Understanding Human Driving Behavior through Computational Cognitive Modeling

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Abstract. As per an article in *The Economist*, someone, somewhere, dies in a road crash every 30 seconds, and about 10 people are seriously injured. Currently, there are about 1.3 million global deaths per year due to road accidents. Most of these deaths and injuries are caused by either factors that are internal to the driver (e.g., driving experience), or due to factors that are external to the driver (e.g., track complexity). However, currently little is known on how these factors influence human driving behavior. In this research, we investigate the role of an external factor (track complexity) on human driving behavior through computational cognitive modeling. Eighteen human participants were asked to drive on two tracks of the same length: simple (4 curves; N=9) and complex (20 curves; N=9). Later, we used two computational models to fit the human steering control data: an existing near-far-point model and a new heuristic model involving tangent and car-axis angles and a position-correction term. Our modeling results show that the fit of the heuristic model to human data on the simple and complex tracks was superior compared to that by the near-far-point model. We highlight the implications of our model results on human driving behavior.

Keywords: Road accidents, external factors, heuristics, human driving, computational cognitive modeling.

1 Introduction

According to *The Economist*, every 30 seconds someone, somewhere, dies in a road accident, and about 10 people are seriously injured [1]. World Health Organization (WHO) estimates that currently 1.24 million people die due to road accidents world over and this number is expected to increase to 2 million by 2030 (WHO, 2014). More worrisome is the fact that 91% of the world's deaths on the roads occur in low- and middle- income countries (like India), even though these countries have approximately half of the world's vehicles [7]. Young adults aged between 15 and 44 years account for 59% of global road traffic deaths and it is very likely that a number of these road accidents are due to external factors (like track complexity and prevailing weather conditions) [7]. Thus, it is important to investigate the role of these factors on the driving behavior of young adults in the low- and middle- income countries.

R.C.-H. Hsu and W. Shangguang (Eds.): IOV 2014, LNCS 8662, pp. 56–65, 2014.

However, up to now, only little research has taken place that investigates the role of external factors on the decision making of a driver in a vehicle. Cognitive Science is concerned with understanding the processes that the brain uses to accomplish complex tasks like learning, thinking, problem solving and decision making. The goal of a cognitive model is to scientifically explain one or more of these basic cognitive processes or interaction between them [9]. In this regard, driving is one of the complex tasks for which researchers have developed variety of models to simulate human driving behavior. Some researchers have used Hidden Markov Models (HMMs) to characterize and detect driving maneuvers [10]. Beyond HMMs, rule-based models have been proposed as a promising approach towards modeling human driving behavior [11].

Among the rule-based models developed more recently, Dario Salvucci has presented a model for human driving using a popular cognitive architecture [2]. This model has been used for studying driving behavior and distraction during driving [2]. In this paper, we consider a Near-Far-Point model (section 3.1) and this model is the same model as presented by [2].

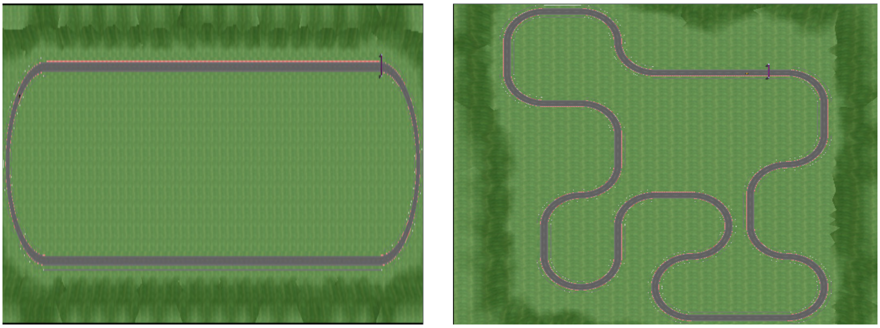
Beyond the Near-Far-Point model, research has shown that simple heuristic rules seem to perform very well to account for human decision making in a wide variety of decisions tasks [3]. Although heuristic models have been tested in a large number of decision tasks, yet there is less evaluation of such models in complex decision tasks like driving. Thus, we develop a heuristic model (section 3.2) involving tangent and car-axis angles and a position-correction term. The steering-control equation used in this model tries to minimize the car deviation from the center of the track and the model tries to drive the car parallel to the track axis.

