term

\( w(t) \) - Noise

The routine involved solving equation 4.26 in a least squares sense. A correlation coefficient, \( R \), can also be calculated to determine the quality of the fit. The correlation coefficient squared varies from 0 to 1 where 1 indicates an exact fit [79].

The regression analysis was carried out on data measured for all eight test subjects in the presence of a PRBS torque disturbance. When test subjects held the steering wheel under relaxed conditions only very small variations in EMG activity were seen, indicating that there was no real reflex activity. However, significant EMG activity was seen under conditions when the PRBS torque disturbance was +/-8Nm and test subjects were tensing and co-contracting their muscles; this data was used in the regression analysis. The data was ensemble averaged with respect to the PRBS torque excitation which is periodic with four repeats. The data was also low-pass filtered at 5Hz in order that the SREMG signal was comparable with the steering wheel angle and velocity signals.

The results from the regression analysis are given in Table 4.13. It can be seen that a substantial proportion of the variance in the EMG based torque prediction is accounted for by the regression model (equation 4.26) as indicated by the high values of \( R^2 \). A typical plot showing the model fit to the measured data is shown in Figure 4.22. The negative sign, seen in the identified reflex damping and stiffness, is due to the negative feedback structure of the reflex action (Figure 4.19). The identified reflex damping is considerably larger than the values identified for the arm as a whole and shown in Table 4.9. This may be due to the fact that the reflex damping has been calculated based on the measured EMG activity. In reality there is a lag between muscle activity, measurable through EMG, and the force generated by the muscle. This lag may reduce the effect of the reflex action.
The identified reflex stiffness values are small in comparison to the total muscle stiffness identified using the frequency domain direct method (Table 4.9). Further investigation showed that the correlation between steer angle and EMG based steering torque predictions was low; typically around $r^2 > 0.05$. Hence only limited confidence can be placed on the values identified for the reflex stiffness parameters. To address this issue the regression analysis was repeated with the term $\beta_2$ omitted. The results are shown in Table 4.14. It can be seen that the reflex damping terms are consistently identified between Table 4.13 and Table 4.14. Furthermore in Table 4.14 high values of $R^2$ are still observed confirming that the reflex stiffness term, $\beta_2$, does not contribute significantly to the observed variance in the EMG based torque prediction.

Table 4.13: Regression analysis results showing reflex parameters identified from EMG data. The regression model used was: $\hat{M}_z(t) = \beta_1[\dot{\theta}_m(t)] + \beta_2[\theta_m(t)] + \beta_0 + w(t)$

<table>
<thead>
<tr>
<th></th>
<th>$\beta_1$ reflex damping/ Nms/rad</th>
<th>$\beta_2$ reflex stiffness/ Nms/rad</th>
<th>$\beta_0$ / Nm</th>
<th>Correlation coefficient squared $R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject A</td>
<td>-1.88</td>
<td>4.27</td>
<td>4.05</td>
<td>0.75</td>
</tr>
<tr>
<td>Subject B</td>
<td>-5.15</td>
<td>-7.83</td>
<td>0.65</td>
<td>0.79</td>
</tr>
<tr>
<td>Subject C</td>
<td>-3.58</td>
<td>-16.90</td>
<td>-7.93</td>
<td>0.62</td>
</tr>
<tr>
<td>Subject D</td>
<td>-4.02</td>
<td>-4.91</td>
<td>4.78</td>
<td>0.73</td>
</tr>
<tr>
<td>Subject E</td>
<td>-4.38</td>
<td>-7.59</td>
<td>-2.65</td>
<td>0.75</td>
</tr>
<tr>
<td>Subject F</td>
<td>-4.98</td>
<td>-16.8</td>
<td>-6.03</td>
<td>0.62</td>
</tr>
<tr>
<td>Subject G</td>
<td>-5.04</td>
<td>-5.16</td>
<td>-5.21</td>
<td>0.67</td>
</tr>
<tr>
<td>Subject H</td>
<td>-1.15</td>
<td>-0.51</td>
<td>-0.19</td>
<td>0.68</td>
</tr>
</tbody>
</table>
Figure 4.22: Regression model fit to EMG based steering torque prediction to show reflex action.

Table 4.14: Regression analysis results showing reflex parameters identified from EMG data. The regression model used was: \( \dot{M}_c(t) = \beta_1 \dot{\theta}_{sw}(t) + \beta_0 + w(t) \)

<table>
<thead>
<tr>
<th>Subject</th>
<th>( \beta_1 ) reflex</th>
<th>( \beta_0 )</th>
<th>Correlation coefficient squared ( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject A</td>
<td>-1.88</td>
<td>4.01</td>
<td>0.72</td>
</tr>
<tr>
<td>Subject B</td>
<td>-5.15</td>
<td>0.66</td>
<td>0.78</td>
</tr>
<tr>
<td>Subject C</td>
<td>-3.57</td>
<td>-7.69</td>
<td>0.55</td>
</tr>
<tr>
<td>Subject D</td>
<td>-4.02</td>
<td>4.82</td>
<td>0.72</td>
</tr>
<tr>
<td>Subject E</td>
<td>-4.34</td>
<td>-2.78</td>
<td>0.73</td>
</tr>
<tr>
<td>Subject F</td>
<td>-4.97</td>
<td>-4.85</td>
<td>0.58</td>
</tr>
<tr>
<td>Subject G</td>
<td>-5.04</td>
<td>-4.88</td>
<td>0.67</td>
</tr>
<tr>
<td>Subject H</td>
<td>-1.15</td>
<td>-0.18</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Attempts were made to identify the reflex time delay by advancing and delaying the data sets in the regression analysis. However as the data is noisy no significant improvement in the model fit could be obtained and it was not found to be possible to
identify the reflex time delay using the regression method. In addition as the EMG based torque prediction is based on the response from several muscles a single value for the reflex time delay may not be appropriate.

4.9.2 Frequency domain analysis of EMG data to establish reflex action

Strong correlation was seen between the deltoid muscle EMG and the steering column velocity signals. A typical response is shown in Figure 4.23 for test subject A showing the EMG signal measured at the deltoid. The data is noisy and the problems associated with closed loop identification (discussed in section 4.3) apply here. However, although the phase data is noisy it is not inconsistent with a reflex time delay of 0.05s or less. If the time delay was greater than 0.05s a phase lag of over 45 degrees would be observed in the measured frequency response above 2.5Hz. As the phase lag is less than this, it can be concluded that the time delay is less than 0.05s

Attempts to model the reflex feedback as a simple pure time delay in the frequency domain were unsuccessful. The difficulty might be explained by the fact that the time delay may be of varying length because different motor units are recruited at different rates depending on their size, as highlighted by Zhang and Rymer [51]. By measuring the system response to high frequency torque disturbance signals (above 10Hz) it may be possible to gain better measurements of the reflex action.
Figure 4.23: Frequency response between deltoid EMG signal and steering column velocity.
4.10 CONCLUSIONS

This chapter describes measurements made aimed at identifying the neuromuscular dynamic properties with particular reference to driver steering control. A method of identifying the neuromuscular dynamics by applying a random torque disturbance through the EPS system was developed. Measurements of steering torque, muscle activity and steering wheel motion were made. The results and conclusion are summarised:

a) An indirect method has been successfully used to establish the driver’s neuromuscular dynamics. The frequency response of the EPS system alone has already been established in Chapter 2. The frequency response for the coupled driver and EPS system was measured. From the frequency response and the results described in Chapter 2, the driver’s neuromuscular dynamics were extracted. The method confirmed an appropriate structure for the driver’s neuromuscular dynamics. Additionally, the method was used to establish estimates for physical parameters representing the driver’s arm inertia, damping and stiffness. However, the accuracy of the neuromuscular parameter estimates is limited by the accuracy of the EPS model used. In particular, non-linearity in the EPS system causes systematic errors to occur.

b) To eliminate the systematic errors generated by the indirect method, a direct approach was used. The preliminary results gained using the indirect method, along with a simulation of the direct method identification routine confirm the validity of the direct method and allow confidence in its use. A caveat to this is that the direct method is only applicable to the low frequency data (frequencies<10Hz). At higher frequencies, dynamic interaction with the compliant torque sensor corrupts the data. However, the direct method was used to successfully identify properties and characteristics of the neuromuscular system specific to the driver steering task. The dominant features in the frequency response were found to occur at frequencies below 4Hz. McLean and Hoffman [89] note the limited frequency content of driver input in terms of steering angle. The results obtained in this chapter show that the bandwidth of the neuromuscular system may form a physiological limit to the driver input.
c) Linear transfer functions were successfully fitted to measured frequency responses of the neuromuscular system at various system operating points. The observed system behaviour was non-linear. In particular increased muscle activity through application of offset torques or muscle co-contraction, was accompanied by an increase in the damping and stiffness of the driver's arms. The stiffening was seen to be linearly proportional to the offset torque. Similar results were observed by Zhang and Rymer [51] when measuring neuromuscular response about the elbow joint of a single arm.

d) The results show that the non-linearity in the neuromuscular system is more sensitive to torque offsets than angular offsets. When the amplitude of the random disturbance torque was increased causing larger angular displacements, no significant difference was observed in identified neuromuscular dynamic properties. If the muscles were to behave like a stiffening spring over the range investigated, an increase in the amplitude of random torque disturbance would be expected to result in larger stiffness being identified.

e) Determining frequency responses for the measured data required ensemble averaging of repeated runs of data to remove random noise. A necessary assumption is that the data is time invariant. To verify this assumption and based on the identified structure for the neuromuscular system recursive identification was carried out. The recursive identification confirmed that the initial assumption was valid. Additionally the results show the recursive method can also be used to successfully identify driver neuromuscular dynamics. It may be possible to track changes in the neuromuscular dynamics during simulated driving tasks using this method.

f) Reflex activity proportional to steering column velocity was seen in the measured EMG signals. The results indicate that a major role of the reflex system is in providing damping to the system. The measured values of reflex stiffness were found to be small. It was not found to be possible to identify a value for the time delay associated with reflex action from the measured data. The fact that the time delay could not be measured indicates that any delay must be small. The results suggest that the reflex time delay associated with steering control is likely to be less than 0.05s.
g) The hardware was sufficient to identify and highlight many of the interesting characteristics of the neuromuscular system. However, based on the current results it may be of interest to measure the neuromuscular response to torque disturbances at higher frequencies. In their current form, the EPS system and direct identification method are limited to data with frequency content up to 10Hz. The hardware could be modified by stiffening or removing the integral column torque sensor. Modifying the hardware would allow a higher bandwidth torque excitation to be applied and reduce the problem associated with identifying the closed loop feedback dynamics. This may allow better measurement of the reflex dynamics.
Chapter 5: Driving Simulator Experiments

5.1 INTRODUCTION

In Chapter 4 the adaptive properties of the neuromuscular system were measured. Changes in muscle co-contraction have been shown to increase the stiffness and damping of the arm muscles. The extent to which the driver utilises the adaptive properties of the neuromuscular system during typical driving tasks is unknown and is investigated in this chapter.

This chapter reports measurements made during a double lane change manoeuvre, as measured from the CUED driving simulator, with the aim of investigating the role of the neuromuscular system during the tasks. A review of the published literature has revealed few reports of measured driver steering behaviour during lane change manoeuvres in either real vehicles or by using simulators. The measurements that are presented often only describe the mean driver performance. Variation, between drivers, or in their learning rates, cannot be identified [10, 40, 67]. The variation in performance, between drivers and with driver experience, is analysed in this chapter for a range of test subjects.

Section 5.2 outlines the test procedure. Section 5.3 gives the results and analysis, while section 5.4 presents some conclusions.
5.2 TEST PROCEDURE

Eight test subjects performed a series of lane change manoeuvres using the CUED driving simulator. All test subjects had held a driving licence for at least three years and were asked to perform a number of tasks using the driving simulator. The eight test subjects also participated in the experiments described in Chapters 3 and 4. The measurements from each test subject were taken in a single session. Hence parameters identified in the preceding chapters for the EMG instrumentation and neuromuscular dynamics can be used in the analysis of the results in this chapter.

Thirty lane change manoeuvres were performed, ten for each of three vehicles simulated with different steering dynamics. The steering dynamics of the three vehicles were varied to make them progressively less stable. The aim was to establish any changes in the driver’s neuromuscular dynamics in response to the changes in steering dynamics. Closed loop stable control can be provided by the driver, but requires the driver to provide additional damping and self-centring torque to the steering wheel. A comparison of EMG activity during the lane change manoeuvres was made to aid investigation of the driver’s control strategy. In addition, by comparing path error between successive runs, the rate of learning of the control strategy can be examined. It is expected that an increase in path error will be seen following a change in the steering dynamics, because the driver is unfamiliar with the new dynamics. As each driver gains experience the path following performance is expected to improve.
5.2.1 Road path

Test subjects were asked to perform a lane change manoeuvre at 140km/h. The high vehicle speed was chosen because the vehicle dynamics become progressively more oscillatory at higher speeds and thus require significant driver attention and control action. This creates a non-trivial control task and the role of the neuromuscular system in achieving this task can be investigated.

The trajectory and road path were indicated to the test subject by a series of cones on the simulator display. A lane width of 3.5m was used. Initially the test subject was given a 300m straight run and then instructed to make a lane change to the adjacent lane and back again as marked out by cones (Figure 5.1) and described in Table 5.1. Following the lane change a further section of straight road was displayed. In each successive run test subjects were asked to make alternate lane changes in left and right hand directions.

