Models of Human Learning Applicable to the Vehicle Steering Task

Julius Rix and David Cole

Dynamics and Vibration Group, Department of Engineering, University of Cambridge,
Trumpington Street, Cambridge CB2 1PZ
Telephone: +44 1223 332600
Fax: +44 1223 332662
Email: djc13@eng.cam.ac.uk

Human learning of the vehicle steering task is identified as an important process, the understanding of which may aid the design and development of vehicle dynamic behaviour. Existing driver models are reviewed and it is apparent that little attention has been given to the learning process. Research in the field of human motor learning and control is reviewed, where some progress has been made in developing models for particular motor tasks. Models discussed include feedback error learning and distal supervised learning. The relevance of this research to the driving task is discussed and research needs are identified.

Keywords/ driver, human, vehicle, model, learning, adaptation, steering, control, handling

1. INTRODUCTION

Mathematical models of vehicle dynamic behaviour have been developed to such an extent that they are now sufficiently accurate for many needs [1]. However, techniques for modelling driver behaviour are less well developed and appear to be inadequate for the reliable design of vehicles with good subjective handling behaviour. In the absence of sufficient theoretical understanding of the driver–vehicle system, much research effort is still directed at correlating subjective ratings with objective measurements, see [2] for a recent example.

Active controls for suspension, steering and braking have been developed for cars and trucks to extend the range of performance over which the driver can easily maintain control. Examples of such devices include anti-lock brakes, active anti-roll bars, traction control and dynamic stability control. There is some evidence to suggest that such systems might encourage drivers to operate the vehicle closer to the physical limits, thereby reducing the intended safety benefit [3].

Existing driver models usually provide a fixed control law for any particular vehicle. In practice a driver learns to improve control with experience of the vehicle. Learning is action in which past information is used to improve future behaviour. It is possible that insight into the control behaviour of a driver and the subjective assessment by a driver, can be obtained by understanding and modelling the driver’s learning process.

Learning in the driver-vehicle system has received some attention in the past. For example, Wewerinke [4] put forward two strategies for modelling driver learning behaviour. Neural network and system theoretic (extended Kalman filter) approaches were discussed in relation to simulating a lane-keeping task, but limited results were presented. Kageyama et al. [5] analysed driver behaviour using an artificial neural network and found some evidence of learning when repeating a task. Sharp [6] has more recently noted the possibility of modelling driver steering control using an artificial neural network and using the learning process of the network to make judgements about the control qualities of the vehicle. However, despite this and other activity, much progress needs to be made before driver models are capable of predicting driver-vehicle response as a function of driver experience.

In the next section, models of driver steering control for path following and disturbance rejection are reviewed briefly. In section 3 another field of research, human motor learning and control, is selectively reviewed. The prospects for applying knowledge from this field to the vehicle steering task are discussed in section 4. Conclusions are given in the final section of the paper.

2. DRIVER MODELS

Driver-vehicle interaction has been a subject of research for many years and several papers review the field [6-8]. A summary is provided in this section to serve the remainder of the paper. The driver’s use of visual information in controlling the direction of a vehicle is obviously very significant and has been investigated extensively. There is general consensus that control occurs at two levels [9]: preview control (open-loop feedforward), in which the driver anticipates the path ahead and makes an appropriate steering action based on knowledge of the vehicle dynamics; and compensatory control (closed-loop feedback,) where the driver compensates for errors in the preview control and for disturbances. In both cases attention has focussed on representing fully-learnt behaviour; the learning process appears to have received relatively little attention.
A significant body of research carried out in the 1950s and 1960s into the control behaviour of the human operator in compensatory tasks led to the idea of a ‘crossover’ model of control. The compensatory task involves the human operator \((G_c)\) controlling a system \((G_v)\) to minimise an error. Measurements performed with a wide range of systems \((G_v)\) showed that the response of the human operator can be fitted closely to a transfer function of the form
\[
G_c = K_p \left( \frac{T_L j\omega + 1}{T_f j\omega + 1} \right) e^{-j\omega(\tau + T_v)}
\]
(1)
where \(\tau\) is the cognitive time delay and \(T_v\) is the neuromuscular time delay. These two parameters are usually considered to be invariant. \(K_p\) is a proportional gain, \(T_L\) is a first-order lead time constant and \(T_f\) is a first-order lag time constant. It has been observed that the human operator adjusts these three terms to ensure that: the closed loop system is stable, the open-loop transfer function \((G_cG_v)\) has a slope of about -20 dB per decade in the region of unity gain (the ‘crossover’ region), and the low frequency gain is large to minimise steady state errors. In practice the vehicle driver has more than one feedback signal available. It has been found experimentally that the crossover model ideas can be applied to the case of multi-loop feedback, for example, lateral displacement and yaw angle of a vehicle. In addition to visual feedback there is also motion information fed back through the driver’s vestibular and kinaesthetic senses. The main research activity on the role of these additional senses has been in relation to aircraft control, for example by Hess [10]; some of this work has been applied to the road vehicle case, for example [11]. Weir and McRuer [12] summarize the application of the crossover model to compensatory control in the driver vehicle system with single and multi-loop feedback.

