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Identifiability and Specificity of the Two-Point Visual Control Model of Steering

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Abstract

Estimating parameters of cognitive models is crucial to be able to accurately describe cognitive processing of individuals, under varying circumstances. To ensure that individual parameter estimates represent individual cognitive processes, it is important to consider *model identification* and *specific influence*. Model identification refers to whether a unique set of parameter estimates is associated with a particular pattern in the data; Specific influence means that certain experimental manipulations affect only specific cognitive processes, reflected in changes in only those parameters that represent those processes, and not others. These two general concepts also apply to cognitive models of more applied tasks and settings, such as driving. In the current work, we specifically test whether these two requirements hold in a commonly used cognitive model of visual control of steering behavior. For this model, we test the identifiability, and then estimate parameters of two experiments to understand how cognitive load and driving speed specifically influence parameter estimates of the model. The results indicate that the two-point visual control of steering model is identified, and that cognitive load and driving speed are related to different parameters.

Keywords: cognitive models; parameter estimation; model identifiability; specific influence; driving.

Introduction

Manually driving a vehicle involves various cognitive processes ranging from the basic control and operation of the steering wheel, to maneuvering to change lanes, to strategically deciding what is the best way to move from A to B (e.g., the fast or scenic route) (Michon, 1985). Managing these requirements involves perception, decision-making, as well as executive control. Due to the dynamic interleaving and execution of all these tasks, driving is highly complex (Chong et al., 2014; Michon, 1985). This complexity causes driving error to be a high causal factor in road accidents (e.g., Dingus et al., 2016; Strayer et al., 2015).

Cognitive science and cognitive modeling have the potential to inform our understanding of such complex dynamic tasks, and a wide variety of models exists for both manual and semi-automated driving (for reviews see e.g., Brumby et al., 2018; Janssen et al., 2020). Cognitive models help to quantify the extent to which specific cognitive processes (e.g., visual attention, memory) and environmental factors (e.g., amount of traffic on the road, weather) impact driving performance, and thereby safety. Such a quantified understanding can then eventually also help to guide the design of safer vehicles and in-car systems.

In this paper we focus on one particularly promising cognitive model: the two-point visual control model of steering (TPVC, Salvucci & Gray, 2004). This model has been the basis of a wide variety of other driving models, specifically in the cognitive architecture ACT-R (Salvucci & Taatgen, 2010), which in turn inspired other cognitive models of visual attention interleaving in driving (e.g., Janssen & Brumby, 2010; Jokinen et al., 2020).

The central idea of the TPVC model (Salvucci & Gray, 2004) is that steering motion is determined by two focus points that the driver is assumed to monitor: a far point and a near point (Neumann & Deml, 2011). The far point can for example be the back of another vehicle or the distal point where the road disappears. The near point can be thought of as a target immediately in front of the car. In the context of lane-changing, the model assumes that both the far and near points change position to the target lane, to enable the driver to steer to that lane (Figure 1).

The TPVC model controls the steering movement by controlling the angle between the car's bearing and the two focus points. In particular, the model minimizes the change in angle with the near and far points. This allows for a smooth steering motion. To maintain a stable position on the road, the model additionally minimizes the angle of the car's heading with the near point. Salvucci and Gray (2004) show that in principle this model accounts for a wide range of driving behaviors, by showing qualitative comparisons between simulated car movements, and measured car movements from a range of experimental studies. To show the match between simulated and measured car movements, Salvucci and Gray estimated parameters that determine the relative contributions of the angle with the near and far points, revealing how different movement patterns are supported by different sets of parameter estimates.