![Figure 5.1: Cone positions for left and right hand double lane change at 140km/h.](image-url)
Table 5.1: Lateral offset of road path centre line with vehicle longitudinal position for double lane change.

<table>
<thead>
<tr>
<th>Longitudinal position $x$ / m</th>
<th>Lateral offset $y$ / m</th>
</tr>
</thead>
<tbody>
<tr>
<td>$&lt;321$</td>
<td>$0$</td>
</tr>
<tr>
<td>$363$ to $398$</td>
<td>$3.5$</td>
</tr>
<tr>
<td>$&gt;433$</td>
<td>$0$</td>
</tr>
</tbody>
</table>

Each run commenced with the vehicle at the origin ($x=0, y=0$ with reference to Figure 5.1) and lasted for 20s. Transients were seen in the first 5s of logged data if the run commenced with the steering wheel slightly off centre or as the driver took hold of the steering wheel. As a result of these transients, the first 5s of data in each run was omitted from analysis. At a vehicle speed of 140km/h this relates to discarding approximately the first 200m.

5.2.2 Variation in steering dynamics

The steering dynamics of the driving simulator can be tuned by varying the feedback gains to the EPS motor. In order that the effect of variations in the torque feedback gains could be evaluated a linear model was set up to represent the dynamic response of the EPS hardware coupled to the vehicle model Figure 5.2. In Chapter 2 a two degree of freedom non-linear model of the EPS system was described. However, to simplify the analysis, a reduced order one degree of freedom (1DOF) linear model of the EPS hardware was used in the model. In generating the 1DOF model, the inertia of the steering wheel, load cell and motor are lumped together to give an equivalent inertia term $J_{eqv}$ (Equation 5.1). An equivalent viscous damping term, $B_{eqv}$, is also used as a describing term to represent friction in the steering column, although in reality the friction was found to be mainly coulomb. A viscous approximation for the damping of the 1DOF model is given as the reciprocal of the steady state gain between column velocity and motor torque demand. A suitable value for the EPS unit, as measured from Figure 2.6 and given in equation 2.2 in Chapter 2 is

$$B_{eqv} = 0.41 \text{Nms/rad}.$$

$$J_{eqv} = J_{sw} + J_{lc} + J_{mot} n_{gb}^2 = 0.172 \text{kgm}^2$$  \hspace{1cm} (5.1)
Chapter 5: Driving Simulator Experiments

Figure 5.2: Composite model used to investigate vehicle-steering dynamics.

The vehicle model (equation 2.18) parameters are defined in Table 2.4 with $v_x = 38.9 \text{ m/s} \ (140 \text{ km/h})$. The vehicle model remained unchanged and so the relationship between steer angle and vehicle trajectory was constant. However the steering dynamics were varied by progressively increasing the slip angle feedback gain ($G_\alpha$), and also reducing the velocity feedback $B_e$; the effect was to increase the steering torque feedback to the driver. Three sets of torque feedback gains were used as given in Table 5.2.

The dynamic response of the combined vehicle and steering system was evaluated using the model (Figure 5.2). The response can be characterised by the eigenvalues of the system (Figure 5.3). It can be seen that the dynamics become progressively more oscillatory between test car one and test car two characterised by the dominant eigenvalues (closest to the imaginary axis) moving towards the right hand plane and away from the real axis. The feedback gains were chosen to give car three a marginally unstable response to steering torque inputs characterised by the right hand plane eigenvalues in Figure 5.3. To cause this instability it was found necessary to remove the angle feedback, $K_e$, which acts to self-centre the steering wheel.
Table 5.2: EPS motor steering torque feedback gains.

<table>
<thead>
<tr>
<th>Car</th>
<th>$K_e$ (Nm/rad)</th>
<th>$B_e$ (Nms/rad)</th>
<th>$G_\alpha$ (Nm/rad)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test car 1</td>
<td>2.29</td>
<td>1.15</td>
<td>-1920</td>
</tr>
<tr>
<td>Test car 2</td>
<td>2.29</td>
<td>0.57</td>
<td>-3840</td>
</tr>
<tr>
<td>Test car 3</td>
<td>0</td>
<td>0</td>
<td>-5760</td>
</tr>
</tbody>
</table>

Figure 5.3: Eigenvalues characterising vehicle and steering system dynamic response for the three test cars.
By implementing the torque feedback gains shown in Table 5.2 in the vehicle simulator the dynamic response of the system was confirmed. The steering dynamics were measured following a step change in the driver steering torque; the step change was generated by holding the steering wheel at 45deg and then suddenly releasing it. The response for all three systems is shown in Figure 5.4. As expected the steering dynamics become progressively more oscillatory. The steering wheel angle for test car three is expected to grow exponentially due to the open loop instability in the system. In fact a limit cycle is reached due to the motor torque demand exceeding its torque output limit.

![Step response of steering and vehicle dynamics](image)

Figure 5.4: Measured response of vehicle and steering system following a step change in steering torque. The steering wheel was held at 45deg until a steady state response was achieved then suddenly released.
Experiments were carried out to see how the driver’s control strategy varied between the three simulated vehicle dynamic characteristics. In particular, it is of interest to observe the strategy used by the driver to damp out oscillations and stabilise the vehicle. Based on the results measured in Chapter 4, muscle co-contraction has been shown to increase arm stiffness and damping. Therefore, if the driver uses a strategy of co-contraction to stabilise the vehicle, more co-contraction may be expected for test car three than the other test vehicles.
5.3 RESULTS

In Sharp and Valtetsiotis’ model [43], and many other driver models, the control characteristics are generated subject to minimisation of a cost function. Costs are often placed on lateral position error, heading angle error and steer angle. The cost on steer angle is used as a measure of driver workload. A more appropriate measure of driver workload or metabolic energy consumption might be the measured steering torque or muscle activity as measurable using EMG instrumentation. By analysing the parameters that make up these cost functions, as measured while test subjects performed lane change manoeuvres on the driving simulator, the suitability of the cost functions can be investigated. Other parameters that influence driver steering control can also be investigated.

A linear regression model (Equation 5.2) was used to establish if there were any underlying trends in the measured data. Various parameters were taken as the dependent variable \(y(n)\), for example mean squared path error or mean squared heading angle error. The independent variable, \(x(n)\), was chosen as the number of lane change manoeuvres completed. In this way changes in driver performance with experience can be investigated as well as comparing the responses to changes in the test car steering dynamics. The analysis was carried out on the logged data from 5-20s for each lane change manoeuvre.

\[
y(n) = \beta_0 + \beta_1 x(n) + w(n)
\]  
\[ (5.2) \]

where:
- \(y(n)\) – Dependent variable
- \(x(n)\) – Independent variable
- \(\beta_1\) - Regression coefficient
- \(w(n)\) - Noise

The significance of the identified regression model can be tested. The \(t\)-statistic (equation 5.3) for the data is calculated to test the null hypothesis, \(H_0\), that no trend exists in the data, i.e \(H_0(\beta_1=0)\). If no trend exists in the data the best-fit regression line is given by \(\beta_0\) equalling the mean of the data and \(\beta_1=0\). At a given level of
significance, if the calculated \( t \)-statistic is larger than the \( t \)-distribution (with equivalent degrees of freedom) the null hypothesis can be rejected [79]. A suitable threshold chosen for the level of significance is 0.05, this means that the probability of the observed trend appearing by chance is less than 0.05 or \( p(H_0) < 0.05 \).

\[
t = \frac{|R\sqrt{n-2}|}{\sqrt{1-R^2}}
\]  
(5.3)

where:
- \( t \) – Observed \( t \)-statistic variable with \( n-2 \) degrees of freedom
- \( n \) – Number of data points
- \( R \) – Correlation coefficient  (See Chapter 3, Equation 3.7)

### 5.3.1 Path error

The path error is defined as the difference between the vehicle lateral position, \( y \), and the centre line of the road path shown in Figure 5.1. The mean squared path error, \( Y_e \) (Equation 5.4), for each test subject, for each lane change manoeuvre completed, in each of the three test vehicles is shown in Figure 5.5.

\[
Y_e = \frac{1}{N} \sum_{n=1}^{N} (y_p(n) - y(n))^2
\]  
(5.4)

where:
- \( Y_e \) – Mean squared path error
- \( y_p \) – Road path lateral position
- \( y \) – Vehicle lateral position
- \( N \) – Length of data set

It was initially expected that a learning trend would be seen for each test subject, characterised by a reduction in mean squared path error with number of lane change manoeuvres completed. Although attempts were made to fit a regression line to the mean squared path error data for each individual test subject, it was found that the data was too noisy and the trends were not found to be significant. The variance and noise seen in terms of path error could be the result of the learning mechanism used by the driver; essentially being a ‘trial and error’ approach. If test subjects A to H are grouped together as a representative sample from a population of drivers, then a significant trend can be observed in the test subjects’ learning rates.
Three regression lines are shown in Figure 5.5, one for each test car. The regression lines show the change in mean squared path error with number of lane changes completed (run number) for the sample group as a whole. For both test cars one and two, the slope of the regression line, $\beta_1$, is negative. This indicates some improvement in path following performance with experience. The slopes are significant and the null hypothesis can be rejected because $p(H_0) < 0.05$. For test car three there is no significant trend in the data and the null hypothesis cannot be rejected. The mean squared path errors get progressively smaller as the drivers change from test cars one to three (indicated by parameter $\beta_0$). This is of interest because it suggests that the drivers remain robust to the changes in steering dynamics. A trend was expected showing an increase in mean squared path error directly following the change in test cars; this trend was not seen. The mean squared path error reaches a minimum for test car three, despite this car having the most oscillatory steering dynamics, and no further significant reduction in path error was observed.

The data is more clearly displayed by showing the regression lines along with the sample mean (average across test subjects) of the mean squared path error calculated for each run number in each vehicle (Figure 5.6). Standard deviations are shown as error bars. In subsequent plots the regression lines for the sample of drivers will be presented in this way.
Figure 5.5: Mean squared path error showing data for all test subjects and regression lines for grouped analysis of data.
Figure 5.6: Regression analysis of mean squared path error for all test subjects.
It is also of interest to compare the mean path taken by each driver in each of the three test cars. For each test car drivers performed ten lane changes. Because there was significant variation in each driver’s response between each successive run (illustrated by the scatter shown in Figure 5.5), the ten runs were averaged together (the sign of the lateral position in the left hand lane changes was reversed in order that it could be compared with right hand manoeuvres) to give the mean path taken. The mean path taken is essentially the ensemble mean of the ten lane change manoeuvres made in each vehicle by each test subject. The mean squared path error, $Y_e$, of the mean path taken was calculated with respect to the road path centre line. The calculated mean path taken and mean squared path errors are displayed in Figure 5.7. A comparison between test subjects shows a considerable difference in the mean path taken by each test subject. However for each test subject the changes in trajectory following a change in the steering dynamics, from test car one to three, are small.

The mean squared path errors shown in Figure 5.7 confirm the trends in driver behaviour shown by the regression analysis and results displayed in Figure 5.5 and Figure 5.6; it can be seen that for most subjects, there is a reduction in mean squared path error, $Y_e$, as the driver gains experience and moves from test car one to three. The mean path taken highlights some further key properties of driver behaviour. When the vehicle longitudinal position $x$ is between 300 and 350m, all the drivers show some degree of anticipation and begin to steer before the vehicle reaches the deviation in road path centre line. When the longitudinal position, $x$, is between 350 and 400m there is some overshoot as the vehicle changes to the offset lane. Finally, following the manoeuvre there is further overshoot and oscillation of the vehicle about the original lane.
Figure 5.7: Mean path taken through lane change for each test subject in each of the three vehicles. Mean squared path error for the mean path taken is also shown ($Y_e$).
5.3.2 Heading error

The mean squared heading angle error was calculated for each run in each vehicle by each test subject (Equation 5.5). The mean squared heading angle error is calculated by comparing the vehicle attitude angle, \( \psi \), with the angle of the road path centre line. The calculated values for test subjects A-H were grouped and three regression lines were fitted (one line for each of the three test cars) to show the change in mean squared heading angle error with number of lane change manoeuvres completed (run number) Figure 5.8. It can be seen that there is a significant reduction in the mean squared heading angle error when test subjects were driving car one. This indicates that the driver learns to control the heading angle of the vehicle during the first ten runs. No further significant change in mean squared heading angle error is seen in test cars two and three. This indicates that, once learnt, the control strategy employed is robust to the changes in steering dynamics between test cars one to three.

\[
\Psi_e = \frac{1}{N} \sum_{n=1}^{N} (\psi_p(n) - \psi(n))^2
\]  \hspace{1cm} (5.5)

where:
- \( \Psi_e \) – Mean squared path error
- \( \psi_p \) – Road path heading angle
- \( \psi \) – Vehicle attitude angle
- \( N \) – Length of data set

Heading angles for the ten runs made by each test subject were averaged together (the sign of the heading angle for left hand lane changes was reversed in order that it could be compared with right hand manoeuvres) to give the ensemble mean heading angle taken for each test subject in each vehicle. The mean squared heading angle error (\( \Psi_e \)) for the mean heading angle taken was calculated with respect to the road path centre line. The resulting mean heading angle and mean squared heading angle error are displayed for each test subject in each of the three vehicles (Figure 5.9). The different control strategies employed by each driver begin to become apparent when the data is displayed in this way. For example it is clear that subject B attempted to straighten the vehicle, so that the vehicle attitude angle matched the road path heading angle, as it passed through the offset lane at time 10s. Other test subjects did not appear to attempt to make this straightening correction.
Chapter 5: Driving Simulator Experiments

Figure 5.8: Regression analysis of mean squared heading error for all test subjects.
Figure 5.9: Mean heading angle taken through lane change calculated for each test subject in each of the three vehicles. Mean squared heading angle error for the mean path taken is also shown ($\Psi_e$).
5.3.3 Steer angle

The mean squared steer angle was calculated because this is often used in driver models as a measure of driver workload [40, 43]. The calculated values for test subjects A-H were grouped and three regression lines were fitted (one line for each of the three test cars) to show the change in mean squared steer angle with number of lane change manoeuvres completed (run number) Figure 5.10. It can be seen that there are no significant trends in the data as indicated by $p(H_0)$ > 0.05. Hence despite drivers optimising their control in terms of improved path error and to some extent heading angle error (as shown in Figure 5.6 and Figure 5.8), there is no reduction in the mean squared steer angle input.