In this paper, we investigate the role of track complexity on a person's driving and further model the human driving behavior computationally. We model track complexity in terms of the number of curves on the driving track. Specifically, we take two tracks, simple (with 4 curves) and complex (with 20 curves) and collect human driving data on these tracks. Given that a high 59% of road accidents involve younger population, participants in our study were young people with age ranging from 21 to 24. Furthermore, given the lack of studies in low- and middle- income groups in developing countries, we took participants from the hill state of Himachal Pradesh (in Northern India). The Himachal's terrain is also complex as people drive on roads with a number of mountain curves and steep slopes. For the purpose of modeling human driving, we use the Near-Far-Point model and the heuristic model on a simple and a complex track. Here, we evaluate the ability of these models to steer vehicles in ways similar to those done by humans. We close the paper by highlighting the implications of our models and their mechanisms for human driving behavior on simple and complex tracks.

2 Methods

2.1 Experimental Design

Participants were randomly divided to perform on one of the two driving scenarios: a track having 20 curves (complex; N = 9 participants; see fig. 1.a) and a track having 4 curves (simple; N = 9 participants; see fig. 1.b). Both the tracks were of equal length and width (length = 2,200 meters; width = 10 meters). The average time taken by participants to complete the simple and complex tracks was 1.5 and 2.5 minutes, respectively. In both the track conditions, the goal for participants was to drive in a way that their car remains at the centre of their track as much as possible.



(a) (b)

Fig. 1. (a) Simple Track Map (4 curves) (b) Complex Track Map (20 curves)

2.2 Simulation Environment

We used The Open Racing Car Simulator (TORCS) [4], an open-source driving simulation program written in the C++ language, for running the study with human and model participants (see fig. 2). The tracks were created using the TORCS's *track editor* program. The track editor allows designing of the track (i.e., a track's shape, length, and elevation). Additional features like track's slope, background and coefficient of friction were added using the trackgen utility of TORCS.

Fig. 2. TORCS Simulation Environment

2.3 Participants

Eighteen undergraduate students from various disciplines at Indian Institute of Technology Mandi participated in this experiment. Ages ranged from 21 to 24 years (average = 21.5 years; st. dev. = 0.61 years). Around 70% of the participants possessed a valid driving license. The average driving experience of the participants was around 1.5 years. All participants received a base pay of INR 10 for their participation.

2.4 Procedure

Participants were given full instructions about the car controls buttons and the tracks before the experiment. Before the actual driving began, participants were given some training in which they played on a demo track. The purpose of the training was to make participants familiar with the simulation environment and the car controls. Once the participants acknowledged that they had fully understood the car controls and task goals, they were allowed to drive on the complex or simple tracks. The assignment of participants to simple and complex tracks was done randomly. Finally, participants were reminded that they have to drive in a way that their car remains at the centre of their track as much as possible.

3 Implementation and Execution of the Models

Both the Near-Far-Point model and the Heuristic model were implemented in Visual C++, i.e., within the TORCS environment as driving bots.

3.1 Near-Far-Point Model

The steering control in this model centers on a new steering model [8] that utilizes "two-level" control based on the perception of two salient visual points ([5], [6]). First, the *near point* represents the vehicle's current lane position, used to judge how close the vehicle is to the center of the roadway (see fig. 3). The near point is characterized as a point in the center of the near lane visible in front of the vehicle, set at a distance of 10 m from the vehicle's center. Second, the *far point* (see fig. 3) indicates the curvature of the upcoming roadway, used to judge what the driver should execute to anticipate the upcoming curvature. The far point is characterized as one of two targets: (a) the vanishing point (up to a maximum distance equivalent to 3 seconds of time headway) of a straight roadway; or, (b) the tangent point of an upcoming curve.

