

Chapter 10

Human factors

Summary of chapter. The driving task is a comprehensive term that comprises all tasks which must be executed by the driver to reach his/her destination safely, comfortably, and timely. It is performed by execution of *vehicle control actions*. For an accurate performance of the driving task, it can be assumed that the traffic state is continuously monitored and estimated, expectations about future states are continually being made, and control actions are initiated according to driver's objectives and preferences. The control actions affecting the vehicle's status and thus the status of the traffic system itself, by for instance braking, accelerating or decelerating by adjusting the throttle position, changing gear, change foot from one pedal to another, change course by adjusting steering wheel, apply turn indicator, etc.

In this intermezzo chapter, we discuss the execution of driving tasks and human performance aspects in the context of person-machine control systems with the aim to provide a theoretical rationale for the microscopic models discussed in the ensuing chapters. First, we provide an classification of the different (sub)tasks of driving. After this classification has been presented, we will discuss a conceptual driver model. We will describe the discrete components of performance, largely centered around time lags which are fundamental parameters in human performance. These include perception-reaction time, control movement time, responses to the presentation of traffic control devices, responses to the movements of other vehicles, etc. Next, the kind of control performance that underlies steering, braking and speed control (primary control functions) will be described briefly.

List of symbols

$\mathbf{x}(t)$	-	state vector at time t
$\mathbf{u}(t)$	-	control vector at time t
$\mathbf{y}(t)$	-	observation vector at time t
τ	s	reaction time
$\mathbf{r}_q$	m	location of vehicle q
$\mathbf{v}_q$	m/s	velocity vector of vehicle q
RT	s	total reaction time
MT	s	movement time

10.1 The driving task

Driving requires the driver to possess many perceptual and cognitive skills for steering, changing gears, operating the pedals, prediction, fault analysis, making control decisions, etc. Driver experience will play an important role in controlling the vehicle. For example, controlling the vehicle will occupy much of the conscious attention of the novice driver, leaving little reserves for attending other tasks, such as hazard detection. More experienced drivers will execute more driving tasks automatically and subconsciously, leaving more resources for other tasks.

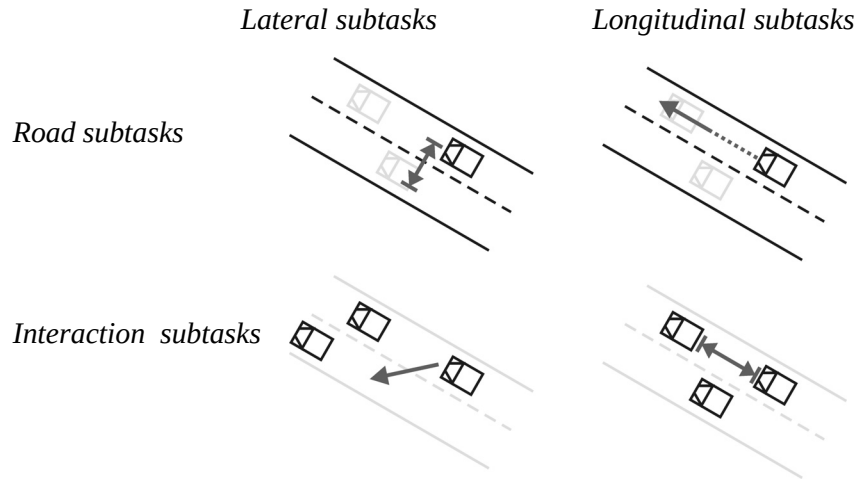


Figure 10.1: Schematisation of driver subtasks

Several researchers have considered the driving task as a hierarchical process, where three levels can be distinguished [45]:

1. Control (operational level)
2. Guidance (manoeuvre or tactical level)
3. Navigation (strategic level)

The *control* level of performance comprises all activities that involve split-second-to-second exchange of information and control inputs between the driver and the vehicle. This level of performance is at the control interface. Most control activities are performed “automatically”, that is, with little conscious effort. In short, the control level of performance is *skill-based*. Since the vehicle control task itself is a skill-based activity, humans are generally considered to perform quite well and errors are minimal. Accidents hence stem mainly from risk-taking behaviour, influence of alcohol, and violations of traffic rules.