Two possible conclusions can be drawn. One, the driver does not attempt to reduce workload by minimising mean squared steer angle and two, mean squared steer angle may not be a good measure of driver workload. However it may be the case that test subjects were optimising their control by optimising the phasing of the steer angle inputs rather than the magnitude.

Steering wheel angle data sets for the ten runs made by each test subject in a particular test car were averaged together (the sign of the steering angle for left hand lane changes was reversed in order that it could be compared with right hand manoeuvres) to give the ensemble mean steer angle input for each test subject in each test car (Figure 5.11). Differences in control strategy between the test subjects are now clearly visible. In particular there is a wide range in the magnitude and frequency content of the applied steer angles with test subject B and test subject D showing the two extremes of this range.
Figure 5.10: Regression analysis of mean squared steer angle for all test subjects.
Figure 5.11: Mean steer angle for each test subject in each of the three vehicles.
5.3.4 Steering torque

An alternative measure of driver workload is the mean squared steering torque applied by the driver. As in the previous section a regression line was fitted to the data grouped together for test subjects A-H to show the change in mean squared steering torque with experience Figure 5.12. Because the mean squared steering torque for test cars one to three is progressively larger due to the progressive increase in steering torque feedback an increase in the intercept of the regression line, parameter $\beta_0$, from car one to three is to be expected. However the slope of the regression line, parameter $\beta_1$, indicates the rate of learning and a significant reduction in steering torque input during the first ten runs can be seen. Following this there is no significant learning or reduction in applied torques despite the changes in steering dynamics. This is further evidence that the driver and their neuromuscular system are robust to changes in the torque feedback strategy and steering dynamics.

The ensemble mean of applied steering torque for ten lane change manoeuvres was calculated for each test subject in each of the three test cars, Figure 5.13 (again the sign of the steering torque for left hand lane changes was reversed in order that it could be compared with right hand manoeuvres). The three levels of steering torque required to steer the three vehicles can clearly be seen. Additionally the considerable variation in frequency content of the test subjects’ control strategies is still evident.
Figure 5.12: Regression analysis of mean squared steering torque for all test subjects.
Figure 5.13: Mean steering torque for each test subject in each of the three vehicles.
5.3.5 Co-contraction

A measure of muscle co-contraction was described in Chapter 3, section 3.5.3. Using the measure, muscle co-contraction was calculated for each lane change manoeuvre performed by each test subject in each of the three test cars. The calculated muscle co-contraction was averaged across the ten runs, giving the ensemble mean muscle co-contraction generated through the lane change by each test subject in each of the three test cars (Figure 5.14).

A spike in the co-contraction can be seen at time 0-5s; this is of no significance and was generated when drivers placed their hands on the steering wheel. In general significant co-contraction occurs between time 8-12s. This represents the region where the driver was generating steer angles to move to and from the offset lane. The most striking change in co-contraction is displayed by test subject B. Test subject B was also observed to generate the highest frequency input to the steering wheel in terms of steer angle (Figure 5.11). The co-contraction could arise from a strategy to stiffen the muscles in order that the driver’s control bandwidth is increased as predicted in Hogan’s study of limb control [52]. An alternative mechanism for the co-contraction could be that the higher bandwidth control requires overlap in muscle activation. The overlap compensates for the lag between muscle activation and force generation and allows rapid changes from positive to negative muscle force to be generated.
Figure 5.14: Ensemble mean co-contraction for each test subject in each of the three vehicles.
Table 5.3 gives test subject’s mean level of co-contraction measured for each vehicle (this is the mean value of the lines plotted in Figure 5.14). It can be seen that the change in co-contraction between vehicles is small. However a considerable difference in the overall level of co-contraction between test subjects is seen. The observed difference seen between test subjects is a result of drivers supporting different proportions of the weight of the arms on the steering wheel. When drivers do not support the weight of the arms on the steering wheel the support must be generated by muscle activation in both arms, which is measured as co-contraction. In order that the co-contraction between test subjects is comparable, and the test subjects can be analysed together as a group, the co-contraction measure must be normalised (equation 5.6).

\[ I_N(t) = \frac{I_c(t)}{\bar{I}_c} \]  

(5.6)

where:

- \( I_N(t) \) – Normalised co-contraction
- \( I_c(t) \) – Muscle co-contraction
- \( \bar{I}_c \) - Mean level of co-contraction

<table>
<thead>
<tr>
<th>Test Subject</th>
<th>( \bar{I}_c ) Mean co-contraction</th>
<th>( \bar{I}_c ) Mean co-contraction</th>
<th>( \bar{I}_c ) Mean co-contraction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>test car 1/ Nm</td>
<td>test car 2/ Nm</td>
<td>test car 3/Nm</td>
</tr>
<tr>
<td>Subject A</td>
<td>10.4</td>
<td>10.6</td>
<td>10.3</td>
</tr>
<tr>
<td>Subject B</td>
<td>5.7</td>
<td>6.33</td>
<td>6.82</td>
</tr>
<tr>
<td>Subject C</td>
<td>4.28</td>
<td>4.47</td>
<td>4.74</td>
</tr>
<tr>
<td>Subject D</td>
<td>13.8</td>
<td>12.5</td>
<td>10.3</td>
</tr>
<tr>
<td>Subject E</td>
<td>5.95</td>
<td>6.08</td>
<td>5.95</td>
</tr>
<tr>
<td>Subject F</td>
<td>5.46</td>
<td>4.7</td>
<td>5.34</td>
</tr>
<tr>
<td>Subject G</td>
<td>6.91</td>
<td>6.71</td>
<td>6.66</td>
</tr>
<tr>
<td>Subject H</td>
<td>4.91</td>
<td>4.42</td>
<td>4.85</td>
</tr>
<tr>
<td>Mean</td>
<td>7.18</td>
<td>7.20</td>
<td>6.87</td>
</tr>
</tbody>
</table>
In order to establish if there is a reduction in muscle co-contraction with driver experience, values for the mean squared normalised co-contraction were calculated. The values for test subjects A-H were grouped and three regression lines were fitted (one line for each of the three test cars) to show the change in mean squared normalised co-contraction with number of lane change manoeuvres completed (run number), Figure 5.15. It can be seen that there is a significant reduction in muscle co-contraction as the test subjects gain experience in all three vehicles indicated by $p(H_0)<0.05$ and a negative slope to the regression lines. The slope for the regression line for test car one was the steepest, which might be expected as in this car drivers had the least experience of the task, vehicle and steering dynamics. The results measured here, showing a reduction in co-contraction with experience, are consistent with the notion that muscle co-contraction is a characteristic of unlearnt or unfamiliar movements [48].
Figure 5.15: Regression analysis of normalised mean squared co-contraction for all test subjects.
5.3.6 Driver energy consumption

An estimate of the driver’s energy consumption can be made by considering the muscle activation levels and the forces generated by the muscles. While muscles are actively in tension there is an associated metabolic cost even if the limbs and steering wheel are static. In contrast the power transmitted to the steering wheel under such conditions may be zero if there is no movement of the steering wheel. Hence the total muscle activity must be considered to establish the driver’s metabolic energy consumption. A measure \( E \), that is proportional to the rate of energy consumption, is therefore given by the mean level of muscle activation (equation 5.7) as measured through EMG and the steering torque prediction based on the EMG measurements.

\[
E = \frac{1}{N} \sum_{k=1}^{N} (M_{+ve}(k) - M_{-ve}(k))
\]  

(5.7)

where:

- \( E \) – Measure proportional to rate of energy consumption
- \( M_{+ve} \) – EMG prediction of torque from muscles that generate positive steering torques
- \( M_{-ve} \) – EMG prediction of torque from muscles that generate negative steering torques
- \( N \) – Number of samples

It is of interest to establish if there is any change in the metabolic energy consumption as the driver gains experience and acts to optimise their control strategy over the vehicle. Because the overall measure of energy consumption categorised by equation 5.7 varies considerably between each test subject due to various levels of co-contraction, it is necessary to normalise the energy consumption. The measure of energy consumption was normalised for each test subject by dividing by the mean muscle activity (equation 5.8), calculated for that driver in the same particular vehicle (Table 5.4). As expected there is a slight increase in the rate of energy consumption going from test cars one to three due to the progressively larger steering torques required.
\[ E_N = \frac{E}{\bar{E}} \]  

(5.8)

where:

- \( E_N \) – Normalised measure of rate of energy consumption
- \( \bar{E} \) – Mean of \( E \) averaged for all runs made by each test subject in each test car

Figure 5.16 shows the normalised measure of energy consumption. It can be seen that there is a significant reduction in energy consumption as drivers gained experience in each of the three test cars. This suggests that drivers optimise their control strategy and reduce the workload in terms of reducing the overall level of energy consumption. An appropriate measure of driver workload is therefore the mean level of muscle activity.

<table>
<thead>
<tr>
<th>Subject</th>
<th>( \bar{E} ) test car 1/ Nm</th>
<th>( \bar{E} ) test car 2/ Nm</th>
<th>( \bar{E} ) test car 3/ Nm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject A</td>
<td>13.2</td>
<td>13.7</td>
<td>13.5</td>
</tr>
<tr>
<td>Subject B</td>
<td>8.11</td>
<td>9.48</td>
<td>10.3</td>
</tr>
<tr>
<td>Subject C</td>
<td>6.07</td>
<td>6.79</td>
<td>7.7</td>
</tr>
<tr>
<td>Subject D</td>
<td>16.1</td>
<td>15.1</td>
<td>13</td>
</tr>
<tr>
<td>Subject E</td>
<td>8.15</td>
<td>8.89</td>
<td>8.86</td>
</tr>
<tr>
<td>Subject F</td>
<td>7.72</td>
<td>7.63</td>
<td>8.85</td>
</tr>
<tr>
<td>Subject G</td>
<td>8.65</td>
<td>8.89</td>
<td>9.53</td>
</tr>
<tr>
<td>Subject H</td>
<td>6.79</td>
<td>6.66</td>
<td>7.59</td>
</tr>
<tr>
<td>Mean</td>
<td>9.35</td>
<td>9.64</td>
<td>9.92</td>
</tr>
</tbody>
</table>
Figure 5.16: Regression analysis of normalised mean squared muscle activity for all test subjects.
5.4 CONCLUSIONS

A series of double lane change manoeuvres was performed using CUED driving simulator. Eight test subjects drove three vehicles that had different steering dynamics. The resulting vehicle and driver responses were measured and analysed.

a) In general drivers were found to steadily reduce path error over the first 20 runs. Having completed 20 lane change manoeuvres no further significant reduction in path error was observed.

b) Changes in the steering dynamics and torque feedback were not found to cause degradation of drivers’ path following abilities. This leads to the conclusion that the drivers’ control strategies were robust to these changes.

c) The relationship between steer angle and vehicle response remained invariant throughout the experiments. Only the torque feedback changed as the steering dynamics were varied. The fact that the driver remained robust to the changes in torque feedback indicates that the driver builds up an internal model of the relationship between the vehicle response and steer angle rather than steer torque. This goes part way to answering the question of whether the driver uses angle or torque control when steering vehicles. To investigate this issue further, a set of vehicles could be devised that required the same torque input but varying degrees of steer angle input to complete the double lane change manoeuvre.

d) A significant learning trend was seen in the mean level of co-contraction displayed by the drivers as a group. The level of co-contraction was observed to reduce with driver experience in each of the three vehicles. The results indicate that the driver may co-contract muscles initially to compensate for changes in steering dynamics and ensure robust control. As the driver gains experience of the new steering dynamics less co-contraction is necessary.

e) Considerable co-contraction was seen while the driver generated the large steer angles necessary to complete the lane change manoeuvre. Co-contraction could therefore be a mechanism used to increase control bandwidth over the steering
system. Test subject B displayed the greatest level of muscle co-contraction and also generated the highest frequency control inputs to the vehicle.

f) A learning trend in the steer angle input was not seen and no reduction in the mean squared steer angle input was observed with increasing driver experience.

g) A significant reduction in muscle activation was seen as drivers gained experience in the three test cars. The reduction in muscle activation results in a reduction in the driver’s energy consumption. This provides evidence that the driver optimises control to reduce energy consumption.
Chapter 6: Mathematical Model of Driver Steering Control

6.1 INTRODUCTION

In Chapter 5, measurements of driver performance during a simulated double lane change manoeuvre were reported. The measurements showed some key characteristics relating to driver steering control behaviour. In this chapter, the performance of a driver model, which incorporates the neuromuscular dynamics, is investigated with the aim of predicting the salient features of the measured driver steering control.

