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The Application of Human Mental Models for Engineering to Improve Acceptance and Performance of Driving Automation

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Abstract

The vision of advanced information technologies to provide intelligent driving assistance and automation is currently being reconciled with humans operating these technologies in complex, real-time environments where sometimes unpredicted situations need to be mastered under time pressure. Could automation technologies be designed such that humans can collaborate with them more quickly and effectively to solve the Unpredicted? We investigate the utility of computational Human Mental Models for Engineering (HMMEs) toward developing automation systems that are more similar to human behavior. We validate and compare an HMME with a control model for a basic steering task and compare them both with driving data from 16 human drivers in a driving simulator. We report on the observed characteristics of the HMME to support multi-tasking, graceful degradation, and multi-sensory driver state integration.

Keywords: cognitive modeling; human-computer interaction; automation

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1. Introduction

Two views about the future of advanced automotive research and developments currently often contradict each other. On one hand, technological leaders focus on technological advances in computing power and machine-learning to expand automation to new markets and business opportunities. In the automotive domain, unsafe human driving is viewed as an argument for pushing toward intelligent driving automation. Similar discussions occur in aviation where highly automated drones should be flying in civil airspace and industrial information automation intends to change the roles of human workers. On the other side are human operational researchers who are confronted with the operational reality that humans not only cause accidents but also prevent an estimated 50 to 60 times more accidents than they produce (Zimmer, 2017). Also, that high level automation not only improves but also deteriorate operational performance (see e.g. Abbott, McKenney, & Railsback, 2013; Strauch, 2016). They also point to the fact that currently available automation often only addresses relatively predictable and controlled situations such as parking, lane keeping, or emergency braking but leave risky situations such as left turns in cities or complex intersections to the human driver outside (Bengler, Winner, & Wachenfeld, 2017).

The polarity of discussions resembles a schism between stakeholders with different perspectives, values, experiences and objectives. Technological solutions can be marketed and sold whereas the real operational problems may not be the ones that promise the largest profit margin. Also professional segregation contributes to the differences where engineers and human factors are often on different teams that are separated by education, job profile, and professional career models or where one discipline is hierarchically placed under another.

The figure below depicts several aspects of the schism between technological and human operational views. While automated systems are often intended to provide outputs that are similar to human behavior such as when steering a vehicle or playing chess, they achieve their performance in rather different ways. Also, automation processes are not usually visible to the human operator and are also difficult to predict. The consequence is the difficulty for the human to interact with the automation when the environment requires sudden transitions or when the automated system fails. It takes time for the human to reengage when the side markings disappear or when automation miscategorizes a white truck as billboard. This leads to the so called automation conundrum: the better automation gets, the harder it is for the human to reengage in case he is needed (Endsley, 2016; Eriksson & Stanton, 2016).

To ultimately bring these different perspectives together, we explore in this paper a human-centered approach that explores the use of human mental models for engineering (HMME) to make algorithmic solutions and humans more transparent to each other and therefore facilitate faster transition interactions between them. Also automation should be better able to adjust to the human if it knew its state and could offer adaptive functionality (see Parasuraman, Sheridan, & Wickens, 2000; Reinhart et al., 2017). Even if the automation fails, human

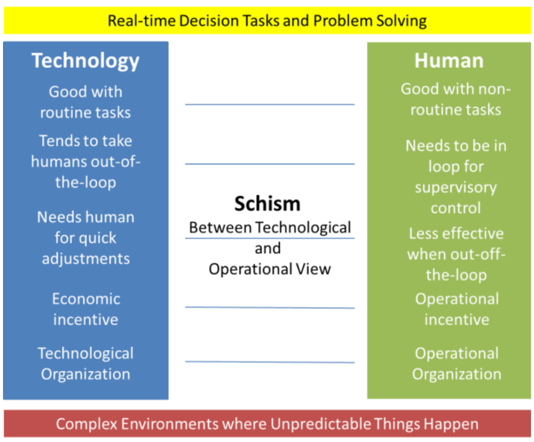

Figure 1 Schism between Technological and Human Operational Disciplines

operators and automation should be able to better collaborate when they are transparent (see e.g. Boy, 2013).

In the next section we introduce a cognitive architecture and model modeling approach that we compare with the performance of a control based steering model that is not based on psychological principles. We compare their performance and report on the main differences.