Once a person has learned the rudiments of control of the vehicle, the next level is the rule-based *guidance level*. The driver’s main activities “involve the maintenance of a safe speed and a proper path relative to the roadway and traffic elements”. Guidance level inputs to the system are dynamic speed and path responses to roadway geometrics, hazards, traffic and the physical environment. Information presented to the driver-vehicle system is from traffic control devices, other traffic and other features of the environment, continually changing as the vehicle moves along the roadway.

The former two levels of vehicle control are of great importance to modelling for instance a roadway stretch. The third level is *navigation*, comprising for instance route planning and en route guidance. This behaviour is *knowledge based* will be of lesser importance in the ensuing of this chapter.

Minderhoud [37] proposes a more elaborate description of the driving task, explicitly distinguishing between subtasks dealing with the interaction of the driver-vehicle unit and the roadway, and the interaction between the driver-vehicle unit and other traffic participants. In doing so, the following five subtasks are identified (see Fig. 10.1):

1. The *strategic route navigation* is a subtask in which drivers choose their destination, travel direction, route and roads. The choice for a destination or route depends on specific goals and preferences of the drivers, and on the traffic conditions.

2. The *lateral roadway subtask* is defined as a collection of decisions of the driver which are needed to guide the vehicle properly and comfortably over the available infrastructure and its elements such as driving lanes, curves and on- and off-ramps, while dealing with the lateral direction. Examples of this task are: maintaining an adequate lateral position on the lanes or roadway, given the prevailing traffic rules.
3. The *longitudinal roadway subtask* pertains to the decisions needed to guide the vehicle properly and comfortably over the available infrastructure and its elements while dealing with the longitudinal direction. Examples are maintaining an adequate speed to avoid unsafe situations, e.g. in curves or with bad road conditions, given the prevailing traffic rules (e.g. speed-limits).
4. The *lateral vehicle interaction subtask* describes the collection of decisions needed to guide the driver-vehicle unit properly and comfortably around obstacles, vehicles, and possible other traffic participants, while focussing on the lateral direction. Examples are lane-change decisions and gap acceptance behaviour.
5. Finally, the *longitudinal vehicle interaction subtask* pertains to all decisions needed to guide the driver-vehicle unit around obstacles, vehicles, and possibly other traffic participants, while focussing on the longitudinal direction. Examples are speed and distance keeping with respect to the vehicles in front.

In the remainder, the above classification will be used. In particular, chapter 11 discusses car-following models (longitudinal vehicle interaction subtasks); chapter 12 discusses lane changing behaviour and gap acceptance modelling (lateral vehicle interaction subtasks).

10.2 Sharing attentional resources

Drivers frequently have to deal with several sources of information concurrently. For example, the manoeuvres of other traffic participants, traffic signals, and other local traffic conditions and traffic control measures, as well as information from inside the vehicle. The concept of limited pools of attentional resources states that drivers share their attention among the tasks that need their attention. A direct result of this theory is that the allocation of attentional resources to one task will leave fewer resources in performing the other tasks.

Under certain conditions, the driver may find the demands of multiple concurrent tasks overwhelming, and may decision not to perform certain tasks. In illustration, drivers will not frequently check their rear-view mirror when following another vehicle under bad weather conditions.

10.3 Driver objectives

It can be concluded from several studies that drivers differ in driving style. The differences can be explained by different preferences (such as desired speed, desired minimum gap distance), and driving control objectives (e.g. safe, comfortable, or efficient driving) of the drivers, given the possibilities of their vehicles and their own driving capabilities. The distribution of preferences over the driver population and car types also explains the stochastic nature of the maximum traffic volumes and other macroscopic flow characteristics.