The measurements made in Chapter 5 showed considerable variation between test subjects when performing the same lane change task. The results showed that drivers placed different relative importance on path-following accuracy. Some drivers achieved small path errors, but at the cost of larger steering torque inputs with increased energy consumption. Other drivers applied smaller torques but had larger path-following errors. It is therefore clear that the balance between energy consumption and path-following accuracy is of key importance in generating a predictive driver model.

Section 6.2 of this chapter gives a review and comparison of two existing driver path-following models. Modifications are made to one of the models to allow the driver’s time delay to be included. In section 6.3 a model of the neuromuscular dynamics is developed. The neuromuscular model is incorporated within a path-following driver model to generate a new driver model that is sensitive to changes in steering dynamics (section 6.4). In section 6.5 the performance of the new driver model is investigated through simulation. The simulation results are compared with the trends shown in the measured data as reported in Chapter 5. Finally, conclusions are given in section 6.6.
6.2 PATH-FOLLOWING CONTROLLERS

6.2.1 Multi-point preview path-following controllers
Sharp and Valtetsiotis [43] use linear quadratic regulator control theory to derive a model of driver path-following control that makes use of road path preview. The control model can be generated from a discrete time version of the yaw/side slip vehicle model presented in Chapter 2, equation 2.18. The discrete yaw/side slip model can be represented in the form shown by equation 6.1. The discrete model can be generated by using the Matlab function ‘c2d’, which assumes a zero order hold between inputs.

$$\begin{align*}
x(k+1) &= A_d x(k) + B_d u(k) \\
y(k) &= C_d x(k) + D_d u(k)
\end{align*}$$

(6.1)

where: \( k \) - Time step index

$$x(k) = \begin{bmatrix} y(k) & \omega(k) & y(k) & \psi(k) \end{bmatrix}^T$$ at time step \( k \)

The control model assumes that the driver previews the road at \( N_p + 1 \) equally spaced points ahead of the vehicle (Figure 6.1). The spacing between points is \( \nu_x T \), where \( \nu_x \) is the vehicle speed and \( T \) is the time step for the discrete time model.

![Figure 6.1: Vehicle and previewed road path showing global position of vehicle and road at time \( kT \) where \( y_{pi} \) is the road path lateral displacement and \( \psi_{pi} \) is the road path heading angle.](image)

Sharp and Valtetsiotis [43] show that by using a shift register operation the road path preview can be incorporated with the vehicle state space equations (equation 6.2):

$$\begin{bmatrix} x(k+1) \\ y_p(k+1) \end{bmatrix} = \begin{bmatrix} A_d & 0 \\ 0 & D \end{bmatrix} \begin{bmatrix} x(k) \\ y_p(k) \end{bmatrix} + \begin{bmatrix} 0 \\ E \end{bmatrix} y_{p(N+1)}(k) + \begin{bmatrix} B_d \\ 0 \end{bmatrix} \theta_{sw}(k)$$

(6.2)
where: \[ y_p(k) = [y_{p0}(k) \ y_{p1}(k) \ y_{p2}(k) \ \ldots \ldots \ y_{pN-1}(k) \ y_{pN}(k)]^T \] at time \( kT \).

\[
D = \begin{bmatrix}
0 & 1 & 0 & \ldots & 0 \\
0 & 0 & 1 & \ldots & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
0 & 0 & 0 & \ldots & 1 \\
0 & 0 & 0 & \ldots & 0
\end{bmatrix} \quad E = \begin{bmatrix}
0 \\
0 \\
0 \\
0 \\
1
\end{bmatrix}
\]

A quadratic cost function (equation 6.3) is used to evaluate the optimal steering control. Although the road path preview is uncoupled from the vehicle model in equation 6.2, the cost function provides coupling between the two systems. For path-following control, weights \( q_y \) and \( q_\psi \) are placed on lateral position and attitude angle errors respectively to form the weighting matrix \( R_1 \). \( R_2 \) is a scalar and is the weighting placed on the control input.

\[
J = \lim_{T \to \infty} \sum_{k=0}^{\infty} \left( z^T(k)R_1z(k) + \theta_{sw}(k)R_2\theta_{sw}(k) \right) \tag{6.3}
\]

where: \[ z(k) = [x(k) \ y_p(k)]^T \]

\[
R_1 = C^TQC
\]

\[
C = \begin{bmatrix}
0 & 0 & 1 & 0 & -1 & 0 & 0 & 0 & \ldots & 0 \\
0 & 0 & 0 & 1 & 1/\nu_xT & -1/\nu_xT & 0 & 0 & \ldots & 0
\end{bmatrix}
\]

\[
Q = \begin{bmatrix}
q_y & 0 \\
0 & q_\psi
\end{bmatrix}
\]

Equation 6.3 simplifies to equation 6.4 for the weighting functions used here:

\[
J = \sum_{k=0}^{\infty} q_y \left( y(k) - y_{p0}(k) \right)^2 + q_\psi \left( \psi(k) - \psi_{p0}(k) \right)^2 + R_2 \left( \theta_{sw}(k) \right)^2 \tag{6.4}
\]

A Linear Quadratic Regulator LQR, \( K_p \), can be found that minimises the cost function \( J \). The LQR controller can be generated using Matlab’s DLQR function, given \( R_1 \), \( R_2 \) and the composite vehicle and road path model (equation 6.2). When \( K_p \) is applied in state variable feedback (equation 6.5) the cost function is minimised and the optimal control input is generated.

Optimal control input: \( \hat{\theta}_{sw}(k) = -K_p[x(k) \ y_p(k)]^T \) \tag{6.5}
where: \( \mathbf{K}_p = [k_1 \ k_2 \ k_3 \ k_4 \ \ k_{p1} \ \ k_{p2} \ \ \cdots \ \ k_{pn}] \)

Hence \( \mathbf{K}_p \) contains a number of gains: \( k_1 \) to \( k_4 \) acting on the vehicle states \( [v_y(k) \ \ \omega(k) \ \ \ y(k) \ \ \ \psi(k)]^T \) and \( k_{p1} \) to \( k_{pn} \) acting on the previewed path information.

The gains are known as the state gains (\( k_1 \) to \( k_4 \)) and the preview gains (\( k_{p1} \) to \( k_{pn} \)).

### 6.2.2 Comparison of predictive and LQR controllers

MacAdam’s predictive optimal preview controller [40] can also be derived from a discrete linear vehicle model. In MacAdam’s model, a prediction of the vehicle position is made at \( n = 1 \) to \( N \) points ahead of the vehicle. The prediction is generated by assuming that the driver applies a constant control input \( u_0 \) across the preview interval. This allows the vehicle response to be predicted \( n \) time steps ahead of the vehicle:

\[
y_n = \mathbf{F}_n \mathbf{x}_0 + \mathbf{G}_n u_0
\]

where:
- \( u_0 \) – Control input at time \( kT \), for the vehicle model this is \( \theta_{sw} \)
- \( \mathbf{x}_0 \) – State at time \( kT \), for the vehicle model: \( [v_y(k) \ \ \omega(k) \ \ y(k) \ \ \psi(k)]^T \)
- \( y_n \) – Predicted output at \( (k+n)T \), for vehicle model: (lateral position) \( y(k+n) \)
- \( \mathbf{F}_n \) – Free response array
- \( \mathbf{G}_n \) – Control response scalar

The free response array \( \mathbf{F}_n \) relates the initial state \( \mathbf{x}_0 \) to the predicted output \( y_n \), which in this case is the vehicle lateral position. In addition, the control response scalar \( \mathbf{G}_n \) relates the constant control input \( u_0 \) to the output. \( \mathbf{F}_n \) and \( \mathbf{G}_n \) can be generated from the state space matrices (equations 6.1) as shown the Appendix, section A.4. The predicted vehicle lateral position \( y_n \) can be compared to the previewed road path ahead of the vehicle \( y_{pn} \) to evaluate the predicted path error. The optimal steering control is determined by minimising a quadratic cost function, \( J \), of predicted path errors across the preview interval (equation 6.7).

\[
J = \sum_{n=0}^{N} (y_{p(n)} - y_n)^2
\]

(6.7)
In MacAdam’s formulation of the optimal preview steering controller [40] no cost is assigned to the control input (steer angle). In order that MacAdam’s model is comparable with the model proposed by Sharp and Valtetsiotis [43], a cost on steer angle should be added to equation 6.7 (equation 6.8).

\[
J = \sum_{n=0}^{N} q_y \left( y_{p(n)} - y_n \right)^2 + R_2 \theta_{sw}^2
\]  
(6.8)

Substituting equation 6.6 into 6.8 gives:

\[
J = \sum_{n=0}^{N} q_y \left( y_{p(n)} - (F_n x_0 + G_n \theta_{sw}) \right)^2 + R_2 \theta_{sw}^2
\]  
(6.9)

The cost function (equation 6.9) is minimised by taking the partial derivative with respect to \( \theta_{sw} \) and setting it equal to zero. Rearranging this minimisation gives the optimal steering control:

\[
\hat{\theta}_{sw} = \frac{\sum_{n=0}^{N} q_y G_n \left( y_{p(n)} - F_n x_0 \right)}{\sum_{n=0}^{N} (q_y G_n^2 + R_2)}
\]  
(6.10)

MacAdam’s predictive controller uses both the vehicle states and previewed road path. By rearranging equation 6.10 to give equation 6.11 it can be shown that the predictive controller has the same structure as Sharp and Valtetsiotis’ LQR controller (equation 6.5):

\[
\hat{\theta}_{sw} = \frac{1}{\sum_{n=0}^{N} G_n^2 + R_2} \left[ -\sum_{n=0}^{N} G_n F_n \begin{bmatrix} G_0 & G_1 & \cdots & G_{N-1} & G_N \end{bmatrix} \begin{bmatrix} x_0 \\ y_{p0} \\ \vdots \\ y_{pN} \end{bmatrix} \right. 
\]  
(6.11)

This is time invariant state variable feedback. Although the controllers have the same structure, the feedback gains are very different. A comparison of the feedback gains for vehicle state and road preview, produced by both Sharp and MacAdam’s models, is shown in Figure 6.2. The comparison of controller gains shown in Figure 6.2 highlights some interesting differences between the predictive and LQR controllers. MacAdam’s predictive controller is simplified by the assumption that the driver
applies a constant control input across the preview interval. This leads to road path points previewed furthest ahead having the highest preview gains. Hence for the predictive controller the preview distance is critical in determining the controller performance. In contrast Sharp and Valtetsiotis’ model gives a preview gain of zero to the road path previewed furthest ahead. Hence the preview distance is inherently specified by the preview gains, provided the preview horizon is sufficiently long for the preview gains to tend to zero. There is considerable contradiction in published literature as to the most appropriate preview distance or time (see section 1.3.3). Using the LQR controller is beneficial because it avoids the need to explicitly define a preview time.

For MacAdam’s predictive steering control model, long preview distances can lead to excessive corner cutting and therefore poor path-following performance. This problem is avoided by using the LQR controller formulation.

Drivers may employ similar control strategies to those described above in generating the desired steer angle in vehicle control. However, rather than the driver establishing the control vector, $K_p$, through explicit solution of the optimal control problem, it is conceivable that the control gains are learnt over time with experience.
6.2.3 Vehicle fixed reference frame

The predictive and LQR path-following driver-models are generated using absolute global coordinates. As discussed by Sharp and Valtetsiotis [43], it seems more plausible that the driver uses the relative error between the vehicle and the previewed road rather than absolute position. It is possible to make a transformation that preserves the optimal performance of the steering controller and converts the path preview problem from a global reference frame to a driver reference frame (Figure 6.3).

In section 6.2.1, the driver-models were formulated from a linear vehicle model with a linearised calculation of the vehicle trajectory. The model is valid provided the changes in yaw angle and lateral path deviation are small; for example during a lane change manoeuvre. However, if more complex path trajectories are to be followed...
that require large yaw angles, the control problem must be converted to the driver reference frame.

\[ y_{mn}(k) = y_{rn}(k) + y(k) + n v_x T \psi(k) \]  \hspace{1cm} (6.12)

Optimal steer angle in global reference frame:

\[ \hat{\theta}_m(k) = k_1 y_y(k) + k_2 \omega(k) + k_3 y(k) + k_4 \psi(k) + \sum_{n=0}^{N} k_{pn} y_{m}(k) \]  \hspace{1cm} (6.13)

The optimal steer angle in the driver reference frame is given by:

\[ \hat{\theta}_{sn}(k) = k_1 y_y(k) + k_2 \omega(k) + \sum_{n=0}^{N} k_{pn} y_{m}(k) \]  \hspace{1cm} (6.14)

For the optimal steer angle to be invariant between driver and global reference frames, equations 6.13 and 6.14 must be equal which implies:

\[ k_3 = -\sum_{n=0}^{N} k_{pn} \quad \text{and} \quad k_4 = -\sum_{n=0}^{N} k_{pn} n v_x T \]  \hspace{1cm} (6.15)

Numerical results have shown that, for the LQR controller, the conditions in equations (6.15) are satisfied provided the preview horizon is sufficiently long for the preview gains to tend to zero.
6.2.4 Numerical analysis of LQR controller performance

The performance of the LQR steering controller was evaluated when directly linked to a vehicle model. Directly linked means that the optimal reference steer angle, $\hat{\theta}_w$, is fed instantaneously and directly to the steering wheel. The road path centre line for the double lane change manoeuvre described in Chapter 5, section 5.2.1, was used as the target path. The vehicle speed was 140km/h or $v_x=38.9\text{m/s}$. The vehicle model and parameters given in Chapter 2, section 2.5.1, were used in generating the LQR controller and the effect of varying the cost function weights was investigated. Cost function weights used to represent four different driver steering strategies are listed in Table 6.1. The large relative difference between the weights is necessary to account for the difference in magnitude of the squared variables $y$, $\psi$ and $\theta_w$ in the cost function.