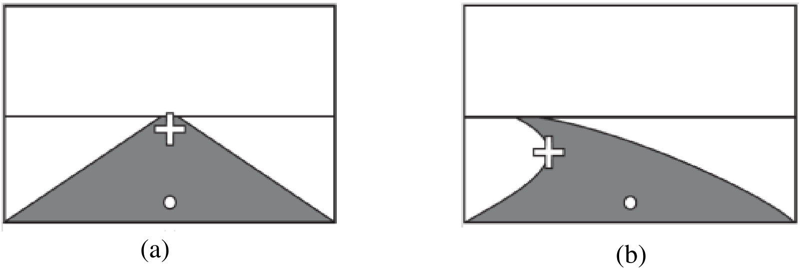


Fig. 3. Near and far point on (a) straight track (b) curve (" ○" represents near point and "+" represents far point) [2]

The model used the following equation for steering control:

$$\Delta\Phi = k_{far}\Delta\theta_{far} + k_{near}\Delta\theta_{near} + k_I\theta_{near}\Delta t$$

Where,

$$\Delta\Phi = change\ in\ steering\ angle$$
$$\theta_{near} = current\ near\ angle\ (see\ fig. 4)$$
$$\theta_{far} = current\ far\ angle\ (see\ fig. 4)$$
$$\Delta\theta_{near} = change\ in\ near\ angle\ (see\ fig. 4)$$
$$\Delta\theta_{far} = change\ in\ far\ angle\ (see\ fig. 4)$$

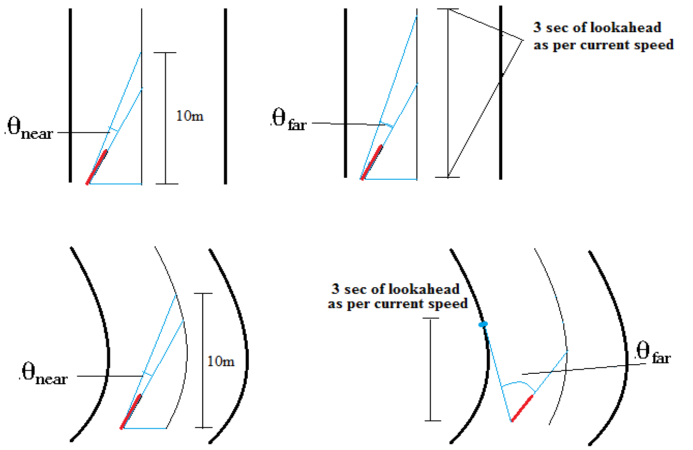


Fig. 4. θ_{near} and θ_{far} angle on a straight track and on a curve (red/bold line represents car axis)

3.2 Heuristic Model

The second model we have implemented follows a heuristic rule, where the goal is to keep the car at the center of the track. In the Heuristic model we calculate the angle that car axis makes with the tangent to the track axis and uses this information along with a position correction term to control steering.

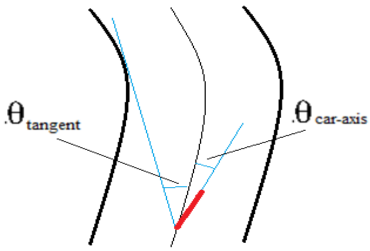


Fig. 5. $\theta_{tangent}$ and $\theta_{car\text{-}axis}$ angle on a sample track

The model used the following equation for steering control:

$$\Phi = \theta_{tangent} + \theta_{car-axis} + pos\_correc$$

Where, $\Phi = new\ steering\ angle$

$$\theta_{tangent} = angle\ that\ tangent\ to\ the\ track\ makes\ with\ the\ track\ axis$$

$$\theta_{car-axis} = angle\ that\ tangent\ to\ the\ track\ makes\ with\ the\ car\ axis$$

$$pos\_correc = \frac{car\ distance\ from\ the\ center\ of\ the\ track}{width\ of\ the\ track}$$