Driving objectives are generally a combination of the following options:

1. Maximise safety and minimise risks;
2. Minimise lane-changing manoeuvres;
3. Maximise travel efficiency (restricting speed deviations with the desired driving speed);

4. Maximise smoothness and comfort;
5. Minimise stress, inconvenience, fuel consumption, accelerations, decelerations, etc.

The importance of each objective will also vary among the individuals. Experienced, trip purpose, age, driver's conditions, time-of-day, etc., are factors affecting the subjective valuation of these objectives. Vehicle characteristics, such as length, manoeuvrability, maximum speed, acceleration and deceleration capabilities, are also influencing factors, as are the prevailing weather and environmental conditions.

10.4 Modelling driving tasks

Traditionally, two modelling approaches have been followed to describe human control behaviour. The first approach is the conventional servo-system approach. The second approach is rooted in the optimal estimation and control theory, resulting in the widely used *optimal control model*. The latter approach is based on the fundamental hypothesis that the human operator, in this case the driver, behaves optimally, given his inherent limitations and constraints. The approach generally assumes that the driver first estimates the state of the system, based on his knowledge of the system dynamics and the inaccurate observations. Next, the driver applies the control strategy that optimises some performance criterion, which is usually a trade-off between the different driver objectives that have been discussed in the previous section. The approach optimal control approach has been used to provide a theoretical framework to describe driving behaviour as well as to derive mathematical models.

10.4.1 Car-driver-roadway system diagram

This section discusses the driver-vehicle system as a block diagram, first developed by Weir (1976). Fig. 10.2 shows the resulting block diagram describing the car-driver-roadway system. Let us briefly discuss the diagram. The *inputs* enter the driver-vehicle system from other vehicles, the roadway, and the driver him/herself (acting at the navigation level of performance). The main source of information for the driver is the visual field as seen through the windshield, and the dynamic changes to that field generated by the motion of the vehicle. The driver attends only to selected parts of this input. Factors such as the experience of the driver, his state of mind, and stressors (e.g. being on a crowded facility when being late for a meeting) all imprint on the supervisory or monitoring level of performance, and directly or indirectly affect the control level of performance. The actual control movements made by the driver couple with the vehicle control and the interface of throttle (T), brake (B) and steering (S). The vehicle in turn, as a dynamic physical process in its own right, is subject to inputs from the road and the environments. The resolution of control dynamics and vehicle disturbance dynamics is the vehicle path.

As will be discussed, a considerable amount of knowledge is available for some of the lower blocks in Fig. 10.2, i.e. the ones associated with braking reactions, steering inputs, and vehicle control dynamics. Before discussing some research results pertaining to perception-response time and control movement times, we present an model adopted from [37] describing driving as a feedback-oriented control task. In fact, this conceptual model is simplification of the model discussed in this section, which can be used to derive mathematical models.

10.4.2 Optimal control model

This section discusses a conceptual model to describe driving behavior in terms of a closed feedback control system, where the driver predicts the behavior of him/herself and of other drivers (referred to as opponents in game-theoretic terms), including the presumed opponents'