Table 6.1: Parameters used in cost function to represent various driver control strategies with time step $T=0.02s$ and $N=200$ preview points.

<table>
<thead>
<tr>
<th>Controller</th>
<th>$R_2$ -Steer angle weight</th>
<th>$q_y$ - Path error weight</th>
<th>$q_\psi$ - Heading error weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>Controller 1</td>
<td>1</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>Controller 2</td>
<td>1</td>
<td>0.25</td>
<td>100</td>
</tr>
<tr>
<td>Controller 3</td>
<td>1</td>
<td>0.25</td>
<td>0</td>
</tr>
<tr>
<td>Controller 4</td>
<td>1</td>
<td>0.025</td>
<td>10</td>
</tr>
</tbody>
</table>

Figure 6.4 and Figure 6.5 show the state gains and preview gains for LQR controllers generated from the weights listed in Table 6.1. There is significant variation in both the state gains and the preview gains following changes in the cost function weights. In particular it can be seen that varying degrees of preview are necessary depending on the cost function used.

The path-following performance of each of the controllers, during a double lane change manoeuvre, is shown in Figure 6.6. Controller 1 shows performance when no cost is assigned to lateral position error, but the cost on yaw angle error is large. Under this control the path-following performance is poor. Path-following performance is improved by increasing the weight on lateral position error as shown by Controller 2. Controller 3 represents the case when no cost is assigned to attitude angle errors, it can be seen that in this case the driver steers in the wrong direction
ahead of the lane change manoeuvre before correcting and completing the manoeuvre (counter steering action). Sharp and Valtetsiotis [43] make note of this counter steering phenomenon and liken it to the behaviour of rally drivers who often apply oscillatory steering inputs prior to a bend. However, the counter steering behaviour prior to the manoeuvre was not consistently observed in the measurements obtained from the CUED simulator, described in Chapter 5. When the weights on lateral position error and attitude angle error are both small (controller 4) the cost on steering angle dominates, which leads to corner cutting.

![State feedback gains](image)

**Figure 6.4:** Comparison of state feedback gains for controllers generated from cost functions in Table 6.1.
Figure 6.5: Preview gains evaluated for various weights in the LQR controller cost function.

Figure 6.6: LQR controller path-following performance. Shows direct steering angle controlled vehicle using optimal preview driver.
6.2.5 Modelling the driver time delay

In their published form, neither Sharp and Valtetsiotis’ [43], nor MacAdam’s [40] preview control driver-models include the inherent time delay associated with human control. The human time delay in responding to visual stimuli is typically thought to be around 150-200ms [35]. Having previewed the road path ahead, the driver generates the target steer angle, \( \hat{\theta}_{sw} \), as a cognitive process; this incurs the time delay.

A method has been devised here to include this time delay in Sharp and Valtetsiotis’ model by placing another shift register, \( D_q \) and \( E_q \), between the vehicle and the feedback optimal steer angle (equation 6.16).

\[
\begin{bmatrix}
\theta_q(k+1) \\
x(k+1) \\
y_p(k+1)
\end{bmatrix} =
\begin{bmatrix}
D_q & 0 & 0 \\
0 & B_d & A_d \\
0 & 0 & D
\end{bmatrix}
\begin{bmatrix}
\theta_q(k) \\
x(k) \\
y_p(k)
\end{bmatrix} +
\begin{bmatrix}
E_q & 0 \\
0 & 0 \\
0 & E
\end{bmatrix}
\begin{bmatrix}
\theta_{sw}(k) \\
y_{ps}(k)
\end{bmatrix}
\]

(6.16)

where:

\[
D_q =
\begin{bmatrix}
0 & 0 & \cdots & 0 & 0 \\
1 & 0 & \cdots & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & \cdots & 1 & 0
\end{bmatrix}
\quad \text{and} \quad
E_q =
\begin{bmatrix}
1 \\
0 \\
\vdots \\
0
\end{bmatrix}
\]

The optimal steer angle must pass down the shift register before being applied to the vehicle. The associated driver time delay is given by equation (6.17).

\[
\tau_d = n_q T
\]

(6.17)

where: \( n_q \) – Number of states in the shift register

The additional shift register introduces a set of new states, \( \theta_q \), which represent a queue of delayed steer angles waiting to be applied to the vehicle. The discrete linear quadratic regulator problem is solved with the new states included. State gains and
preview gains, for the system given by equation 6.16, are shown in Figure 6.7 and Figure 6.8. The new feedback gains that arise due to the new states added to the system can be considered to be a filter that acts on the delayed steering angle signal.

The state gains for the LQR controller with time delay, shown in Figure 6.7, are comparable with those shown for Controller 2 in Figure 6.4. Comparison shows that when the time delay is modelled, the state gains for states $v_y$ and $\omega$ increase. Because time delays can make system dynamics more oscillatory, the effect of the increase in the state gains could be to add additional system damping. It was found that, with the time delay modelled, the state gains for $y$ and $\psi$ still satisfied the necessary conditions for invariant control between driver reference frame and global reference frame (as expressed by equation 6.15).

![State feedback gains with time delay $\tau_d=0.16s$](image)

![State feedback gains with time delay $\tau_d=0.16s$](image)

Figure 6.7: State gains calculated for $q_y = 0.25$, $q_{\psi} = 100$, $N=200$ $T=0.02s$ $\tau_d=0.16s$.

The preview gains with and without driver time delay (Figure 6.8) are identical apart from a time advance of $\tau_d$ seconds. The time advance arises because the driver’s time delay prevents the driver from reacting to the road path previewed directly in front of the vehicle. In Hess’ driver-model [10], it is hypothesised that driver preview can be
modelled by including a time advance function $e^{sT_p}$ (where $T_p$ is a positive value). In the model, the current vehicle position is compared to the road path previewed some distance in front of the vehicle. The analysis carried out here, using LQR theory, shows that in the presence of a time delay the optimal strategy is for the driver to look further ahead. This finding provides justification for preview models like the one proposed by Hess.

By previewing the road further ahead of the vehicle, the time delay is compensated for by the LQR controller. However, the response to disturbances and errors induced by differences between the actual vehicle model and the linear approximation used in generating the LQR controller are still impaired by this time delay.

Figure 6.8: Comparison of preview gains with and without driver time delay calculated for $q_y=0.25$, $q_\psi=100$, $N=200$, $T=0.02s$ and $\tau_d=0.16s$.

6.2.6 Adding a logging state to the LQR controller

The cost function used in generating the LQR controller can be used to penalise the squared sum of any signal made up as a linear combination of the state variables. Additionally, costs can be placed on the squared sum of the control inputs. However, it is not possible to include signals in the cost function that are dependent on both the
system states and control inputs. When these signals are squared they contain products of both the system states and inputs. One such signal, which cannot be included, is the vehicle lateral acceleration (equation 6.18).

\[ A_y = \frac{1}{m} \left( (C_f + C_r)v_y + (aC_f - bC_r)\omega - C_f \frac{\theta_{sw}}{n_{sw}} \right) \]  \hspace{1cm} (6.18)

A method is devised here for placing costs on signals that are linear sums of input and state variables. A logging state \( x_L \) is introduced to the discrete-time system model (equation 6.19). The logging state logs outputs that are generated through the \( C_d \) and \( D_d \) matrices of the vehicle model (equation 6.1). The logging state stores the output, as calculated in the previous time step. Costs can then be placed on the logged states in the cost function even though they contain both input and state variables.

\[
\begin{bmatrix}
   x_L(k+1) \\
   x(k+1) \\
   y_p(k+1)
\end{bmatrix} =
\begin{bmatrix}
   0 & C_d & 0 \\
   0 & A_d & 0 \\
   0 & 0 & D
\end{bmatrix}
\begin{bmatrix}
   x_L(k) \\
   x(k) \\
   y_p(k)
\end{bmatrix} +
\begin{bmatrix}
   D_d & 0 \\
   B_d & 0 \\
   0 & E
\end{bmatrix}
\begin{bmatrix}
   \hat{\theta}_{sw} \\
   y_p
\end{bmatrix} \hspace{1cm} (6.19)
\]

The effect of using the logging state concept has been investigated by weighting lateral acceleration in the cost function \( q_{A_y} \). The state gains and preview gains with costs on lateral acceleration are shown in Figure 6.9 and Figure 6.10. It is interesting to note that the state gain on the new logging state relating to \( A_y \) is zero. This might be expected because the logging state contains information relating to the previous time step only.

The performance of the controller with costs placed on lateral acceleration \( q_{A_y} \) was evaluated for the double lane change manoeuvre. The lateral acceleration and path-following performance is shown in Figure 6.11 and Figure 6.12 respectively for control with and without weight \( q_{A_y} \). It can be seen that the new controller with weight \( q_{A_y} \) significantly reduces the lateral acceleration, but at the cost of path-following error.
Chapter 6: Mathematical Model of Driver Steering Control

The logging state is not used in the analysis in the remainder of this chapter. However, if more complex cost functions are to be evaluated, a logging state may be needed.

Figure 6.9: Comparison of state feedback gains for a system with logging state on lateral acceleration with weight \( q_{Ay} \).

Figure 6.10: Comparison of preview gains for system with logging state on lateral acceleration with weight \( q_{Ay} \).
Figure 6.11: Controller performance during lane change manoeuvre with and without a cost on lateral acceleration.

Figure 6.12: Comparison of path-following performance using controller with and without a cost on lateral acceleration.
6.3 NEUROMUSCULAR DYNAMIC MODEL

The LQR control model and predictive controller reviewed in the previous section generate the optimal steer angle for vehicle control. However the driver can only generate this optimal steer angle through activation of the neuromuscular system. The neuromuscular system provides control, through activation of appropriate muscles and reflex control, to generate the optimal steer angle at the steering wheel. In this section the structure for a model of the neuromuscular dynamics is discussed based on the parameters measured and reported in Chapter 4 and the models reviewed from published literature in Chapter 1.

6.3.1 Neuromuscular dynamics
Magdaleno and McRuer [64] proposed a model for the neuromuscular system based on studies of aircraft pilots controlling joysticks. The physiological components of the model are shown in Figure 6.13. The model represents the combined response from an agonist/antagonist muscle pair and therefore both positive and negative muscle forces can be produced. There are two control inputs, the expected muscle force and expected muscle length. Either one or both of these inputs can be used to control the limb position. Additional control over the neuromuscular system response is possible by varying the parameters of the reflex controller. The contractile element represents the muscle machinery that converts the alpha motor neuron firing rate to muscle force. The contractile element can be modelled as a first order lag acting on the muscle activation signal [62].

![Figure 6.13: Physiological components of simplified neuromuscular system.](image-url)
The intrinsic properties of the arm dynamics were measured in Chapter 4. In the relaxed state, the arm dynamics were shown to be well represented by a simple mass spring and damper system. The stiffness and damping in the relaxed state can be considered to arise from the passive properties of the tendons, skin and muscle tissue and can be modelled as a grounded spring. For driver steering control it is assumed that when the steering wheel is held at zero degrees rotation and the arms are holding the steering wheel at the “quarter to three” position the muscles are at their resting length and relaxed.

The measurements described in Chapter 4 also showed that the neuromuscular dynamics are non-linear. Increased muscle activity was found to be generated by muscle co-contraction and by applying offset torques to the steering wheel. An increase in the intrinsic stiffness and damping of the arm was seen in response to increased muscle activity. The mechanism for this active stiffening can be understood from Huxley’s sliding filament model of muscle contraction [49] as described in Chapter 1, section 1.4.1. The mechanism involved indicates that active stiffening occurs with respect to the current muscle operating point rather than about the muscle’s free or resting length. The active stiffening must therefore be modelled as a spring with moving base. If the muscle stiffening occurred only about the muscle’s free length considerable muscle activation would be necessary to hold the arm at a position other than its free length.

Figure 6.14 shows the simplified neuromuscular dynamics with the proposed active stiffening included. The active stiffening block produces a force proportional to the difference between muscle length and required muscle length. The muscle stiffness depends on the degree of contraction of the muscle. However the force produced is intrinsic and is not generated directly by muscle activity in the contractile element.
It is hypothesised and quoted in published literature [48] that in controlling the neuromuscular dynamics the human operator generates the muscle force and length inputs (alpha and gamma motor neuron commands) together, using an internal reference model of the limb and manipulator dynamics as discussed in Chapter 1 (sections 1.4.4 and 1.4.6). The internal reference model is built up based on past experience of the limb and manipulator dynamics. The internal reference model is based on the inverse of the limb and manipulator dynamics. By using the internal reference model of the arm and manipulator dynamics the necessary muscle force can be generated. The control performance depends on the accuracy of the driver’s reference model. If the internal reference model predicts the required muscle force correctly no reflex action takes place.

Figure 6.14: Simplified neuromuscular system dynamics with active stiffening included.