3.3 Acceleration and Braking Control

Our main focus in this paper is on steering control. We made a number of simplifications for acceleration and braking control in the models. Both the model and humans try to drive the car with the maximum possible speed. On a straight track, the car uses full acceleration. On a curve we use following equation to get the allowed speed:

$$\frac{mv^2}{r} = mg\mu$$

$$v = \sqrt{\mu r g}$$

Where,

$$m = car\ mass$$

$$v = allowed\ speed\ on\ the\ approaching\ curve$$

$$r = radius\ of\ approaching\ curve$$

$$\mu = coefficient\ of\ friction$$

3.4 Model Execution

Both the Heuristic and Near-Far-Point model were made to run on the simple and complex track once. The driving data was collected for each of the model on both the track. The models were not given any training but the parameter values for the Near-Far-Point model were set to 8, 8 and 3 for k_{far}, k_{near} and k_I respectively. The model parameters values were determined experimentally by a trial-and-error procedure till the models drove the car like humans did. There were no parameters in the heuristic model.

3.5 Human and Model Data

We recorded the car steering angle for each meter of the track covered by both model and human participants. Therefore, for each participant, we had a vector v of length 2,200 where v_i is the steering angle of the car at a distance of i^{th} meter from the start of the track. We had 9 such vectors for each of the track (simple and complex). We calculated average steering control for each track by taking the average of the 9 participant's data for that track.

The steering angle values ranged from $-\pi$ to $+\pi$ which was normalized to the range -1 to +1. The negative value for steering angle means steering towards the right side of the track and the positive value means steering towards the left side of the track.

4 Results

The models' steering control was compared with average human steering control on both the tracks. We used Mean Square Deviation (MSD) and Correlation coefficient (r) as the two measures to compare model performance with respect to human steering control.

4.1 Comparison of Steering Control on Simple Track

Fig. 6 shows that Heuristic model correlates slightly better with human steering control than Near-Far-Point model on simple track. Since there were two major right curves on this track, we find more negative steering control values in the graph (negative steering control value means steering to the right side of the track while driving clockwise). The two models do not differ much in MSD values with respect to human steering control.

4.2 Comparison of Steering Control on Complex Track

Fig. 7 shows that the Heuristic model correlates significantly better to human steering control as compared to Near-Far-Point model. The MSD value for Heuristic model is also slightly better than the Near-Far-Point model.