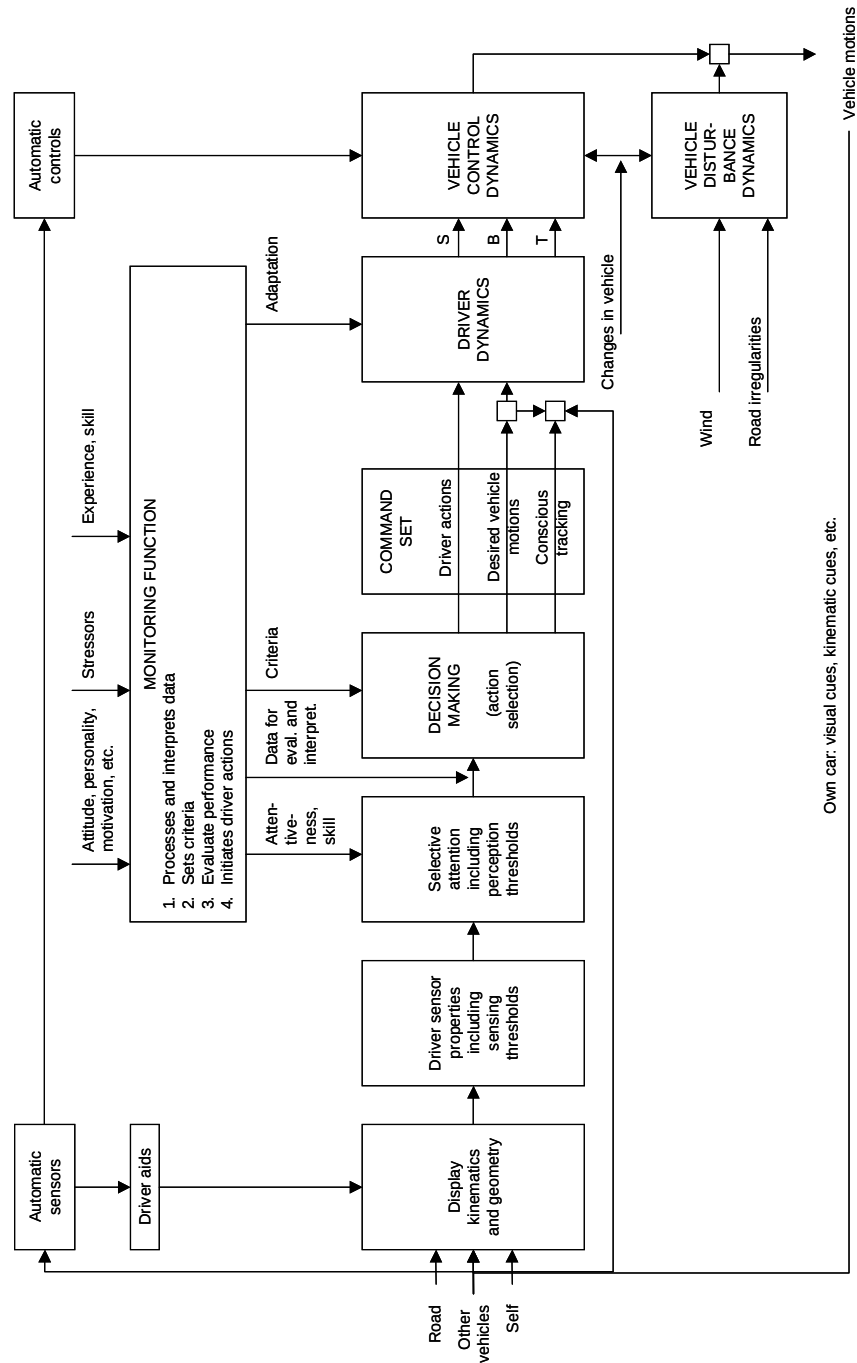


Figure 10.2: Generalised block diagram of the car-driver-roadway system.