2. Psychological Steering Model

2.1. Human Processing Architecture

We selected a cognitive modeling architecture that we describe in more detail in (Moertl, Wimmer, & Rudigier, 2017) where we adopted a human cognitive architecture that is similar to the Model Human Processor (MHP) (Card, Moran, & Newell, 1986). The MHP was originally developed for human interface designs to summarize and combine psychological knowledge and principles and make them applicable for interface designs. Because of the similarity in purpose we adopted this approach to model specific driving tasks.
In the context of the driving task, the architecture consists of three types of processes that are interlinked with

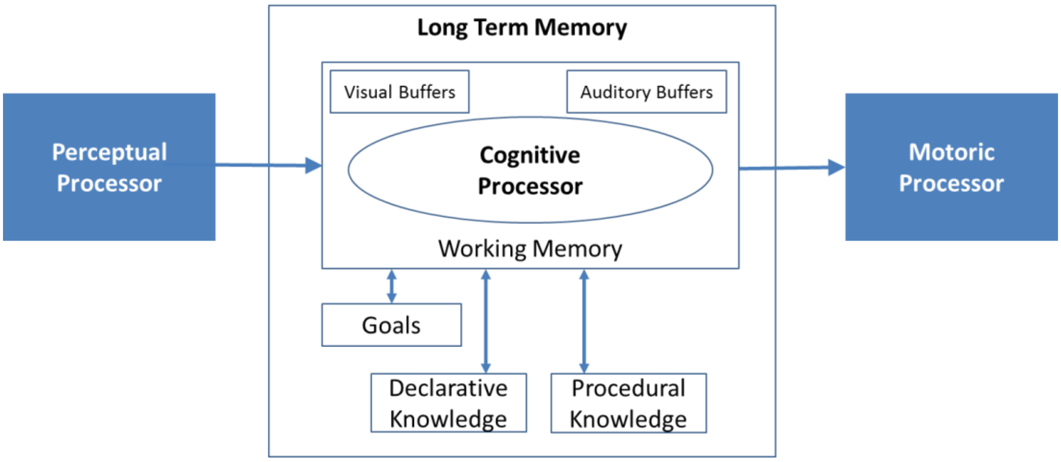

Figure 2 Adopted Elements for the MHP

basic constraints and limitations of human working and long term memory. The three process classes consist of perceptual, motoric, and cognitive processes. The cognitive processor updates information in discrete process cycles either from memory or from the perceptual processes about the external world and forwards them to the motoric processes that control (here only "steer") the vehicle. Each cycle takes a certain amount of time which determines the overall task duration and timing of interactions with the components. Parallel task performance of certain perceptual and motoric tasks is of course possible but was not implemented in our first steering model. That current model only considers steering but is not limited to that, also accelerating, braking, and other multitasking could be incorporated. The primary cognitive task is a kind of scheduling task that determines the next driving action ("Determine Driving Action"). While such scheduler can be theoretically quite complex and could dynamically adjust based on present and past conditions, we use only a very basic scheduler for our steering model. Once initiated, each actual driving (here only "steering" task) draws information either from the environment or from the long term or working memory, performs a cognitive process to process the information and then forwards the information to the next process, in our case always a motor process. For our task at hand, the transfer of information into memory is minimal because most of the information is visually available in the environment and just needs to be looked at so that explicit memory storage would be unnecessary.

2.2. Psychological Steering Model

Our psychological steering model is based on the ACT-R model by Salvucci (Salvucci, 2006; Salvucci & Gray, 2004) and is described in more detail there. The steering model is supported by empirical evidence gained from visual exclusion experiments where human drivers drove in a driving simulator and some areas of the visual scenery were obscured (Land & Lee, 1994). This psychological steering model utilizes both a far point and a near point for steering, both points are ahead of the driver's own vehicle. The near point is constant distance ahead and is located in the middle of the driving lane. The far point is further ahead and consists of the tangent point of any upcoming curve or the vanishing line of the road ahead on straight road segments. The far point could also be a vehicle ahead, but this situation was not modeled in our study described here. The far point is intended to steer the vehicle into and out of curves whereas the near point helps to center the vehicle on the driven lane. The point selections are to some extent psychologically validated in that they deteriorate driving significantly when covered, see e.g. (Land & Horwood, 1995; Land & Lee, 1994). Furthermore, they are based on information that is available to human drivers when negotiating a road.

We implemented this steering model in our cognitive architecture by only considering three cognitive processes that are executed in turn: a perception, a cognitive, and a motoric process. As initial condition, each process was assumed to take 50 ms see e.g. (Card et al., 1986), so that one full cycle of steering update would take 150 ms. We also updated the main parameters of the model. In (Salvucci, 2006), the three parameters were given as k_{far} = 16, k_{near} = 4.0, and k_I was 3.0. These parameters did not work at all in our model and we had to use different parameters, we found following parameters to work significantly better k_{far} = 1.6, k_{near} = 0.4, and k_I was 0.09 (the last factor being much weaker in our model than in Salvucchi's parametrization).