The extensive body of research supporting the crossover model has encouraged many researchers to continue its use to the present day. However, it has been demonstrated that modern optimal control theory generates control strategies that are consistent with the crossover model of compensatory control, see for example [13-15].

To account for the preview control aspect of the path following task, a popular approach has been to assume single point preview, for details see the review by Guo and Guan [7]. More recently, with the benefit of advances in feedback control theory and in neural networks, single point preview has given way to multi-point preview [6, 15-17]. This approach is thought to better represent the driver’s use of the visual information ahead of the vehicle [6].

MacAdam [15] used linear optimal control theory to calculate the optimum steer angle necessary to minimise future path error over a finite previewed distance. A shortcoming of the approach according to Guo and Guan [7] and Sharp [6] is that the optimum steer angle is assumed to be held constant over the previewed distance.

Sharp [6, 16] used ideas originally developed for linear discrete-time preview control of active suspension to propose a multi-point preview model of path-following steering control. The inputs to the model are effectively the previewed path errors, and the lateral and yaw velocities of the vehicle. The output of the model is the steer angle. Applying optimisation theory he showed that the feedback gains depended on the weights applied to path and heading errors and steering control action, and that the preview gains reflect the vehicle dynamics. Sharp et al. [6] demonstrated that the control structure could be extended to the nonlinear vehicle by incorporating saturation functions, and in this form the controller bore some resemblance to a neural network. He noted the possibility of examining the learning process of such a network to assess the control quality of a vehicle.

Prokop [17] proposed a model that involves the driver optimizing simultaneously the vehicle path (within the bounds of the road width) and the corresponding open-loop steer and throttle/brake inputs. The driver’s preferences for speed and comfort are expressed in the weightings of a cost function. To account for different levels of driver skill, the optimization calculation employs vehicle models of various complexities; for example, a single point mass to represent a novice driver, or a nonlinear lateral/yaw model to represent an experienced driver. The process by which the driver accumulates experience and learns the model was not considered. Compensatory control is provided by a PID action on lateral path error.

The similarity of artificial neural networks to the human brain has led some researchers to examine their suitability as a driver model. MacAdam and Johnson [18] demonstrated the use of an elementary neural network to represent driver steering control. The network consists of single hidden layer. The input data are lateral position errors at three points ahead of the vehicle. Time delayed inputs are also used to provide rate information. The network is trained using video data collected from a car being driven on a highway. The resulting network is found to give realistic steering behaviour when used in a simulation. Kageyama et al [5] used a neural network with 94 inputs, trained with data from a vehicle on a highway. According to their analysis, there was evidence of the driver learning when negotiating a curve a second time. It was not clear to what extent the trained network could be used for predicting the driver response to inputs other than those used in the training set.

Adaptation, a process related to learning, has been the subject of some study. The human controller has the ability to control a wide range of system dynamics and therefore may be described as adaptive. In the present context however, adaptation is taken to mean the ability of a driver to change control action in response to sudden changes in the input, the vehicle dynamics or the control objectives. For example, if a vehicle moves from a high friction surface to a low friction surface, the driver adapts the steering control law to suit the changed condition. Adaptation is most easily studied in relation to changes between previously learnt conditions. If a change is made to an unfamiliar condition, an additional learning phase is to be
expected. Nagai and Mitsuhas [19] modelled driver adaptation to changes in friction coefficient using model reference adaptive control. There was good agreement of the model to experiments performed with a driving simulator.