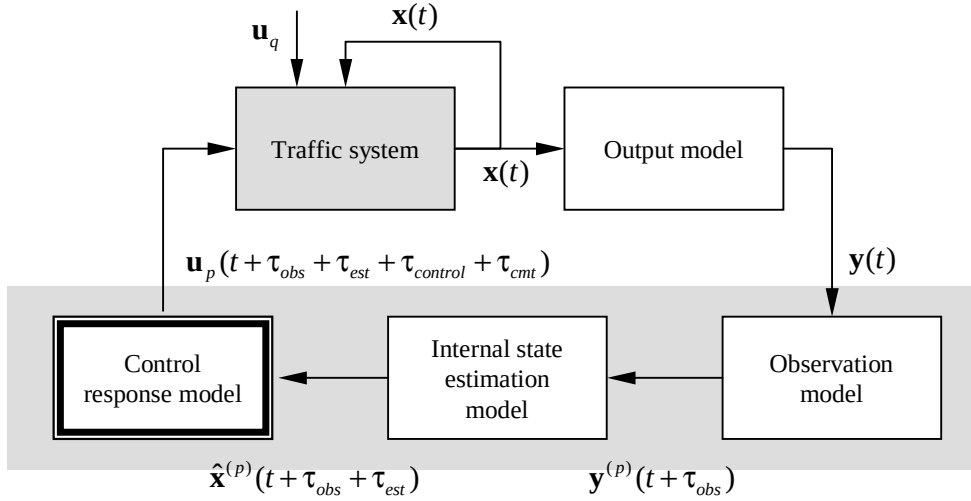


Figure 10.3: Driving as feedback-oriented control.

reactions to the control decisions of the driver. As mentioned in the introduction, these driver task comprise both control and guidance of the vehicle.

To describe the driving task, often the concept of utility maximisation is put to use. A good example pertaining to execution of the driving task is the *Risk Homeostasis Theory* proposed by Wilde, which is based on the hypothesis that drivers seek to maintain a target level of risk despite changes in the environmental risk. If the environment becomes safer, drivers will engage in riskier behaviour and conversely. Application of the utility optimisation approach entails that drivers are assumed to optimise their control actions taking into account their individually estimated risk, comfort, and preferred safety levels.

Minderhoud [37] applies the utility optimisation principle to conceptually describe the performance of the driving task. Hoogendoorn and Bovy [29] use a similar approach to describe the walking behaviour of pedestrians, as well as to derive mathematical walker models.

The driver is assumed to use an internal model for determining an appropriate guidance control decision, thereby aiming to optimise his/hers task performance. Experience and knowledge have skilled the driver in performing these tasks, and hence the assumption of optimal behaviour is justified. The optimisation includes the limitations of the driver in terms of observation, information processing and internal state estimation, as well as processing times and reaction times. Moreover, the optimisation includes the driving strategy.

A driver is constantly monitoring his position and velocity relative to the other vehicles in the flow, as well as relative to the road. This monitoring allows the driver to perform corrective actions, implying that driving is *feedback-oriented*. A continuous feedback control system consists of a comparison between the input (positions, velocities) and the controlled output (acceleration, deceleration and direction changes).

Fig. 10.3 depicts the continuous control loop for a certain driver. The traffic system describes the *actual traffic operations*. The state $\mathbf{x}(t)$ of the system encompasses all information required to summarize the system's history, typically including the locations $\mathbf{r}_q(t)$ and the velocities $\mathbf{v}_q(t)$ of all vehicles q in the traffic flow

$$\mathbf{x}(t) := (\mathbf{r}, \mathbf{v}) \text{ where } \mathbf{r} := (\mathbf{r}_1, \dots, \mathbf{r}_n) \text{ and } \mathbf{v} := (\mathbf{v}_1, \dots, \mathbf{v}_n) \quad (10.1)$$

The location consists of a longitudinal component r_1 , describing the locations of the vehicles along the roadway, and a component r_2 reflecting the lateral position. In principle, the latter is described in terms of a continuous variable. In most applications, the lateral position of vehicles only indicates the lane in which vehicles drive, and hence is discrete. It is emphasized that the state of the system will also include other issues which are relevant to describe the

future behavior of the system, for instance including driving mode, driver fatigue, awareness, etc.

The dynamics of the traffic system are described by kinematic equals described the changes in the system state over time. These are reflected by a coupled system of ordinary differential equations

$$\dot{\mathbf{x}}(t) = \mathbf{f}(t, \mathbf{x}(t), \mathbf{u}(t)) \quad (10.2)$$

where $\mathbf{u} = (\mathbf{u}_1, \dots, \mathbf{u}_n)$ denotes the control vector, reflecting how the drivers influence the state $\mathbf{x}$ (e.g. by accelerating and changing directions). The state dynamics Eq. (10.2) describe the dynamics of the traffic system and its constituent entities. The output model maps the state $\mathbf{x}(t)$ onto the observable system output $\mathbf{y}(t)$.