2.3. Control Based Steering Model

The lateral controller of the control based steering model is a preview controller, see (Rudigier & Horn, 2010). It does not minimize the current error of a signal in our case the position, but tries to reach a point in front of the vehicle, which means it minimizes the future error. The Controller has the structure of a cascade. The outer loop follows a given line, the track. In our case the middle of the lane is used, but it is possible to use an ideal line, computed by an appropriate optimization. The outer loop compares the positions and computes a demanded curvature. The inner loop takes a demanded curvature and controls the steering wheel angle. The inner loop consists of a feedforward control, which uses vehicle dynamic knowledge (Ackermann steering angle) (Rill, 2012), and a compensational feedback control (PI-Controller)
The first step of the position control is to estimate the reference position of the vehicle on the track xref. For that matter is s1 the distance travelled along the track and s2 is the lateral offset to the track. The second step is to determine the preview point xpre. This point is a preview distance spre in front the vehicle reference point on the track. The main part of the preview distance is a velocity depend part. It is the vehicle speed vx times the preview time tpreview. The minor parts are a constant distant s0 and the current lateral offset s2.

$$s_{pre} = v_x . t_{pre} + s_0 + s_2$$

Then the idea is that the vehicle should reach the preview point on a circle with constant radius r respectively a constant curvature κ. The circle is computed with 3 features, the 2 points xveh and xpre and the direction of the vehicle movement vxas tangent to the circle. This curvature is the demand curvature κdemand the inner loop takes as control variable.

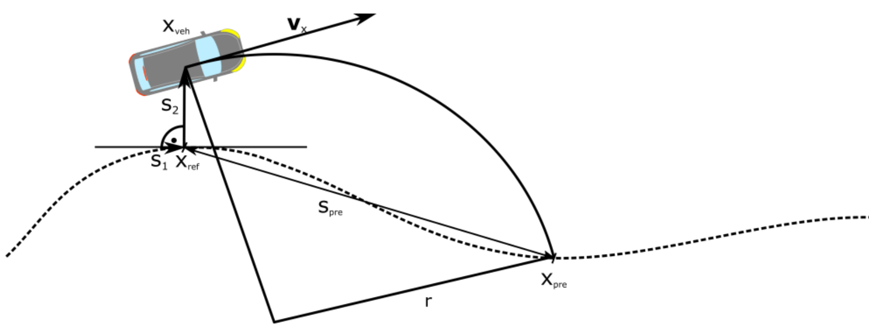

Figure 3 Schematic of Control Based Steering Model

$$\tilde{\mathbf{x}}^{Tr} := (\mathbf{x}_{veh}^{Tr} - \mathbf{x}_{pre}^{Tr}) = \begin{pmatrix} \tilde{x}_1 \\ \tilde{x}_2 \end{pmatrix}$$

$$\kappa_{demand} = \frac{1}{r} = -2\frac{(n_1\tilde{x}_1 + n_2\tilde{x}_2)}{(\tilde{x}_1^{\,2} + \tilde{x}_2^{\,2})}$$

3. Method

Sixteen human drivers drove in a fix-based driving simulator along a curvy road of 10 km length with two 4 m wide lanes. They drove at a preset speed of 90 km/h to isolate the steering component from other driving tasks. Since speed selection would have strong impact on the steering this would not have allowed us to assess steering per se.
All participants were between 20 to 60 years in age, 12 were male and 4 female. All had driver licenses and most drove between 5,000 and 20,000 km per year.
Participants were encouraged to drive how they would drive in the real world, avoiding oncoming traffic and staying as much as they really would on the right side of the road. To strengthen their desire to stay on the right lane, oncoming traffic was simulated as well. The constant speed of 90 km/h was perceived as fast and resulted in all drivers to laterally leave their lane at least once. However, all drivers were able to complete this scenario in their first trial without losing control.

4. Results

The figures below show the lateral deviation of the various drivers on the center of their lane. All drivers were driving at a constant speed of 90 km/h, the blue lines depicts their 90 percentile corridor (from 5% to 95 %). This serves to compare the two steering models. Positive numbers indicate deviations from the lane center to the left. The solid red line (PBSM50) depicts the results of the psychological based steering model based on a 150 ms cycle rate and the black dashed line depicts the control based steering model (CBSM). It can be seen that the control based steering model was almost always positioned within the human driving corridor whereas the red line shows several outliers. The variable width of the corridor indicates that human drivers varied considerably in their steering behavior from each other (e.g. at 1,500 m) but also converged (e.g. at 5,250 m).