In summary, existing mathematical models of driver-vehicle directional control have been shown to predict realistic behaviour. However, theoretical understanding is still evolving and the precise roles of the visual and other sensory inputs remain to be fully investigated. The human learning process in the driver-vehicle system has not received significant attention. However, a relevant learning task that has been studied extensively is human motor control (‘motor’ refers to human muscles and movement, not the motor vehicle!). A review is presented in the next section.

3. HUMAN MOTOR LEARNING AND CONTROL

Human learning takes place in a wide variety of mental and physical tasks. Neuroscientists and experimental psychologists study the learning process to obtain insight into the functioning of the central nervous system. The motor control tasks most commonly studied are discrete arm reaching movements and eye movements (tracking and discrete). It is believed that by understanding how the central nervous system functions in the learning and control of these tasks, general theories applicable to a wider range of motor control tasks will arise [20]. For a general introduction see Rosembaum [21].

3.1. Physiology

Much current understanding of human motor control and learning has developed from theory put forward by Marr [22] and further advanced by Albus [23]. Their work was based on an understanding of the anatomical and physiological details of the cerebellum, which is a region of the brain associated with supervised learning of motor skills. Supervised learning is possible when there is a training or feedback signal available that quantifies the magnitude and direction of the output (performance) error [24], see figure 1.

![Fig. 1 Areas of the CNS and generic learning structures. [24].](image)

The details of exactly how the cerebellum performs supervised learning are not fully understood and are tied up in the details of the different types of specialised neurons present and their interconnections. A review paper by Houk et al. [20] covers the details of this area. A key objective in most studies is to devise structural models of motor learning and control that can be mapped onto, and are consistent with, the biological system.

Before looking in detail at some of the models that have been proposed it should be noted that, in addition to the cerebellum, two other regions of the brain are associated with learning [24]. The basal ganglia is associated with reinforcement learning for which the training or feedback signal contains less information than in supervised learning, for example a binary signal representing a reward or penalty. Although supervised learning is the main process in motor control, reinforcement learning is also thought to have a role [24, 25].

The cerebral cortex is associated with unsupervised learning, also known as self-learning. In this case there is no external teacher or training signal, although an internal performance index may be calculated and minimised. A typical unsupervised learning task is pattern recognition.

3.2. Theories of Human Motor Learning

Many theories of human motor learning have been proposed [20]. Several of these are based on engineering control theory and involve one or more internal models of the controlled system so that fast open-loop control can be performed, see figure 2. Fast motor control using only closed-loop (negative) feedback would not be possible because of significant sensory delays (up to 0.25s) [20].

![Fig. 2 Feedforward Open Loop control.](image)

**3.2.1. Direct Inverse Model**

In this theory control of the system is provided by an inverse model performing feedforward control, figure 2. The inverse model is learnt off-line in a ‘direct’ approach using supervised learning as shown in figure 3. The output of the system to be controlled is input to the inverse model. The inverse model is adjusted until its output matches the input to the system.

![Fig. 3 Direct Inverse modelling approach to learning an inverse model.](image)

There are several difficulties with this approach to generating an inverse model [24-26]. If the system is nonlinear, or if there are multiple inputs, there may not be a unique inverse, and an incorrect inverse may be calculated. Another difficulty is that the learning process acts on a control action quantity (U), whilst the control process involves minimising an output quantity (Y). It is thought more likely that learning involves acting on the same quantity as the output of the control system. These shortcomings suggest that the direct inverse modelling approach may not be a good representation of the human learning process.
3.2.2. Feedback Error Learning

To address some of the shortcomings of the direct approach to finding an inverse model, ‘feedback-error-learning’ was proposed by Kawato et al. [27], see figure 4. The controller is an inverse model of the controlled system and therefore provides feedforward control, as before.