Although introduced over a decade ago, it has not been studied whether the parameters of the TPVC model represent single cognitive processes. The current paper fills this gap by addressing two related questions on (1) identifiability and (2)

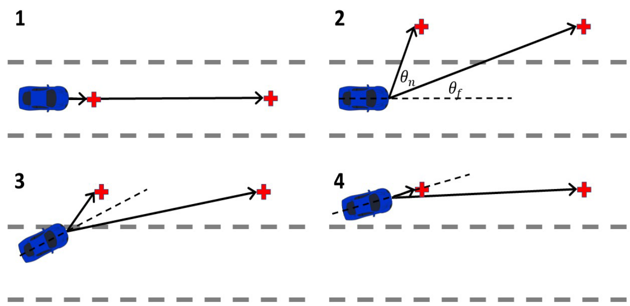

Figure 1: Illustration of a lane change according to the two-point visual control model of steering. θ_f and θ_n indicate the angle between the car and the far and near points, respectively. Initially, the car drives straight (1). Once the decision to change lanes has been initiated, the far and near points change relative to the car, creating a non-zero angle (2). Consequently, the car steers to the left lane (3), minimizing the angle between the heading of the car and the far and near points (4).

specificity. The first question is whether the parameters are identified. That is, given a particular (measured) car movement, is there a unique set of parameters that best predicts that car movement (Moran, 2016; van Maanen & Miletić, 2020). Having a stable set of parameters (identifiability) is needed to make quantitative predictions (based on those models) for novel experiments and settings. If the model is not identified, and it occurs that one particular measured car movement is best predicted by two or more sets of parameters, inferences about these parameters become impossible. That is, there is no guarantee that when optimizing the parameters of the model, two identical car movements give the same optimal set of parameters, since there are more sets that equally well fit the observed data. Consequently, conclusions about the estimated parameters are invalid.

Once the identifiability question has been answered affirmatively, the second question on specific influence then becomes whether estimated parameters systematically vary between empirical conditions. That is, if we assume that each parameter is a reflection of a single cognitive process, then changes in behavior that are hypothesized to reflect changes in specific cognitive processes should uniquely affect only those parameters that represent the cognitive process under scrutiny. No other parameters should be affected.

Implementation of the TPVC Model

Following Salvucci and Gray (2004), we implemented a discrete version of the TPVC model:

$$\Delta\varphi = k_f \Delta\theta_f + k_n \Delta\theta_n + k_I \theta_n \Delta t$$

In this equation, φ indicates the angle that the car makes relative to its original bearing, θ_f and θ_n indicate the angle between the car and the far and near points, respectively, and Δt represents a time constant of the update cycle. k_f, k_n, and k_I are the contributions of each of these components to the angular change.

In addition to the basic model, we assume a visual processing time that leads to a delayed response to visual events that happen while driving. The implementation of the TPVC model in the ACT-R cognitive architecture introduced a similar mechanism (Salvucci, 2006), but in that model optimization of the delay period to the individual driver is not possible.

The delay period (t_0), together with the parameters governing the steering control (k_f, k_n, and k_I) determine the steering behavior of a driver. Figure 2 shows the predicted steering motion for four example parameter sets, with default parameters of $(k_f, k_n, k_I, t_0) = (0.2, 0.2, 0.2, 0.0)$. The first set (in black) represents a driver with a relatively high t_0 ($t_0 = 0.15$) who responds relatively slowly to a warning signal to change lanes. In contrast, a driver with a relatively high k_f of $k_f = 0.7$ focusses mostly on the far point, and therefore steers more smoothly, taking more time to finish the lane change (in green). A driver with a relatively high k_n ($k_n = 0.7$, in red) minimizes the angle between the car and the near point, resulting in a relatively abrupt steering motion. A driver with a relatively high k_I ($k_I = 0.7$, in blue) aims to maintain the bearing to the near point, and attends less the change in angle. Consequently, the steering motion requires overcompensation once the target lane is reached. This appears in Figure 2 by the high lateral deviation at t = 0.6s.