To get a better understanding, the figure below shows a more detailed view of the steering behavior. There a

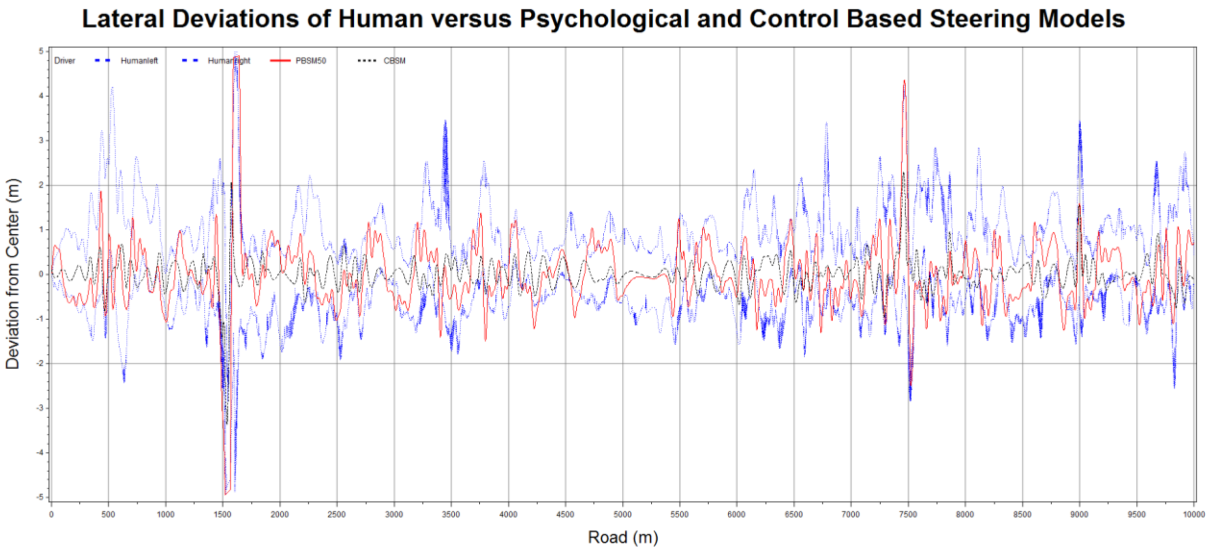

Figure 4 Lateral Deviations over the complete Distance (make bigger labels)

combination of a right curve (at 1,450 m), a left curve (at 1,540 m), and a subsequent right curve (at 1,600 m) resulted in the largest lateral deviation across the whole track. This was the case for human participants as well as for the two steering models. The combination of curves thereby increased the build-up of lateral deviations. It should be noted that the last right curve was initiated slightly earlier by the CBSM than most humans, and that the PBSM50 overshot significantly more than most humans.

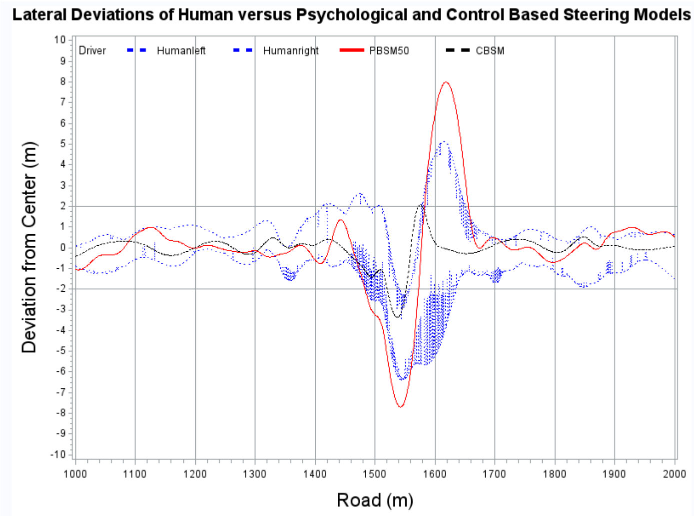

Figure 5 Lateral Deviations for a strong curve

The table below describes several metrics of the lateral vehicle movements. The correlations of the lateral deviations among all 16 drivers was r=0.5 (due to number of data points this and all following correlations are highly significant). The psychological steering models at higher update rate (3 to 150 ms) correlated slightly lower with the human drivers (btw r=0.36 to 0.42). The control based model correlated with the humans at r = 0.12. This indicates that first, the correlations of the lateral deviations indicate a useful measure (i.e. it is strongest among humans) and second, that it differentiates to some extent human steering from computer modeled steering and third that the psychological based model showed clearly more similarity to human driving than the control based model.
In terms of overlap with the 5 to 95 % human steering corridor, the control based model showed the highest overlap (87.4 % of its steering overlapped) whereas the psychological steering model overlapped slightly less with 79.4% to 80.2%). This indicates that the control based steering model was a "smoother" driver than most of the human participants and resulted in the least extreme deviations (following column).