![Fig. 4 Feedback-Error-Learning](image)

In the unlearnt state the inverse model may not provide satisfactory control and so a fixed conventional feedback controller provides stabilisation and a training signal. During the learning of the inverse model the performance error is reduced and the feedback controller contributes less to the control action. When the inverse model is perfect the feedback controller makes no contribution to the control. Compared to the direct approach, a correct inverse is always calculated, but learning still involves using a control quantity instead of an output quantity. Kawato et al suggested that the supervised learning behaviour of this model can be mapped on to the physiology of the cerebellum, although Houk et al. [20] noted several inconsistencies.

3.2.3. Distal Supervised Learning

Another approach to generating an inverse model, ‘distal supervised learning’, was proposed by Jordan and Rummelhart [26]. An inverse model is combined with a forward model, see figure 5. To ensure stability in the early stages of learning, a feedback controller can also be provided.

![Fig. 5 Distal Supervised Learning](image)

The forward model is learnt by comparing the actual output of the system with the output predicted by the forward model and using the difference as a training signal. The inverse model is then learnt by coupling it to the forward model, holding the forward model constant, and training the composite system to give unity gain, using either the actual or predicted performance error. According to Jordan and Rummelhart, if the actual performance error is used as the training signal, an exact inverse model can be obtained even if the forward model is inaccurate. A benefit of the distal supervised approach is that the training signal (the performance error) has the same units as the output of the controlled system. The theory also allows the possibility of training the composite system off-line, in a process that might be termed ‘mental practice’. Bhushan and Shadwehr [28] were intrigued by this possibility and used a similar model to explain the observed learning of arm reaching movements in a force field. They found that performance errors resulted in rapid adjustment of the forward model, combined with a much slower rate of adjustment of the inverse model (five times slower). Their experiments appeared to support the existence of off-line learning.

3.3. Learning Actions

The learning theories described in the preceding section depend on a supervised learning action to adjust the parameters of the forward or inverse models. Mathematical algorithms for performing this learning action are well known in the fields of optimisation and system identification, see for example [29], and so will not be described in detail here.

Numerical iterative search methods involve finding a minimum (usually the least mean square) on a multi-dimensional surface. Many different techniques are available. A difficulty arises when the learning takes place in a non-stationary stochastic environment. The multi-dimensional surface is then also non-stationary and the conditions for convergence of the optimisation will be uncertain. For a good introduction to the subject see Tsypkin [30].

In driver modelling and motor control research, neural networks are often suggested as suitable models, particularly when the system is nonlinear or its structure is unknown. One hidden layer of sigmoid neurons is sufficient for modelling most reasonable systems. The network is usually trained using a steepest-descent algorithm known as back-propagation, and is based on supervised learning. Back-propagation is the technique for calculating the gradients of the output with respect to the inputs and the weights of the neurons, see [31] for details. However, the use of back propagation is regarded by some researchers as physiologically dubious, because it is difficult to implement neurally and is therefore an unlikely training algorithm for the cerebellum [25, 32]. The distal supervised learning theory of Jordan and Rummelhart [26] also requires an algorithm such as back propagation and has been similarly criticised [25].

If a reinforcement learning algorithm is required, for example in the Smith predictor model of Miall et al [25], then a stochastic learning automaton might be appropriate. Two surveys of the field by Narendra and Lashmivarahan [33] and Narendra and Thathanchar [34] cover most of the mathematical details. The automaton selects a control action, out of a potential set of actions, by using a probability distribution. Initially the distribution might be uniform and the probability of choosing a particular action is the same for all actions. The probability distribution is then updated depending on the performance of a particular action. If the action caused a ‘good’ result, the probability of choosing that particular action is increased, and all the other probabilities are reduced to maintain a summed probability of one.

3.4. Adaptation

Adaptation is the modification of a control law...
Learning action, as noted by Wewerinke [4], is to decide is trained. The feedback-error-learning model of Kawato et al. [27] bears some resemblance to the driver model proposed by Prokop, for example. Both models include a feedback controller in combination with an open-loop feedforward control, for example, arm reaching with fast discrete movements. Less attention has been given to the learning of closed-loop feedback control. Steering a vehicle involves continuous and simultaneous open-loop and closed-loop compensatory control. Both tasks can be classified as supervised learning because error information is available. It is not yet clear to what extent the models developed for human motor control are applicable to the driving task.