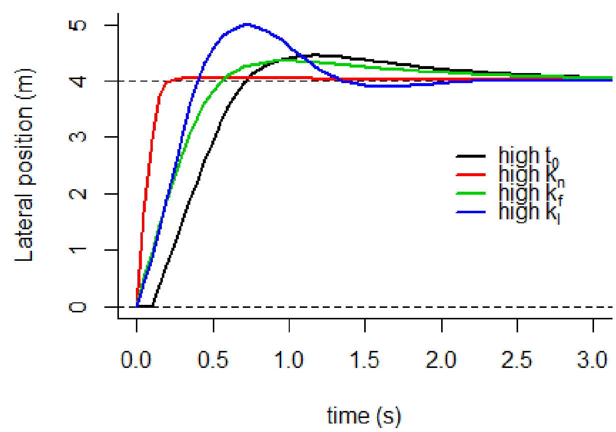

Figure 2: Individual steering profiles predicted by the TPVC model. The goal of the model here is to steer four meters to the left, beginning at time 0.

Estimating Parameters

To reveal individual driver's profiles, we optimize the set of parameters that best describe the steering behavior of every individual. To this end, we predict the lateral deviation of a car under one set of parameters, and minimize the mean squared distance between the observed lateral deviation and the predicted lateral deviation. The lateral deviation depends on the change in angle and the speed of the car in the following way:

$$\Delta x = v \tan(\varphi)\, \Delta t$$

with v the speed of the car (in m/s).

Because of the potential complexity of the parameter space, we applied particle swarm optimization with multiple restarts (Clerc, 2010).

Model Identification

To study whether the model is identified, we generated artificial data using parameters values for k_f, k_n, k_I, and t_0 that were randomly selected from a uniform distribution (between 0 and 2). The range of this distribution was informed by initial analyses of one of the data sets reported below. Then, we applied the procedure introduced above to estimate back the parameters based on the artificial car movement. This process was repeated 100 times. If the model is identified, we should observe that the parameter estimates are close to the parameters used to generate the artificial data (Anders et al., 2016; Miletić et al., 2017; Van Maanen et al., 2019).

The far and near points where set at 1m and 20m in front of the car, similar to Salvucci and Gray (2004). After t_0 seconds had passed, the lateral position of the far and near points was moved 4m to the left, initiating the actual steering movement. The car's speed was kept constant at 80km/h.

Results

We found very high correlations between the true and estimated parameters of the same type (Table 1). Moreover, the strongest correlation between true and estimated parameters of different types was r=-0.18 between the true k_f and the estimated k_n, indicating a small trade-off between these parameters (the inverse correlation between true k_n and estimated k_f was slightly smaller). Overall, these results indicate that the model is identified, since in the absence of noise, there seems to be a unique set of parameters that best predicts a specific car movement.

Table 1: correlation matrix between true (rows) and estimated (columns) model parameters.

	k_f	k_n	k_I	t_0
k_f	.97	-.18	.05	.00
k_n	-.18	1.00	.15	-.07
k_I	.05	.14	1.00	-.13
t_0	-.01	-.07	-.14	1.00

A Test of Specific Influence

After having established that the TPVC steering model is identified, and therefore the estimated parameters are stable across multiple instances of the same behavioral profile, we address the question whether the parameters are systematically related to specific external factors; a test of specific influence (Van Maanen et al., 2019; Van Ravenzwaaij et al., 2012). To this end, we reanalyzed the car movements from two recent studies (Pavlidis et al., 2016; van der Heiden et al., 2019) in which participants were asked to drive a car through a simulated environment in different cognitive load conditions.

Study 1: Van der Heiden et al. (2019)

In this study, participants driving a simulated vehicle were signaled at unpredictable moments that a lane change was required as quickly as possible. The study manipulated cognitive load by a secondary task (3 levels) and vehicle speed (80 km/h or 130 km/h). If the parameters of the TPVC model are meaningful representations of the cognitive processes involved in steering, then these external factors (cognitive load and speed) should affect only a single or limited set of parameters.

Specifically, we hypothesized that an increase in cognitive load increases the delay period t_0. This reflects the idea that a secondary task typically results in distraction (e.g., Iqbal et al., 2010; Kunar et al., 2008; Strayer & Johnston, 2001), and therefore the signal that indicates a lane change may be processed later. We did not have a specific hypothesis regarding the driving speed manipulation.