In Fig. 10.3, the shaded block containing the three boxes describes the driving task model for a driver p , consisting of

1. the observation model
2. the state estimation model, and
3. the control response model.

The *observation model* of driver p describes which of the elements of the traffic system's output $\mathbf{y}(t)$ can be observed by p . The output $\mathbf{y}^{(p)}(t)$ is generally a function of the system's output $\mathbf{y}(t)$, state $\mathbf{x}(t)$, the observation time delay τ_{obs} (also referred to as the perception-response time), and observation errors $\boldsymbol{\varepsilon}_{obs}$. While observing, the driver will collect and process various types of information, such as

- own speed and (longitudinal) acceleration (own visuals and driving aids)
- distances to other vehicles and relative speeds with respect to other vehicles (radial motion detection, driving aids / automatic sensors)
- lane-changing states (turn indicator) of other vehicles
- traffic signs, road geometrics, etc.

The output $\mathbf{y}^{(p)}(t)$ typically describes the locations and velocities of vehicles that p can observe, but will thus also include other types of information on the state of the traffic system. Conceptually, the output can be expressed as follows

$$\mathbf{y}^{(p)}(t) = \mathbf{g}(\mathbf{x}(t - \tau_{obs}), \boldsymbol{\varepsilon}_{obs}) \quad (10.3)$$

Driver p will use his observation $\mathbf{y}^{(p)}$ as well as his experiences to estimate the state of the traffic system, which is described by the *internal state estimation model* of Fig. 10.3. Without going into details, we assume that the internal state estimate can be described by a function of the previous internal state estimate $\mathbf{x}^{(p)}(t)$, the observation $\mathbf{y}^{(p)}(t)$, and the estimation delay τ_{est} and error $\boldsymbol{\varepsilon}_{est}$. Here, $\hat{\mathbf{x}}^{(p)}(t)$ describes estimates of the locations and velocities of driver q . Note that these estimates generally contains more information than the observations $\mathbf{y}^{(p)}(t)$, for instance because driver p uses also information collected at previous time periods. A conceptual model describing the relation between the estimate at time t , the observation, and the previous state estimate is

$$\hat{\mathbf{x}}^{(p)}(t) = \mathbf{h}(\mathbf{y}^{(p)}(t - \tau_{est}), \hat{\mathbf{x}}(t - \tau_{est}), \boldsymbol{\varepsilon}_{est}) \quad (10.4)$$

The *control response model* in Fig. 10.3 reflects the process of determining the control actions of driver p . These control actions are described by the control vector $\mathbf{u}_p(t)$ applied by p , indicating acceleration / deceleration, direction changing, applying turning indicators, etc. The control response model comprises three submodels, namely

1. prediction of the state of the system
2. making the control decision, and
3. taking the control action.

We hypothesize that the control decision depends on the internal state estimate, the driving strategy, reflecting the driving objectives, and the control delay $\tau_{control}$. The control delay $\tau_{control}$ describes the time needed to determine the control decision. On top of the control delay, an additional lag τ_{cmt} is incurred to perform the control movement (referred to control movement time; see section 10.5.2).