Figure 6.15: Structure of neuromuscular model with inverse reference model.
The neuromuscular model system shown in Figure 6.15 is now equivalent to the classical feedback control structure of system (limb and manipulator dynamics), regulator (reflex and active stiffening) and pre-filter (generated from inverse reference model), Figure 6.16. The reflex pathways and active stiffness, generated through muscle co-contraction, can be tuned to ensure robustness to disturbances and noise. The inverse reference model, which can directly activate the muscles, ensures that rapid control of the system is still possible and achievable.

Figure 6.16: a) Neuromuscular system block structure b) Equivalent model structure.
6.4 DRIVER MODEL WITH NEUROMUSCULAR DYNAMICS

A model of the driver-vehicle system can be built up around the neuromuscular model by including path-following control and a vehicle dynamics model (Figure 6.17). For the case of driver steering, the muscle force and length control inputs to the neuromuscular system become expected steering torque and target steering angle respectively. The limb and manipulator dynamics are the steering system and arm dynamics. The neuromuscular system is responsible for generating the target steering angle $\hat{\theta}_{sw}$ through control and regulation of the steering system in the presence of steering torque feedback from the vehicle.

Figure 6.17: Structure for driver path-following model with neuromuscular dynamics incorporated.

The contractile element is essentially a first order lag arising from the delay between muscle activation and generation of force [62]. Its effect can therefore be incorporated into the inverse reference model and reflex controller as a first order filter. The signal $T_{\alpha}$ represents the muscle torque generated by the contractile element through activation of the alpha motor neurons. There is a metabolic energy cost associated with this muscle activation and the rate of energy consumption can be considered to be proportional to the torque generated $T_{\alpha}$. Conversely, the torque generated by the active stiffness component is intrinsic and arises from the mechanical properties of the muscle. The metabolic energy consumption in the active stiffness block arises from
the muscle co-contraction necessary to modulate the muscle stiffness $K_a$ [52]. $T_m$ is the total active muscle torque.

In order that the performance of the driver-model shown in Figure 6.17 could be investigated, parameters were assigned to the various components of the model. The performance was assessed during a double lane change manoeuvre with the road path matching that described in Chapter 5. This allows comparison with the data measured from test subjects on the CUED driving simulator.

### 6.4.1 Parameters used in path-following block

The path-following model used is the LQR preview control model proposed by Sharp and Valtetsiotis [43], but modified to include a time delay as discussed in section 6.2.5. Gains for the LQR controller were evaluated with weights matching those of Controller 2 (Table 6.1) in the cost function. A time delay of $\tau_d=0.16s$ was used to represent the delay associated with human control and $N=200$ preview points were assumed with a time step of $T=0.02s$. The performance of Controller 2, coupled directly to the vehicle, can be compared with the mean path taken by all test subjects in all three test vehicles as measured and reported in Chapter 5 (Figure 6.18). There is good agreement between the model and measured data. The mean path taken by all test subjects shows some overshoot and oscillation. This could be due to the neuromuscular dynamics, which are not yet included. The mean steer angle, generated by test subjects, during the lane change manoeuvre can also be compared with the steer angle from LQR Controller 2 (Figure 6.19). Again reasonable agreement is seen.

In generating the LQR control gains, a discrete model of the vehicle dynamics must be included. The vehicle model described by equation 6.1 was used with parameters matching those given in section 2.5.1 with discrete time step $T=0.02s$ and vehicle speed $v_x=38.9m/s$. In reality, if the driver incorrectly identifies the vehicle dynamics, the LQR controller may be sub-optimal. However in this instance the LQR control gains have been generated based on an exact match to the vehicle model dynamics. The reader is reminded that in the experiments carried out the vehicle dynamics (relationship between steer angle and vehicle motion) remained constant and only the steering torque feedback and steering dynamics were varied.
Figure 6.18: Mean path taken by test subjects through lane change and performance of LQR Controller 2 when linked directly to the vehicle. Error bars show +/-1 standard deviation from the mean path taken by test subjects.

Figure 6.19: Mean steer angle applied by test subjects through lane change and performance of LQR Controller 2 when linked directly to the vehicle. Error bars show +/-1 standard deviation from the mean path taken by test subjects.
6.4.2 Parameters used in arm and steering dynamics block

The arm and steering dynamics are coupled by the driver holding the steering wheel. The steering dynamic parameters used in the simulation were chosen to match those of the three test cars described in Chapter 5. The parameters are listed again here for clarity (Table 6.2).

Table 6.2: Steering dynamic model parameters.

<table>
<thead>
<tr>
<th></th>
<th>( J_{eqv} ) / kgm(^2)</th>
<th>( B_{eqv} ) / Nms/rad</th>
<th>( K_d ) / Nm/rad</th>
<th>( B_e ) / Nms/rad</th>
<th>( G_d ) / Nm/rad</th>
</tr>
</thead>
<tbody>
<tr>
<td>test car 1</td>
<td>0.172</td>
<td>0.41</td>
<td>2.29</td>
<td>1.15</td>
<td>-1920</td>
</tr>
<tr>
<td>test car 2</td>
<td>0.172</td>
<td>0.41</td>
<td>2.29</td>
<td>0.57</td>
<td>-3840</td>
</tr>
<tr>
<td>test car 3</td>
<td>0.172</td>
<td>0.41</td>
<td>0</td>
<td>0</td>
<td>-5760</td>
</tr>
</tbody>
</table>

Values for the intrinsic arm dynamics are also needed. These are taken as the mean values measured in Chapter 4 (Table 4.4 averaged over all test subjects) for the arm in the relaxed state. The values used were arm inertia \( J_{dr} = 0.064 \) kgm\(^2\), arm damping \( B_{dr} = 0.56 \) Nms/rad and arm stiffness \( K_{dr} = 3.8 \) Nm/rad. The equation of motion for the arm and steering dynamics is given by equation 6.20 and the system transfer function is given by equation 6.21.

\[
\begin{align*}
\left( J_{dr} + J_{eqv} \right) \ddot{\theta}_{sw} + (B_{dr} + B_{eqv} + B_e) \dot{\theta}_{sw} + (K_{dr} + K_e) \theta_{sw} = T_m - \frac{M_T}{n_{rss}} 
\end{align*}
\]

where:

\[
M_T = G_d \alpha_f - \text{Steering torque feedback}
\]

\[
\alpha_f - \text{Equivalent front axle slip angle}
\]

\[
G_d(s) = \frac{1}{\left( J_{dr} + J_{eqv} \right)^2 + (B_{dr} + B_{eqv} + B_e)s + (K_{dr} + K_e)}
\]

6.4.3 Parameters used in neuromuscular control blocks

The reflex controller, active stiffness and inverse reference model, shown in Figure 6.17, can be thought of as controllers of the neuromuscular system. The parameters used to evaluate the model performance are described here.
The reflex controller is described by equation 6.22. The first order filter cut off frequency, $\omega_c$, was set at 30rad/s and represents the lag between muscle activation and generation of the muscle torque [57]. Including this first order component also ensures that the system is proper, i.e. the order of the numerator is not greater than that of the denominator. The time delay represents the transport lag in sending messages to and from the spinal cord. The experiments reported in Chapter 4 showed that it was not possible to conclusively identify the time delay associated with reflex control with respect to steering control. However reflex action is typically thought to incur a time delay of around 0.04s [81, 84] and $\tau_r$ was chosen as 0.04s here. Values for the reflex stiffness $K_r$ and $B_r$ were varied in order that their effect on control performance could be established.

\[
\text{Reflex controller: } H(s) = \frac{\omega_c (sB_c + K_c)e^{-\tau_r}}{s + \omega_c} \tag{6.22}
\]

The active stiffness block represents the increased muscle stiffness induced by muscle co-contraction. Because muscle co-contraction increases the intrinsic stiffness of the muscle, no time delay or activation lag occurs. Hence the stiffness arising from co-contraction is simply a gain, $K_a$, measured in Nm/rad. The effect of varying the degree of muscle co-contraction can be investigated.

The effect of the inverse reference model can also be investigated. Typically the inverse reference model must represent the inverse of the steering dynamics; it is also necessary to include a filter in order that the model remains proper. In the following section the performance of various inverse reference models are investigated.
6.5 RESULTS FROM DRIVER MODEL SIMULATION

The driver model’s performance during a double lane change manoeuvre was evaluated through simulation. The lane change manoeuvre matches the manoeuvre described in Chapter 5 in order that the model performance can be compared with the measured data. Parameters in the various sub system blocks of Figure 6.17 were varied and the effect on path-following performance and system stability was investigated. The results of the simulations are presented in the following sections.

6.5.1 Reflex control

The path-following performance was simulated and is displayed in Figure 6.20 with various levels of reflex stiffness. In order that the effect of the reflex dynamics could be investigated in isolation, the driver inverse reference model loop was disconnected.

![Figure 6.20](image)

Figure 6.20: Path-following performance with varying reflex stiffness. Evaluated with $B_r=1\text{Nms/rad}$, $K_r=5\text{Nm/rad}$ and $G_d=0$ for test car 1.

Figure 6.20 shows that increasing the reflex stiffness significantly improves path-following performance. This is to be expected because increasing the reflex stiffness
increases the loop gain, which in turn means the target steer angle is more rapidly generated at the steering wheel.

There is an energy cost associated with increasing the reflex stiffness, because larger muscle torque, $T_\alpha$, must be generated. A cost function has been devised (equation 6.23) by adapting the cost function used in generating the LQR path-following controller (equation 6.4). The cost associated with squared steer angle rotations is replaced with a cost associated with muscle torque $qT_\alpha$

$$C = \frac{1}{N} \sum_{k=1}^{N} q_{T\alpha}(k)^2 + q_y(y(k) - y_p(k))^2 + q_\psi(\psi(k) - \psi_p(k))^2$$  \hspace{1cm} (6.23)

where:
- $N$ – Number of samples taken from the simulation
- $q_{T\alpha}$ - Weight associated with torques produced through muscle activation

By using this new cost function the optimum level of reflex stiffness can be established. The cost function was evaluated using the results from simulated lane change manoeuvres with various values of reflex stiffness. Contours of the cost function are shown with respect to reflex stiffness with various costs $q_{T\alpha}$ in Figure 6.21. The optimum reflex stiffness depends on the cost $q_{T\alpha}$ used in the cost function. When the value of $q_{T\alpha}$ is small, large values of reflex stiffness are optimal. This represents a driver that values path-following accuracy over energy conservation. Conversely, when $q_{T\alpha}$ is large minimising energy consumption is of primary importance and low reflex stiffness is optimal at the cost of reduced path-following accuracy.
In order that variations in the driver’s control strategy can be evaluated following changes to the steering dynamics, the analysis was repeated for all three sets of steering dynamics (test cars one to three). The optimum reflex stiffness for each test car is shown by the cost contours in Figure 6.22. The variation in optimal reflex stiffness between the three test cars is small (approximately 5Nm/rad) for a given cost $q_{T\alpha}$. It is interesting to note that for test car three, there is a large cost associated with increasing the reflex stiffness beyond 45Nm/rad. The large cost arises because the reflex control becomes unstable and large path errors occur.
Figure 6.22: Cost contours, $C$ (equation 6.23), showing optimum reflex stiffness in each of the three test cars. Evaluated with $B_r=1\text{Nms/rad}$, $K_r=5\text{Nm/rad}$, $G_d = 0$ and $q_{T_0}=0.01$. 
6.5.2 Muscle co-contraction

The effect of change in muscle co-contraction was also investigated by increasing the active stiffness, $K_a$. Driver model path-following performance, with various levels of $K_a$, was simulated and is displayed in Figure 6.23. The driver inverse reference model loop remained disconnected.

It can be seen that increasing the active stiffness through co-contraction has a similar effect to that of increasing the reflex stiffness. By increasing the active stiffness, the bandwidth of the steer angle feedback loop is increased and path-following performance is improved. From a control stability perspective, increasing the bandwidth through co-contraction is beneficial, because the forces produced are intrinsic and therefore do not incur the time delay associated with the reflex dynamics.

Maintaining the active stiffness $K_a$ through co-contraction has a considerable associated energy cost due to the large opposing muscle forces that are required. The energy cost associated with muscle co-contraction can be included in the cost function (equation 6.23) as a constant term $C_a$:
\[ C = C_a + \frac{1}{N} \sum_{k=1}^{N} q_{\text{ra}} T_a(k)^2 + q_y (y(k) - y_p(k))^2 + q_\psi (\psi(k) - \psi_p(k))^2 \] (6.24)

where: \( C_a \) – Cost associated with co-contraction

The cost associated with co-contraction \( C_a \) is calculated based on the opposing muscle torque necessary to generate the stiffness \( K_a \). The cost is given by equation 6.25.

\[ C_a = f \left( \frac{K_a}{b} \right)^2 \] (6.25)

where:
- \( f \) – scale factor set at 0.2, to account for co-contraction only occurring when the steering control is needed. Typically co-contraction was seen to occur for 4s of the 20s lane change manoeuvre, see Chapter 5 Figure 5.14.
- \( b \) – gradient (rad\(^{-1}\)), between co-contraction stiffness (Nm/rad) and co-contraction (Nm) where \( b = 1.8 \) as measured in Chapter 4, Figure 4.13.