Experiments demonstrate that adapting to a new condition takes longer than de-adaptation to the original condition. The results suggest that the operator stores multiple controllers, in preference to modifying the parameters of a single controller. Measurements of activity in the cerebellum support the hypothesis [24]. Schemes for selecting the most appropriate controller from a number of stored controllers have been devised [24]. One approach is to pair each controller with a predictor, or forward model. The output of each predictor is monitored continuously and compared with the output of the real system. The controller corresponding with the predictor that gives least prediction error is selected. Such an approach may also represent the human control of nonlinear systems, and is known as ‘multimode control’ in the field of nonlinear control.

4. DISCUSSION

Learning in the field of human motor control has focussed on the use of internal models for open-loop feedforward control, for example, arm reaching with fast discrete movements. Less attention has been given to the learning of closed-loop feedback control. Steering a vehicle involves continuous and simultaneous open-loop preview control and closed-loop compensatory control. Both tasks can be classified as supervised learning because error information is available. It is not yet clear to what extent the models developed for human motor control are applicable to the driving task.

The feedback-error-learning model of Kawato et al. [27] bears some resemblance to the driver model proposed by Prokop, for example. Both models include a feedback controller in combination with an open-loop controller. Neither study considered how the feedback controller is learnt.

A frequent objective in the field of human motor control and learning is to ensure that models map onto the biological system. Such an approach seems necessary to distinguish between many possible learning models and to ensure that future model development is soundly based. In the case of learning actions, doubt about the physiological plausibility of the backpropagation algorithm does not discourage the use of neural networks, only the process by which the network is trained.

Another difficult issue in modelling human learning action, as noted by Wewerinke [4], is to decide the values of the controller parameters at the start of the learning process. Although Prokop [17] did not model the learning process as such, his use of vehicle model complexity to represent different levels of driver experience suggests one approach.

The road vehicle is a nonlinear system, due largely to saturation in the force generating properties of the tyres. In the human motor control field, two approaches to nonlinear control appear to have been taken, either control by a nonlinear internal model (typically in the form of a neural network), or by a series of linear models, one of which is selected to according to the current operating point. In the vehicle driving task, the way in which the compensatory controller and the preview controller learn to deal with nonlinear vehicle behaviour needs to be investigated.

A feature of human motor control research is that the learning task is usually well defined. The human test subject is given no choice of system or desired output. In driving a vehicle, the driver usually has significant choice over the extent to which the vehicle system is learnt. For example, a racing driver is motivated to explore and learn the full performance envelope of the vehicle, whereas a less ambitious driver would be unlikely to choose operating conditions under which the nonlinear regime could be experienced and learnt. The human’s role in choosing the learning task is called ‘problem generation’ and is a recognised feature of learning behaviour, but appears not to have received significant attention in the field of human motor control research. However, in relation to adaptive control it has been noted that optimisation is quickest when the human is provided with opportunities to identify the changes in the system. If the external input is insufficient to achieve this, the human will ‘test’ the system to generate responses; examples are a driver dabbing the brakes [35] or a pilot moving the joystick [25]. The function of the vehicle driver in ‘problem generation’, or generating vehicle responses that facilitate the learning process, requires investigation. The driver’s tasks of path planning and speed control [17] may also be closely related.

5. CONCLUSION

It is believed that an understanding of human learning of the driving task can contribute to the vehicle design process. Research findings in the fields of driver modelling and human motor control have been reviewed. Whilst the learning process has received significant attention in relation to human motor control, little of this work has been applied to the driving task. Research is needed to develop understanding and mathematical models of human learning relevant to the vehicle steering task. The models must account for continuous and simultaneous compensatory and preview control. A desirable practice to be adopted from the field of human motor control is to test the validity of the models against knowledge of the physiology of the central nervous system. Issues that must be addressed are: the structure of the learning model, representation of the learning action, nonlinear control, and problem generation. A programme of research is underway at
REFERENCES