In determining the control actions, we assume that p will predict and optimize the driving cost $J^{(p)}$ incurred during some time interval $[t, t + T]$. The prediction of the internal state $\mathbf{x}^{(p)}$ will be described by an internal state dynamics model, i.e.

$$\dot{\mathbf{x}}^{(p)}(s) = \mathbf{f}^{(p)}\left(s, \mathbf{x}^{(p)}(s), \mathbf{u}^{(p)}(s)\right) \quad \text{s.t.} \quad \mathbf{x}^{(p)}(t) = \hat{\mathbf{x}}^{(p)}(t) \quad (10.5)$$

for $t \leq s \leq t + T$. These state dynamics include the reactions of the drivers q as well. For any control path applied during $[t, t + T]$, p predicts the state $\mathbf{x}_{(t,t+H)}^{(p)}$ using eqn. (10.5), and can thus determine the predicted driving cost $J^{(p)} = J^{(p)}\left(u_{[t,t+T]}^{(p)} | t, \hat{\mathbf{x}}^{(p)}(t)\right)$. These driving cost will generally reflect the driver objectives. The utility optimisation concept then asserts that the driver chooses the optimal control path minimizing this cost $J^{(p)}$. The cost optimization process, its parameters, and its resulting control decisions differ between the drivers, due to different objectives, preferences, and abilities.

In the remainder of this chapter, we will briefly discuss the notions of perception-response times, and control-response times. Within the context of the model presented here, the former summarises the observation delay τ_{obs} , the state estimation delay τ_{est} , and the control delay $\tau_{control}$.

10.5 Discrete driver performance

10.5.1 Perception-response times

If compared to physical or chemical processes, the simplest human reaction to incoming information is very slow. The early 1950's say *Information Theory* take a dominant role in experimental psychology. The linear equation

$$PRT = a + bH \quad (10.6)$$

where a is the minimum reaction time for a particular type of decision, and $b \approx 0.13$ is an empirically derived slope, expresses the relationship between the number of alternatives N represented via the transmitted information content $H = \log_2 N$ that must be sorted out to decide on a response and the total reaction time RT . The reaction time is defined by the time of detection of the input and the start of the response. If the time for the response itself is also included, then the total lag is generally termed “response time”. However, often the term are interchanged. Interestingly, part of the reaction time depends on the choice variables, while another part is common to all reactions. Most models that have been proposed prepresent chaines of the model described above, where different decision components are linked together. As an example, Tab. 10.1 shows empirical estimates of the different components of the Perception-Response-Time (PRT) for a chained model for braking response time.

Each of the elements in Tab. 10.1 are established from empirical data, and represents the 85th percentile for that aspect of time lag. However, since no driver is likely to produce 85th percentile values for each of the individual elements, a more likely *upper limit* for a driver's PRT is 1.50 s.

Component		Time(s)	Cumulative time (s)
Perception			
	Latency	0.31	0.31
	Eye movement	0.09	0.40
	Fixation	0.20	1.00
	Recognition	0.50	1.50
Initial brake application		1.24	2.74

Table 10.1: Hooper-McGee chaining model of perception-response time.

	surprise	expected
mean	1.31	0.54
standard dev.	0.61	0.10

Table 10.2: Mean and variance of PRT for surprise and expected situation.

It has been shown that the distribution of the *PRT* is non-normal, i.e. it is skewed. In most applications known from literature, the probability distribution of the *PRT* is assumed to follow the log-normal distribution

$$f(PRT) = \frac{1}{\sqrt{2\pi}\sigma^*} \exp \left[-\frac{1}{2} \left(\frac{\ln PRT - \mu^*}{\sigma^*} \right)^2 \right] \quad (10.7)$$

where the two parameters that define the shape of the distribution are μ^* and σ^* , which are related to the mean and the standard deviation of the sample data of the *PRT*. Other studies have considered differences between the following situations: 1) the driver does not know when or even if the stimulus for braking will occur (surprise), and 2) the driver is aware that the signal to brake will occur, and the only question is when. Tab. 10.2 shows the results from this study. It is left to the reader to determine the 0.5 and 0.85 percentiles of the resulting log-normal distribution. Also, differences between older and younger drivers in different driving environments have been studied. For details, we refer to [21].