By using the cost function (equation 6.24) the optimal level of co-contraction can be calculated. Contours for the cost function were generated from the simulation data (Figure 6.24). The cost function was evaluated for various weights \( q_{\text{ra}} \). This variation can be used to represent variation in driver’s steering behaviour. The results show that the optimum level of co-contraction is highly dependent on the relative importance the driver places between path-following accuracy and energy consumption. High levels of co-contraction are expected if path-following accuracy is most important (i.e. \( q_{\text{ra}} \ll q_y \)) in the cost function.
The optimal level of co-contraction can be investigated following changes in the steering dynamics. Cost contours showing the optimum level of co-contraction are shown for test cars one to three (Figure 6.25). For test car three, it can be seen that the stability issue experienced with high levels of reflex stiffness (Figure 6.22) is not observed with high levels of co-contraction and stiffness $K_a$. Hence the model shows that co-contraction may be the optimal strategy if high bandwidth control is required; this is in agreement with the findings of Hogan [52].

The optimum level of co-contraction was also calculated following changes in the steering dynamics. The cost contours in Figure 6.25 show that as the steering dynamics become more oscillatory (from test car one to three) there is an increase in the optimal level of co-contraction. The optimum level of co-contraction is compared with the measured co-contraction averaged for all test subjects in Figure 6.26. While the model predicts that the co-contraction increases from test car one to three, the trend was not seen in the measured data. The difference may arise because in reality the driver is also able to optimise their control through use of the inverse reference...
model (Figure 6.17). The inverse reference model has not yet been considered but is discussed in section 6.5.4.

![Effect of change in steering dynamics on optimum co-contraction](image)

Figure 6.25: Cost contours, $C$ (equation 6.24), showing optimum active stiffness $K_a$ generated through co-contraction in each of the three test cars. Evaluated with $B_r=1\text{Nms/rad}$, $K_r=5\text{Nm/rad}$ and $G_d=0$.

![Comparison of model predicted and measured co-contraction](image)

Figure 6.26: Comparison of muscle co-contraction for model prediction and mean co-contraction measured and averaged for all test subjects (data taken from Chapter 5, Table 5.3). The model prediction is taken from Figure 6.26 with $q_{Ta}=0.001$ and using $b=1.8\text{rad}^{-1}$. 
6.5.3 Non-linear muscle stiffness

In Chapter 4, Figure 4.17, intrinsic arm stiffness was shown to increase under pretension, stimulated by an externally applied constant torque at the steering wheel. This indicates that muscles can be modelled with a non-linear spring - a fact that has also been observed by Zhang and Rymer [51]. The increase in intrinsic stiffness is caused by an increase in muscle activation and acts to oppose movement of the arms from their current operating point. The effect of the stiffening mechanism can be investigated by including it as an element in the driver model (equation 6.26). The spring is included in parallel with the active stiffness block as it produces an additional torque that is proportional to steer angle error, \((\hat{\theta}_{sw} - \theta_{sw})\).

\[
T = K(\hat{\theta}_{sw} - \theta_{sw}) \tag{6.26}
\]

where:

\(K = |T_\alpha|b\) - non-linear stiffness/ Nm/rad

\(T\) – Intrinsic muscle torque/ Nm

\(b\) – Gradient of regression line shown in Chapter 4, Figure 4.17 (2.9 rad\(^{-1}\))

The effect of including the non-linear spring in the simulation can be seen in Figure 6.27. The effect of the non-linear spring is small, because it only generates significant torque when \(T_\alpha\) is large. Hence as a simplification, the non-linear spring element has not been considered further in modelling the neuromuscular dynamics. Muscle co-contraction also causes an increase in the arm stiffness. However as large amounts of co-contraction can occur and have been measured, co-contraction is thought to be more significant.
6.5.4 Reference model

In the model discussed in the preceding sections, steer angle error \((\dot{\theta}_{sw} - \theta_{sw})\) is used to generate the control signal. To achieve good path-following performance using this signal, either a high reflex gain is required or significant muscle co-contraction must be generated. An alternative is to use the inverse reference model \(G_d\) (Figure 6.17) to generate the muscle activation signal. This pathway allows the opportunity for feedforward control as shown in Figure 6.17.

The steering dynamics are coupled to the vehicle dynamics through steering torque feedback. By evaluating equation 6.20 (using parameters for test car one) for the coupled driver, vehicle and steering system, a transfer function for the relationship between muscle torque and steer angle can be calculated (equation 6.27).

\[
\frac{\theta_{sw}}{T_m} = \frac{4.22(s^2 + 10s + 48.2)}{(s^2 + 2.72s + 34.3)(s^2 + 16.3s + 117)} \quad (6.27)
\]
If an exact inverse model of the steering and limb dynamics is used in the feedforward path, then the applied steer angle, $\theta_{sw}$, matches the desired reference steer angle, $\hat{\theta}_{sw}$, exactly. In the case of exact control, no reflex action is necessary or generated. It is expected that the driver’s internal reference model is learnt over time with experience of the vehicle. The idea that control is achieved through a learnt internal model is also considered by Osu et al [69] with respect to reaching movements. It is likely that the driver’s internal reference model is of a simpler form (lower order) and only approximates equation 6.27. Three approximations to the true dynamics of test car one are given in Table 6.3 and the frequency response is shown in Figure 6.28.

Table 6.3: Model approximations of system dynamics of test car one (equation 6.27) used as an internal reference model.

<table>
<thead>
<tr>
<th>Reference model</th>
<th>Driver’s reference model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reference model I</td>
<td>$\hat{G}(s) = 0.2$</td>
</tr>
<tr>
<td>Reference model II</td>
<td>$\hat{G}(s) = 0.1$</td>
</tr>
<tr>
<td>Reference model III</td>
<td>$\hat{G}(s) = \frac{0.067}{0.028s^2 + 0.083s + 1}$</td>
</tr>
</tbody>
</table>
Figure 6.28: Bode plot showing vehicle and steering system dynamics (equation 6.27) for test car 1 and reference model approximations to true system dynamics.

The inverse reference model, $G_d$, is simply the filtered inverse of the driver’s reference model $\hat{G}(s)$. A 4$^\text{th}$ order Butterworth filter with 30rad/s cut off frequency was used in order that the system remains proper (higher order denominator than numerator). Figure 6.29 shows a comparison of the true system response along with the various inverse reference models. It can be seen that as the reference model dynamics more closely match the system dynamics improved performance is obtained.
The optimal level of co-contraction can be investigated for the three driver reference models listed in Table 6.3. Cost contours were calculated from simulation data and the results are shown in Figure 6.30. It can be seen that as the reference model dynamics more closely match the system dynamics a lower level of muscle active stiffness $K_a$ and therefore muscle co-contraction is optimal. This is consistent with the idea that muscle co-contraction is a characteristic of unskilled movement (see section 1.4.6). As the driver gains experience of the system dynamics and modifies the reference model to match the system dynamics, less muscle co-contraction is needed. When the reference model matches the true system dynamics exactly, no co-contraction is optimal.

The trend was also observed for the data measured in Chapter 5; the mean level of muscle co-contraction reduced as drivers gained experience of each of the three test cars (Figure 5.15). The active stiffness, calculated from the measured co-contraction, is shown in Figure 6.31. The measured data shows some steady threshold co-
contraction level that is not predicted by the model. The steady threshold level of co-contraction could arise to minimise the effect of noise on the system, which is not considered in the model.

Figure 6.30: Cost contours, $C$ (equation 6.24), showing effect of including reference model on optimum co-contraction. Evaluated with $B_r=1\text{Nms/rad}$, $K_r=5\text{Nm/rad}$ for test car 1.

Figure 6.31: Measured active stiffness, calculated from co-contraction shown in 5.15 and using equation 6.25.
6.5.5 Robustness of driver steering control

In the experiments reported in Chapter 5, no significant degradation in path-following performance was seen following changes made to the steering dynamics. This suggests that drivers were robust to the changes made. The question arises as to whether the simulated driver steering control described here will remain robust to changes in the steering dynamics.

Simulations of the driver model performance were carried out for each of the three test car steering dynamics. Reference model II (Table 6.3) was used throughout. Other values used were $B_r=1\text{Nms/rad}$, $K_r=5\text{Nm/rad}$ and $K_a=10\text{Nm/rad}$. The path-following performance is shown in Figure 6.32. The best path-following performance is seen for test car one. This is to be expected because the reference model dynamics most closely match the steering dynamics of test car one. Although the driver-model remains stable following the changes to the steering dynamics there is some degradation of path-following performance for test cars two and three. In reality the test subjects’ performance, discussed in Chapter 5, did not show this degradation and the change in path-following performance was small following a change in the steering dynamics. The measured change in path-following performance between test cars one and two, averaged for all test subjects, is shown in Figure 6.33. It is clear that there is little change in path-following performance apart from slightly more overshoot of the road path centre line in test car two.

In general a steady improvement in path-following performance was seen in the data measured from the driving simulator despite changes in the steering dynamics, Figure 5.6. This suggests that human drivers quickly adapt their control strategy in response to changes in steering dynamics. The source of the adaptation is most likely to be through muscle co-contraction because the measured data from test subjects showed an increase in muscle co-contraction following changes in the steering dynamics.
Figure 6.32: Robustness of driver-model. Evaluated with $B_s=1\text{Nms/rad}$, $K_r=5\text{Nm/rad}$ and $K_a=10\text{Nm/rad}$ using reference model II.

Figure 6.33: Change in path-following performance following change in steering dynamics from test car 1 to test car 2.
6.6 CONCLUSIONS

a) Sharp and Valtetsiotis’ LQR control model [43] has been extensively reviewed and compared to MacAdam’s predictive control model [40]. It has been shown that the two models can both be expressed in terms of state variable feedback. This is significant because it allows direct comparison of the preview gains. The comparison shows that Sharp and Valtetsiotis’ model is most plausible because road path points previewed further ahead are given progressively smaller weightings towards the overall control input.

b) A limitation of Sharp and Valtetsiotis’ model is that it takes no account of the driver’s time delay. A method of incorporating the time delay in the LQR control structure has been devised here. Additionally a method for evaluating more complex cost functions is given by introducing a logging state.

c) A model of the neuromuscular dynamics has been developed that takes account of physiological data. The model is based on a model originally proposed for aircraft pilots developed by Magdaleno and McRuer [64]. The neuromuscular model has been shown to have equivalent properties to that of a classical feedback controller.

d) The neuromuscular model has been coupled to the vehicle and steering system along with the LQR path-following model, with time delay included. The model allows closed-loop driver performance to be investigated.

e) Numerical simulations were carried out to investigate the performance of the new driver model. It has been shown that the bandwidth of the driver’s neuromuscular system can be increased through either muscle co-contraction or increasing the gain in the reflex controller. Because reflex control is subject to a time delay that can induce instability, under some circumstances co-contraction may be the optimal strategy.

f) An internal reference model was also included in the neuromuscular control model. The reference model allows feedforward control and is generated from an approximation of the true system dynamics. Through use of a cost function it has been shown that, as the accuracy of the internal model improves, less muscle co-
contraction is needed. Therefore the model predicts the characteristics measured in Chapter 5: as the driver gains experience and improves their internal reference model, less co-contraction is observed.

g) The measurements described in Chapter 5 showed that drivers were robust to changes in steering dynamics. The driver model developed in this work has been shown also to provide robust control following changes in the steering dynamics.

h) With some further validation, the driver model described here can be used to predict the effect of steering systems like EPS and steer-by-wire on the closed-loop driver vehicle system.
Chapter 7: Conclusions and Future Research Directions

A program of research has been carried out aimed at understanding driver steering control with particular reference to the role of the neuromuscular system. In this chapter a summary of the research work and main conclusions are given (section 7.1). The results of the research highlight some key areas where further investigation might be appropriate; proposals for future research are given in section 7.2.

7.1 SUMMARY OF MAIN CONCLUSIONS

7.1.1 Review of published literature (Chapter 1)

New developments such as electric power steering and steer by wire systems allow substantial freedom in tuning the steering torque feedback felt by the driver. In order that the full benefits of these new systems can be obtained, the interaction between the driver and these systems must be considered. Chapter 1 reviewed previous work relevant to driver steering control. The review focused on:

- Active steering technology
- Steering dynamics and the mechanism that generates steering torque feedback
- Driver models
- The neuromuscular system

Although a substantial body of literature can be found relating to the neuromuscular dynamics, the review showed little attention has been given to understanding the role of the neuromuscular system specific to driver steering control. In order that the effect of steering torque feedback on the closed-loop driver-vehicle response can be established, the neuromuscular dynamics should be considered.

7.1.2 Driving simulator and hardware (Chapter 2)

A driving simulator was developed to allow measurements of driver steering behaviour to be made. Chapter 2 described the hardware and development of the driving simulator. The driving simulator includes a programmable torque feedback steering wheel, which was used to measure the response of the neuromuscular system...
during typical driving manoeuvres. A method of measuring the steering forces at the rim of the steering wheel, produced by each of the driver’s arms individually, was also described. The method makes use of a six-axis load cell that mounts to the steering wheel.