Methods

The study involved twenty-four participants (9 women, age range 28-70 years). The primary driving task was to stay in the middle lane (3.5 m wide) of a straight three-lane highway. A simulated navigation system was shown at the bottom right of the screen. When a lane change was imminent, the interface showed which lanes were closed. Participants were instructed to change to the open lane once they noticed the alert. On the cognitive load trials, an audio task created distraction. There were two audio conditions. In both audio conditions, participants heard a stream of words, presented at a steady pace of 1 word every 4s. In the Repeat condition, participants had to repeat the word they heard. In the Generate condition, participants had to respond with a new word that started with the last letter of the word they heard. For more details on the experiment see Van der Heiden et al. (2019).

Parameter Estimation The parameters were optimized for all time series of all conditions and individuals, excluding trials in which participants either did not change lanes, or started from the incorrect lane (3.4%). All time series were down sampled to 20 Hz, to obtain Δt=50ms, which has been argued is the update time of the human cognitive system (e.g., Anderson, 2007; Salvucci & Gray, 2004; Stocco et al., 2010), and which also is an interval that is used in other models of driver distraction (Salvucci, 2006, 2009).

Because the fitting results in separate parameter estimates for every time series (i.e., each trial), we can apply linear mixed-effect modeling to analyze the resulting parameter estimates (Baayen et al., 2008). In these regression models, we typically assume a random intercept for individuals, controlling for individual differences. Starting with the full models, we performed stepwise backward regression to identify the most important factors that contribute to the variance in the data (Crawley, 2013).

Results

Goodness-of-fit As a qualitative impression of the fit, Figure 3 (left) shows two example participants' lane deviation during a leftward lane change, which overlaid the model predictions according to the best fitting model parameters. Although the model does not account for brief movements of the car, it captures the overall pattern of the movement very well. The right panels of Figure 3 illustrate that the model also predicts the steering angle of the car, even though it was not fit on this property of the data.

Moreover, Figure 4 shows that the delay period predicts the initial reaction time (T1). T1 was computed as the time at which the driver makes the first steering motion that exceeds one degree (van der Heiden et al., 2019). The delay period seems to be an important component of T1.

Backward stepwise regressions shows that the best regression model predicting T1 includes t_0 ($\beta_{t0}=0.32; t=12.0; p<.001$), a non-significant effect of car speed ($\beta_{speed}=0.06; t=1.9; p=.067$), and the interaction of these factors ($\beta=-0.17; t=-4.1; p<.001$). In addition, the regression model includes a positive intercept of 0.51, suggesting that the t_0 is consistently lower than T1 (Figure 4).

Inferential Analyses For every parameter, we developed linear mixed-effects models that included speed and cognitive load as fixed effects, and participant as random intercept. Backward stepwise deletion of the factors that explained the least amount of variance reveals that the best description of the k_f parameter is a model in which k_f only differs for the speed condition ($\beta_{speed}=0.37; t=5.2; p<.001$). The optimal model for the k_n parameter is the same, but with an inversed effect size ($\beta_{speed}=-0.62; t=10.8; p<.001$). The model for the k_I parameter is also dependent on the speed condition ($\beta_{speed}=-0.67; t=-10.8; p<.001$). Together, these results suggest that when participants drove faster, they shifted their attention from the far point to the near point, resulting in more myopic driving styles.

In contrast, the t_0 parameter seems to differ according to the cognitive load condition drivers were in. In particular, in both load conditions, t_0 was estimated higher than in the Drive only condition ($\beta_{DG}=0.10; t=2.7; p=.006$; $\beta_{DR}=0.11; t=3.0; p=.003$). Thus, compared to the driving only condition, participants required about 100ms more to react to the lane change signal when performing a secondary task.