10.5.2 Control movement times

Control movement times reflect overt movements of the human body, with attendant inertia and muscle fiber latencies that come into play once the efferent nervous impulses arrive from the central nervous system. A very simple relation can be used to describe the relation between the movement time *MT*, the range or amplitude of movement, size of the required control movement (Fitts' law)

$$MT = a + b \log_2 \left(2 \frac{A}{W} \right) \quad (10.8)$$

where

- a = minimum response time lag, no movement
- b = slope, empirically determined, different for each limb
- A = amplitude of movement
- W = width of control device (in direction of movement)

This law does not apply to all movements, especially those that are short. Such movements, usually not involving visual feedback, can be modelled by the following alternative to Fitts' law

$$MT = a + b\sqrt{A} \quad (10.9)$$

Application of these models to for instance modelling braking movements yielded control movement times between 0.15 s and 0.17 s.

A different study concerned the driver responses to the sudden opening of a car door. It turned out that drivers responded with a “ballistic jerk” of the steering wheel. The mean response latency was 1.5 s, and reached the half-way point of maximum displacement from the original path in about 2.5 s.

10.5.3 Response times to traffic control devices

From the standpoint of traffic flow theory and modelling, one of the major concerns is driver response or lag to changing traffic signals. Studies into the *PRT*’s of traffic signals have indicated that the average *PRT* (from the traffic signal change to the response) equals 1.3 s; the 85-percentile is approximately 1.5. It appears that there is little relation between the distance from the traffic signal and the *PRT*.

10.5.4 Response to other vehicle dynamics

Consideration of the vehicle ahead has its basis in thresholds for detection of so-called *radial motion*, referring to the change in the apparent size of the target. When a vehicle approaches another vehicle with constant speed, the magnification turns from linear to geometric. When this occurs, the human visual system triggers a warning that an object is going to collide with the observer (or is pulling away from the observer). If the incoming information is irregular, then the human perceptual system knows that the relative speed to the object is changing. The visual angle of an observed object relates to the visible width of the object. The *time-to-go* (time-to-impact) is roughly equal to the reciprocal of this visual angle.

With respect to detection of distance changes, it has been found by Mortimer that drivers can detect a change in the distance to the vehicle in front when it is varied by approximately 12 percent: if a driver were following a car ahead at a distance of 30 m, at a change of 3.7 m the driver would become aware that the distance is decreasing or increasing, i.e. a change in the relative velocity. Mortimer concludes that “unless the relative speed between two vehicles becomes quite high, the drivers will respond to changes in their headway, or the change in the angular size of the vehicle ahead, and use that as a cue to determine the speed that they should adopt when following another vehicle”.

With respect to the car-following task, let us finally state that the human visual perception of acceleration of an object is very gross and inaccurate. It is very difficult for a driver to discriminate acceleration from constant velocities unless the object is observed for a relative long period of time (10 to 15 seconds).

With respect to the vehicle alongside, it is noted that the motion detection is in this respect (peripheral vision) less accurate than in foveal vision (straight ahead), implying that drivers only respond to larger changes in the relative speeds. On top of this, stationary objects in the periphery (such as a neighbouring vehicle exactly keeping pace with the driver’s vehicle) tends to disappear for all intents and purposes *unless it moves with respect to the viewer* against a patterned background. Relative motion in the periphery also tends to look slower than the same movement as seen using fovea vision. Radial motion detection presumably would follow the same pattern as the vehicle ahead case, although no direct evidence is available to justify this presumption.

10.6 Continuous driver performance

The previous sections have sketched the relevant discrete performance characteristics of the driver in a traffic stream. Driving, however, is primarily a continuous dynamic process of managing the present heading and the future path of the vehicle through the steering function. The first and second derivatives of location on the roadway in time, speed and acceleration, are also continuous control processes.

Steering can be modelled by a tracking model, with the following inputs:

1. the desired path as perceived by the driver
2. the perceived present course

The resulting differential equations can be (and have been) calibrated using experimental data. We refer to [21] for details.