7.1.3 Measurement of driver steering torque using electromyography (Chapter 3)

Although the control output from the driver can be measured in terms of torque or angular displacements at the steering wheel, electromyography (EMG) provides a non-intrusive way of measuring signals from within the neuromuscular system. EMG was used to measure the driver’s muscle activity. The following results were obtained:

a) By using EMG, the key muscles involved in generating steering torque were found to be the front and mid portions of the deltoid, the pectoralis major and the triceps longitudinal head; the role of these muscles in steering control was not previously known.

b) Under static conditions, a method was devised that can be used to predict steering torque from the measured EMG using regression analysis. Results from the regression analysis showed that muscle activity is strongly correlated with the measured steering torque. This result is significant because it allows measurements of the driver’s muscle activity to be quantified in terms of the steering torque generated.

c) EMG steering torque predictions, made under dynamic conditions, also showed reasonable agreement with the measured steering torque. However further investigation is needed to fully validate the prediction method under dynamic conditions.

d) By using the results (a) and (b), a quantitative measure of muscle co-contraction was generated. The measure can be used to establish whether drivers use muscle co-contraction as a control strategy.
7.1.4 Limb dynamic identification (Chapter 4)

The review of the published literature revealed that no measurements of the neuromuscular dynamics had been made with reference to driver steering control. To address this gap in current understanding, experiments aimed at measuring the mechanical properties of the neuromuscular system with respect to steering control were carried out. The findings can be summarised as follows:

a) An indirect method and a direct method were used to identify the driver’s neuromuscular dynamic properties. It was found that the direct method gave the most reliable results.

b) A frequency domain fitting procedure was used and it was found that simple linear models could be used to represent the measured data. Using the linear models, values representing the driver’s arm inertia, damping and stiffness were obtained under a range of conditions. The identified values of damping and stiffness were found to be highly dependent on the level of muscle activation.

c) The stiffness of the driver’s arms was identified while the driver applied various levels of static offset torque to the steering wheel. The results showed a considerable increase in arm stiffness in response to increases in the torque offset. The result has implications for the design of active steering controllers that operate by injecting steering torques into the steering column. The designs must take account of the fact that the driver’s arm stiffness varies depending on the current level of applied steering torque.

d) An RARX (recursive autoregressive) model was also used to identify the limb dynamics. The RARX method allows variation in the system dynamics, with respect to time, to be identified. The RARX method produced similar results to the frequency domain method (b), which confirms the validity of both methods. The recursive method is powerful as it allows the potential for tracking changes in the neuromuscular dynamics over time.
e) Reflex action provides closed loop control within the neuromuscular system. Attempts were made to identify the reflex dynamics using EMG measurements. Although the results were not conclusive (as a time delay could not be identified), the reflex action was found to be proportional to the steering wheel velocity. This indicates that a role of the reflex action is to add additional damping to the system. The identified reflex damping can be incorporated in models of the neuromuscular system.

7.1.5 Driving simulator experiments (Chapter 5)
In order that the response of the driver’s neuromuscular system could be observed during steering control, Chapter 5 reported measurements of driver steering performance during a double lane change manoeuvre. The double lane change manoeuvre was repeated ten times for each of three vehicles. The three vehicles had different steering dynamics to investigate how drivers respond to changes in steering torque feedback. The experiments were carried out using the driving simulator and eight test subjects participated.

a) Considerable differences were seen in the path-following performance between test subjects. In particular some drivers applied larger and more rapid steering torques, which resulted in better path-following performance. Considerable muscle co-contraction was seen to occur in conjunction with the rapid steering torques.

b) A significant reduction in path error was seen for the sample of drivers as they gained experience of the dynamics of each vehicle.

c) Changes in the steering dynamics and torque feedback were not found to cause significant degradation of the driver’s path-following performance. This suggests that the driver and neuromuscular system are robust to changes in the steering dynamics and torque feedback.

d) Following a change in the steering dynamics an increase in the mean level of muscle co-contraction was seen. This is consistent with the premise that muscle co-contraction is a characteristic of unskilled movement and may occur if the
system being controlled is unfamiliar. A significant reduction in the level of muscle co-contraction was then seen as drivers gained experience in each of the three test cars.

e) Many published driver models are based on cost functions that weigh path-following against driver workload. For the measured data, no reduction in the mean squared steer angle input was observed with increasing driver experience. However, a reduction in the overall muscle activity as measured through EMG was seen. Many driver models reviewed in the published literature work on cost functions based on steer angle. However the results suggest that muscle activation may provide a better measure of driver workload than steer angle.

7.1.6 Mathematical model of driver steering control (Chapter 6)
A key objective of the research work was to produce a predictive driver-model that takes account of steering torque feedback. Chapter 6 described a new model of driver steering control. The new model builds extensively on previously published driver models, but also incorporates the neuromuscular dynamics as identified in Chapter 4. In this way the new driver model is able to take account of the effect of changes in steering torque feedback. The key features of the new model are:

a) The model uses LQR (linear quadratic regulator) theory to generate a path-following controller with preview (as originally proposed by Sharp and Valtetsiotis [43]).

b) As an extension to Sharp and Valtetsiotis [43] model, a shift register is incorporated to model the driver’s time delay.

c) The model includes the passive neuromuscular dynamics as identified in Chapter 4.

d) Torque feedback from the vehicle is included in the model structure, enabling the effect of variations in the torque feedback characteristics to be investigated.
e) Reflex dynamics, a driver reference model and the effect of muscle co-contraction are included.

f) A cost function involving muscle energy consumption is included to evaluate the model’s control performance.

The driver model showed the key trends displayed by test subjects as measured from the driving simulator:

- The level of muscle co-contraction was observed to increase as drivers applied higher bandwidth steering control. This trend can be predicted by the driver model.

- The results described in Chapter 5 showed that drivers were robust to changes in steering dynamics. The driver model was also shown to provide robust control following changes in the steering dynamics.

- By using a cost function involving muscle energy consumption, the model shows that the optimal level of muscle co-contraction depends on the driver’s knowledge of the system dynamics. As the driver gains a better internal representation of the system dynamics the model predicts that less co-contraction is optimal. A similar trend was seen in the measured data; as test subjects gained experience of the vehicle dynamics the level of muscle co-contraction was seen to reduce.

With further validation, the driver model proposed in this project can be used to predict the closed-loop performance of active chassis control systems that operate through the steering system. As driver assistance systems are increasingly fitted to vehicles, understanding how drivers respond to these systems becomes more important.
7.2 RECOMMENDATIONS FOR FURTHER WORK

The results and conclusions obtained from this research work highlight some key areas of interest for future research:

a) The torque feedback hardware used in the experiments reported in Chapter 4 was suitable for measuring the neuromuscular dynamics up to approximately 10Hz. This allowed the dominant features of the neuromuscular dynamics to be identified. Modifications to the hardware used for this project are needed if higher frequency components are to be measured. Modifications may allow better estimates of the mechanical and reflex properties of the neuromuscular system to be obtained. The modifications include using a higher resolution angle sensor and increasing the stiffness of the integral column torque sensor while reducing the inertia of the motor.

b) The results obtained in this project show that EMG can be used to successfully measure driver steering behaviour. EMG is therefore a useful tool and can now be exploited in future studies of driver steering control. An obvious extension would be to measure muscle activity using EMG in real vehicles, although it is not clear whether interference from the vehicle ignition system would affect measurements.

c) The role of the neuromuscular dynamics during lane change manoeuvres has been investigated. Muscle co-contraction was seen to occur during the transient phases of the manoeuvre. It is also of interest to investigate whether the driver uses muscle co-contraction during other demanding manoeuvres. One scenario would be to investigate driver performance on a narrow road with bends of varying curvature. It is hypothesised that the driver may increase the level of muscle co-contraction as the road narrows and path-following accuracy becomes more critical.

d) By using an RARX model, recursive identification of limb dynamics has been shown to be possible if a random torque disturbance is applied through the steering wheel. The recursive identification method allows the changes in limb damping and stiffness to be tracked, provided that the changes occur gradually.
The recursive method could be used to establish if there is any relationship between arm stiffness and damping, and road width or curvature of bends.

e) The path-following controller is a key component of the driver model. Although an LQR controller was used in this project other control strategies are possible; for example model predictive control as used by Peng [41]. To evaluate the most appropriate control strategy further validation is needed. The relationship between road path preview and steering action is central to understanding path-following control. Tests in which subjects follow a random road profile with various degrees of preview might be suitable for validating such models. Experiments of this kind can now be carried out using the driving simulator developed for this project.

f) Chapter 5 reports measurements of driver performance following changes in steering torque feedback; the steering torque feedback was varied but the relationship between steer angle and vehicle response was kept constant. The driver was found to be robust to the changes in steering torque feedback. The results suggest that the driver generates an internal model of the relationship between steer angle and vehicle response, rather than steering torque and vehicle response. To confirm this hypothesis, a vehicle could be devised where the relationship between steering torque and vehicle response is kept constant, but the steer angle relationship is varied.

g) A large amount of variance in steering control was seen between test subjects following successive manoeuvres. The variance can be attributed to noise in the driver’s control system; the noise may arise from drivers using a trial and error approach to optimise their control strategy. However, the exact source of this noise is not clear and warrants further investigation.

h) Steering torque feedback has been considered here with respect to the neuromuscular system and driver’s peripheral reflex control system. Drivers may use the steering torque feedback as a perceptual cue in understanding the vehicle’s current operating point. Hence at a conscious level the driver may use the steering torque feedback to identify the road friction condition, tyre-operating point or
establish lateral forces acting on the vehicle. Hence the steering torque feedback may influence the driver’s control strategy. This is an area that has not received substantial attention and as such should be considered for further investigation.

In conclusion this thesis provides new insights and understanding of the role of the neuromuscular dynamics in the vehicle steering task. The knowledge gained has highlighted key areas that warrant further investigation.
A.1: LOAD CELL CALIBRATION MATRIX

Load cell calibration matrix $[X]$ 

<table>
<thead>
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<th>Table A1: Load cell calibration matrix $[X]$</th>
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<tr>
<td>(N/V)</td>
</tr>
<tr>
<td>------</td>
</tr>
<tr>
<td>$V_1$</td>
</tr>
<tr>
<td>$V_2$</td>
</tr>
<tr>
<td>$V_3$</td>
</tr>
<tr>
<td>$V_4$</td>
</tr>
<tr>
<td>$V_5$</td>
</tr>
<tr>
<td>$V_6$</td>
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</tbody>
</table>

where: $[V_1 \ V_2 \ V_3 \ V_4 \ V_5 \ V_6][X]=[F_x \ F_y \ F_z \ M_x \ M_y \ M_z]$ 

A.2: DESCRIPTION OF TEST SUBJECTS 

<p>| Table A2: Description of test subjects that participated in the study. |
|-------------------------|----------|----------|----------|----------|</p>
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<th>Height/ m</th>
<th>Mass/ kg</th>
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<td>81</td>
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A.3: IDENTIFIED LIMB DYNAMICS

Identified limb dynamic properties for test subjects A-H as measured in response to torque disturbance in the presence of a static offset torque.

Table A3.1: Neuromuscular parameters identified for test subject A

<table>
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<th>Torque offset/ Nm</th>
<th>Error $\epsilon$</th>
<th>$J$/kgm²</th>
<th>$B_{dr}$/ Nms/rad</th>
<th>$K_{dr}$/ Nm/rad</th>
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Table A3.2: Neuromuscular parameters identified for test subject B

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Table A3.3: Neuromuscular parameters identified for test subject C

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Table A3.4: Neuromuscular parameters identified for test subject D

<table>
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<th>$J / \text{kgm}^2$</th>
<th>$B_{\text{dr}} / \text{Nms/rad}$</th>
<th>$K_{\text{dr}} / \text{Nm/rad}$</th>
<th>VAF</th>
</tr>
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<tbody>
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Table A3.5: Neuromuscular parameters identified for test subject E

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<th>$J$/kgm$^2$</th>
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<th>$K_{dr}$/ Nm/rad</th>
<th>VAF</th>
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Table A3.6: Neuromuscular parameters identified for test subject F

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<th>$B_{dr}$/ Nms/rad</th>
<th>$K_{dr}$/ Nm/rad</th>
<th>VAF</th>
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</thead>
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Table A3.7: Neuromuscular parameters identified for test subject G

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<th>$B_{dr}$/ Nms/rad</th>
<th>$K_{dr}$/ Nm/rad</th>
<th>VAF</th>
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<tbody>
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Table A3.8: Neuromuscular parameters identified for test subject H

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<th>$B_{dr}$/ Nms/rad</th>
<th>$K_{dr}$/ Nm/rad</th>
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</tr>
</thead>
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</tbody>
</table>
A.4: PREDICTION MODEL FOR STATE SPACE SYSTEMS

For a continuous time state space model the state at time \( t \), \( x(t) \), can be found from the initial state \( x_0 \) and the input \( u(t) \):

\[
\dot{x}(t) = Ax(t) + Bu(t) \tag{A4.1}
\]

\[
x(t) = e^{At}x_0 + \int_0^t e^{A\eta}Bu(\eta)d\eta \tag{A4.2}
\]

A similar equation can be found for a discrete state space system:

\[
x_{n+1} = A_dx_n + B_du_n \tag{A4.3}
\]

\[
y_n = C_dx_n + D_du_n
\]

\[
x_n = A_d^nx_0 + [A_d^{(n-1)}B_d \quad A_d^{(n-2)}B_d \quad \ldots \quad A_d^0B_d] \begin{bmatrix} u_0 \\ u_1 \\ \vdots \\ u_{(n-1)} \end{bmatrix} \tag{A4.4}
\]

When the input is a constant, \( u_0 \), using the definition in equation A4.3 and A4.4 and assuming \( D_d=0 \) allows the output at time \( n \), \( y_n \), to be found:

\[
y_n = F_nx_0 + G_nu_0 \tag{A4.5}
\]

where:

\[
F_n = C_dA_d^n \quad \text{and} \quad F_0 = C_d
\]

\[
G_n = C_d[A_d^{(n-1)}B_d + A_d^{(n-2)}B_d + \ldots + A_d^0B_d] \quad \text{and} \quad G_0 = 0
\]
References


References