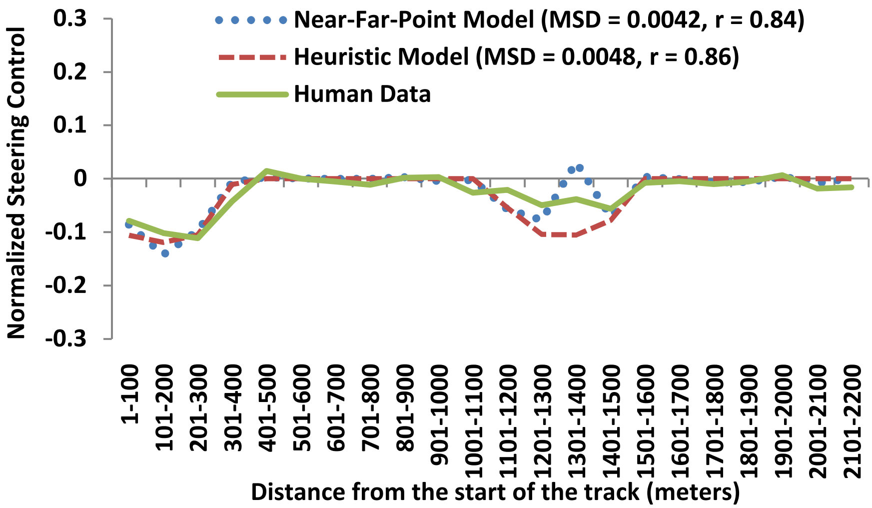


Fig. 6. Steering Control on Simple Track

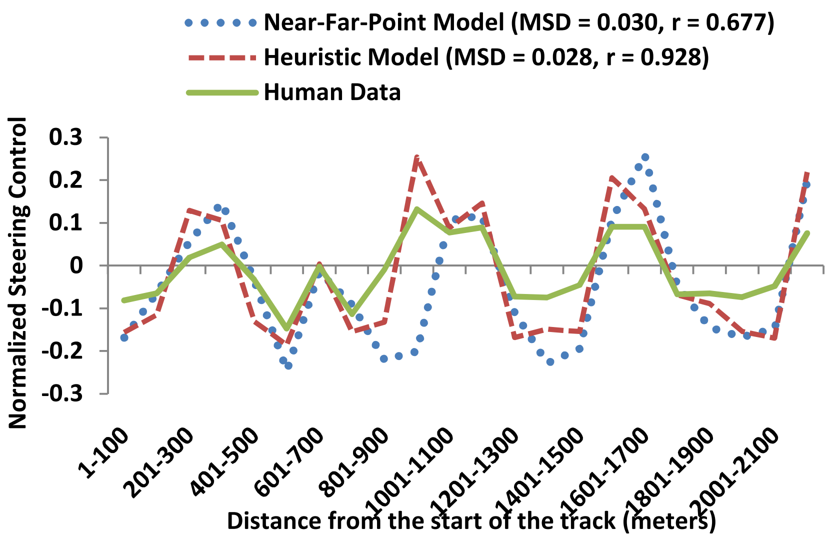


Fig. 7. Steering Control on Complex Track

5 Discussion and Conclusion

Global death rate due to road accidents is very high and is expected to increase in the coming future [7]. Most of these accidents are likely due to the effect of external factors like track complexity or climatic condition on human driving. However, currently, not much research has been carried out in studying the effect of such external factors on human driving behavior. In this paper, we have tried to bring into consideration track complexity as an external factor effecting human driving.

As expected, the performance of human participants was poor in complex track condition compared to simple track condition. That is because human participants were able to drive more smoothly in case of simple track. The steering control of both the models was almost equally close to human steering control in case of simple track; however, their performance varied in case of complex track.

The Near-Far-Point model controls the steering using two perceived visual points namely the near point and the far point. The model steering control graphs show that the model was late in negotiating curves as compared to human participants. This delay is much more visible in case of complex track and that is, perhaps, the reason for poor performance of the model (the complex track have significantly more curves).

The heuristic model basically tries to follow the track axis by steering along the tangent to the track. The role of the position correction term becomes more important when the model tries to steer along a curve. During curve negotiation, the car position shifts from the center of the track towards the edge of the track (right edge in case of left turn and left edge in case of right turn). Further, the better correlation of heuristic model data with human data can be because of the fact that similar shift in car position is also seen for human participants on curves. By varying the weight of the position correction term we can control this shift of the car. This opens some scope for improving the heuristic model by giving weights to the position correction and angle correction terms, which is the focus of our present and future research.

In this research, we used TORCS to simulate the driving scenarios. TORCS has a 2-D visual display and the output is shown on a standard desktop PC monitor. With this simulation environment participants cannot actually feel the ups and downs of the track as they are not physically present in a car; but, they can see it on the monitor. Although up to what extent such hardware limitation affect the presented results is hard to quantify but none of the models presented in this paper take into account any parameter which is directly affected with such limitations of the simulation environment.

Most human drivers drive on some fixed tracks and hence are used to those driving scenarios. We can broadly classify such driving scenarios as simple or complex based on the driving complexity of those tracks. Since drivers occasionally drive on some not-common tracks, it can be helpful to study the effect of such changes in driving scenarios on human driving. In our ongoing research, we are trying to study the effect of such changes by making the model calibrated on simple track to run on complex track and vice versa. These and other interventions form the next steps in this ongoing research program.

Acknowledgements. The students are very thankful for the guidance provided by Prof. Varun Dutt on this project. Also, we are grateful to the computational resources provided by the Indian Institute of Technology, Mandi, India for this project.

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