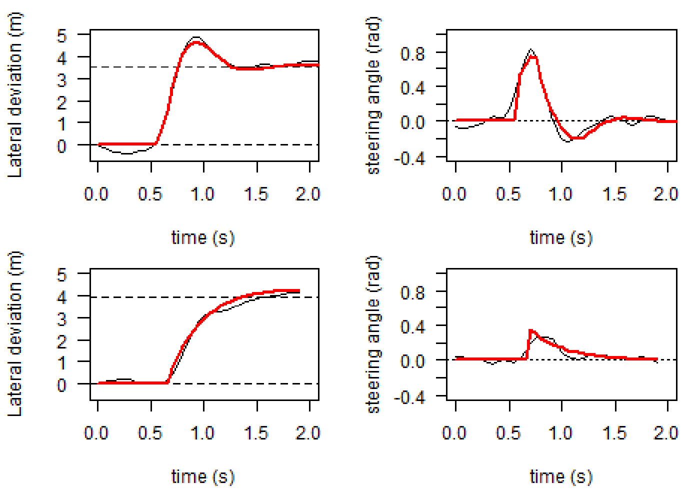

Figure 3: Two example participants with different steering profiles were fit by the TPVC model. Left: Observed (black) and predicted (red) lateral deviation from the initial road location. Dashed lines indicate the initial road location and the target road location. Right: Observed and predicted steering angle. Dotted line indicates that steering wheel is in the upright position.

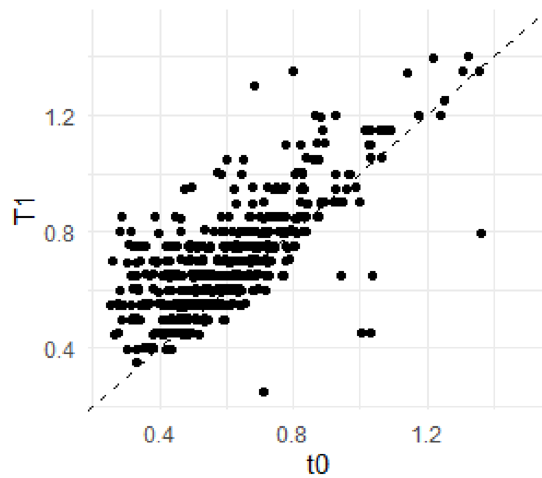

Figure 4: The TPVC model predicts the initial reaction time (T1). Correlation between the T1 computed from the data and delay period t_0 from the model. The dashed line indicates the identity line.

Study 2: Pavlidis et al. (2016)

This section entails a reanalysis of a larger data set (Pavlidis et al., 2016; Taamneh et al., 2017), with multiple cognitive load conditions, to see if we replicate the t_0 effect that was observed in Study 1.

Methods

In this driving simulator experiment, 68 participants drove a 10.9 km stretch of four-lane highway under five different conditions. After 5.2 km[1], the highway contained a lane deviation, forcing drivers towards the left lane. In the relaxed driving (RD) condition, there was limited traffic on the oncoming lanes. In the four other conditions, the cognitive load of participants was increased by increasing the traffic

[1] The data descriptor paper (Taamneh et al., 2017) mentions that the lane change occurred after 4.4 km in all but the RD conditions, but this seems incorrect.

density on the oncoming lanes, by presenting road works along the side of the road, and by asking participants to do a secondary task before and after the lane change. The four conditions differed in the nature of the secondary task. In the no-secondary task (ND) condition, there was no secondary task; In the cognitive secondary task (CD) condition, the secondary task consisted of analytical questions; In the emotional secondary task (ED) condition, the experimenter asked emotionally stirring questions; In the sensorimotor secondary task (MD) condition, participants were asked to type on a smartphone. The highway had a posted speed limit of 70km/h (but participants were free to adjust their speed). Each participant made a single leftward lane change in every condition. For more details see (Pavlidis et al., 2016; Taamneh et al., 2017).