Table 1 Summary of Lateral Deviation Metrics between Humans and Models

	Mean correlation (r) of lateral vehicle movement with human drivers	**Within Human Steering Corridor**	**Max Deviation (better than % of human drivers)**	**Steering Wheel Reversals (count)**	**Sum of abs. Steering Wheel Angle Changes**
16 Human Drivers	0.5	-	8.4 m	Mean=521 (std=115)	88 (std=22)
Psych. Model, 3 ms cycle (PBSM3)	0.42	80.2%	7.1 m (44%)	5036	98
Psych. Model, 75 ms cycle (PBSM75)	0.42	80.9%	7.4 m (32%)	2333	110
Psych. Model, 150 ms cycle (PBSM150)	0.36	79.4%	9.7 m (0 %)	473	166
Psych. Model, 210 ms cycle (PBSM210)	0.20	56.7%	12.6 m (0 %)	344	422
Psych. Model, 225 ms cycle (PBSM225)	0.19	50.1%	16.4 m (0 %)	338	469
Control Model (CBSM)	0.12	87.4%	5.4 m (88%)	1664	102

The last two columns in the table describe the steering performance itself. The count of steering wheel reversals represents the amount of opposing steering control movements. A higher count there may represent a "nervous" driver. Such "nervousness" turned out to be directly determined by the length of the cycle time within the

psychological model: the longer the cycle time, the less nervous the steering behavior (i.e. the fewer reversals). At cycle times of 50 ms and higher, the "nervousness" of the psychological model appeared to approach the human nervousness. The control based model exhibited a "nervousness" that was significantly above the one of human drivers. Finally, the overall sum of steering wheel angle changes showed that the human drivers generally steered less than all the models but that the psychological model at the highest update rate as well as the control based model came close to human performance.
The results lead us to conclude that drivers clearly use additional information when steering than what we captured in our psychological model. However, it was not our purpose to provide a detailed and accurate steering model. Rather we wanted to explore to what extent a relatively simple psychological model was able to capture human performance attributes that a control based steering model (without psychological assumptions) would not be able to capture. We were able to achieve a relative human-like driving behavior as well as human-like control input behavior (measured as steering wheel reversals) by simply adjusting the single parameter of cycle update time. The control based model was able to provide a very good overall steering behavior in terms of lateral deviations but was not able to capture human-like driving or steering input control behavior.

The findings have important positive effects concerning multi-task performance and graceful degradation. By changing the duration of the steering cycle, we could effectively insert additional processes. Also, because steering remained still functional even at slower cycle times, we see an effect that resembles graceful degradation.

5. Conclusions

A relatively simple HMME not only matched human performance remarkably well, it also in principle would allow for graceful degradation whereas the control based model did not. The control model would stop working if the input variables would degrade. While there are of course work-arounds to this but it represents an inherent advantage of the psychological model.

Another important aspect that the investigated psychological model captured was the one of multi-tasking: it would be easy to modify the psychological model to perform additional tasks (such as braking or looking for signs, see e.g. (Deml, Neumann, Müller, & Wünsche, 2008). We would only need to insert additional cycles for such tasks and observe that at some point the addition of additional tasks would deteriorate the main task of steering, similar to how drivers driving with cell-phones deteriorate their steering skills. However, the most important aspect of psychological driving models is that overall human parameters such as fatigue, distraction, or drowsiness could be modeled to impact all of the component processes at the same time. A fatigued driver for example, may show prolonged steering cycles but also slowed detection cycles for sign detection or braking. To capture such models, a common architecture needs to hold the various component models. Transfer effects could not be depicted in such models.

This is only our first study investigating HMME's for the use in the development of automotive automation. Much remains to be done to establish psychological driver modeling as a standard tool for human-centered automotive assistance developments. First we will need to confirm that our HMME are not only valid for data in simulation studies but also for real world driving. Then we need to test how the psychological model can be adapted to capture individual driver styles and states, such as, for example, driving distraction. Finally, we will extend our modeling to other driving aspects, specifically braking, distance keeping, and speed selections.

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