Parameter Estimation We focused the analysis of the steering motion on the section of highway 600m before and after the indicator of the lane change. This way we ensured that the model only describes the critical lane change, and no other unrelated steering motions. The parameters were optimized using the same procedure as before, for all conditions and individuals separately. Δt was set to Δt=1s, which was the measurement frequency of the lane position.

Results

The model's goodness-of-fit was comparable to the fit to Study 1. A mixed-effects regression model with cognitive load condition as fixed effect and random intercepts for participants was fit separately to the optimal parameter estimates. The RD condition was characterized by a substantially higher k_f ($\beta_{RD}=0.072;\ t=4.0;\ p<.001$) as compared to the ND condition (which was set as the reference condition for convenience), as well as a substantially lower t_0 ($\beta_{RD}=-12.7;\ t=-19.4;\ p<.001$). For the other parameters there was no significant difference.

Moreover, the CD and MD conditions differ from ND with respect to t_0 as well ($\beta_{CD}=-3.2;\ t=-5.1;\ p<.001;\ \beta_{MD}=-3.1;\ t=-4.8;\ p<.001;$ but $\beta_{ED}=-0.7;\ t=-1.2;\ p=.25$). There were no other significant differences between the various cognitive load conditions. Thus, compared to the cognitive load condition without a secondary task (ND), participants that performed a cognitive or sensorimotor secondary task prior to the lane change initiate their steering motion sooner.

These effects seem to indicate that the lower traffic density and limited visual input in the RD condition as compared to the ND condition was reflected in a faster identification of the lane change indicator, consistent with the experiment of Van der Heiden and colleagues (2019). However, it is surprising that the two conditions that seem even more cognitively demanding are characterized by a shorter t_0 parameter. Possibly, because the extra cognitive load manipulation was administered before and after the lane change, this additional cognitive demand resulted in a more focused driving style as compared to the ND condition.

Discussion

To understand the applicability of the TPVC model in terms of estimating individual steering profiles, we tested the identifiability as well as the specificity of the model's estimated parameters. With respect to model identifiability, we found that the model parameters have unique contributions to the predicted steering motion. This means that through parameter optimization procedures the set of parameters can be identified that best fits a steering profile in empirical data.

With respect to parameter specificity, we estimated parameters for two data sets in which participants made a steering motion with the intend of a lane change. Both data sets included experimental conditions that involved higher cognitive load, for which we hypothesized that a decreased level of attention towards the primary driving task would result in a higher estimate of the onset of the steering motion. Moreover, we hypothesized that driving speed would influence the focus point that drivers attended when performing a lane change, with a more myopic focus for faster driving. Both hypotheses were confirmed.

Finding evidence for the identifiability and specificity of cognitive models is important, as it allows for the specification of parametrized models of individual users. This can be scientifically interesting, to study how individual differences in cognitive processes (reflected by individual differences in parameters) are related to other measures, such as mental workload scores (e.g., van Maanen et al., 2019), neuroscientific measures (e.g., Turner et al., 2017), or other behavioral measures (e.g., Miletić & van Maanen, 2019).

An important aspect of the original TPVC model that we did not explore here, is the choice of time constant Δt. In Study 1, we set the Δt to 50ms, following the rationale that this possibly reflects the update time of the cognitive system (e.g., Anderson, 2007). In study 2 however, we set Δt at 1s, since this was the sampling frequency of the car locations in this data set. This difference entails that the parameter estimates cannot be directly compared across experiments. Rather, the parameters should be interpreted relative to the time constant (cf. van Maanen & Miletić, 2020).

Relatedly, Salvucci (2006) suggests that the time constant parameter may not be constant at all, but rather that steering updates may be skipped when the cognitive system is already engaged, for example with a secondary task (e.g., Janssen et al., 2012; Janssen & Brumby, 2010; Jokinen et al., 2020; Salvucci et al., 2009; Salvucci & Taatgen, 2008). Such interleaving may affect the precision of the observed steering, and could potentially affect the parameter estimates. Estimating the probability of skipping an update cycle due to interleaving seems an important next step in this line of work.

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