DRIVER BEHAVIOR MODELING USING HYBRID DYNAMIC SYSTEMS FOR 'DRIVER-AWARE' ACTIVE VEHICLE SAFETY

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ABSTRACT

Modern safety systems are transforming vehicles from human-controlled passive devices into human-centric intelligent/ active systems. There is a wide range of systems from fully autonomous vehicles to human-augmented control devices which have emerged in this field. In current trends, co-operative active systems have the driver in the decision and control processes are favored for their 'human-centric' approach. However, these systems pose a challenge in the design process since obtaining reliable human behavior models are difficult due to the complex nature of driving task in a dynamic traffic environment. From a control theory perspective, driving can be seen as a combination of continuous control segments combined with a discrete decision process. In this study, we will model driver behavior utilizing Hybrid Dynamic Systems (HDS) combining stochastic modeling tools (such as Hidden Markov Models) with control theoretic models. A subset of CAN-Bus and video channels from a demographically balanced UTDrive Corpus containing video (2 channels: driver and road scene), audio, and CAN-Bus signals of realistic driving sessions for 77 drivers are used to verify HDS models of lateral and longitudinal control behaviour. The model is used to suggest 'driver-aware' active safety system capable of assisting the driver in several lateral control tasks; lane-keeping, curve-negotiation and lane changing.

INTRODUCTION

Understanding, analyzing and modeling human driver behaviour in a realistic way is extremely important in enhancing the safety of the vehicles. In a study supported by NHTSA, it was found that driver error was the major contributor in more than 90% of the crashes examined **[1].** Cooperative driver assisting systems (DAS) or human-centric active vehicle safety (AVS) presents an opportunity to prevent/avoid some of these accidents. These promising technologies can be realized with an associated cost in research and implementation trials. The difficulty arises because of the co-operation requirement with human and the human driving behavior is a poorly understood subject. The dynamics of driving come from three sources: driver, vehicle and the environment. Although, several systems exist to improve the vehicle dynamics and handling, the driver behaviour and the role of the environment remained the overlooked components of the safety problem until now. The vehicle component was the first one to be examined and improved thanks to precise non-linear, continuous vehicle models and numerical simulations. The uncertain, non-stationary, highly dynamic, stochastic or discrete event-driven characteristics of driving comes mainly from human driver and traffic context imposing on the driver to react in a certain way. These characteristics of driving are more difficult to model, understand and control and they conceal the underlying cause of most of the accidents. Therefore, future active safety systems need to take driver behaviour and traffic context into account for efficient accident avoidance/ prevention. In other words, AVS or DAS should be 'driver-aware' and 'context-aware'. The context awareness can be achieved by monitoring and analyzing the micro-traffic environment around the host-vehicle. The sub-systems of such a system may include a computer vision system for lane mark, vehicle and pedestrian detection and tracking together with road sign recognition. In recent years, such systems are designed and reported with great prospects of being beneficial **[2, 3].** For an example in context-aware systems, one can refer to **[4].** In this paper, the focus is driver-awareness to be able to design human-

centric AVS and adaptive DAS with particular interest in lateral control.

The paper is organized in the following way. First, a critical survey of driver behaviour modeling approaches is given identifying the need for a hybrid realistic model specifically designed for the use of DAS or AVS development. In this section, also the driver models are categorized to give more insight into the problem of which model is more appropriate for what type of applications. Next the main frame of the proposed driver model is presented together with the theoretical methods and implications from human factors engineering studies. It is extremely important that the model delivers both a theoretical framework which is mathematically tractable and an explanation of physical and cognitive processes involved in control strategy of human driver. The proposed model is divided into lateral and longitudinal parts; however, these two models are coupled and the full model is given next. After construction of the theoretical framework supported with experimental observations from previous studies the model is validated using driving data which is collected in real traffic environment. Finally, the advantages and limitations of the proposed model are presented in the conclusion section.

Critical Survey of Driver Modeling Approaches

Driver models are needed for different purposes from assessing vehicle dynamics to monitoring driver status or just simply to better understand the underlying dynamics in driver behaviour. In addition to several types of need for driver models, each related research field emphasizes a different aspect of the driver (i.e. cognition, perception, processing reaction, control). Driver modeling approaches can be roughly divided into following groups: human factors, control theoretic, stochastic/ non-linear and hybrid models. A schematic of driver modeling approaches is given in Fig.1.

It is noticeable that especially lateral control has been modeled by control theoretic approach due to its continuous characteristics. An example of this type of driver model can be found in [5] employing control theoretic approaches for lateral control behaviour. This model includes driver's delays, feedback in form of lateral position error, and neuro-muscular response taken from an earlier work on flight-pilot modeling studies [6].

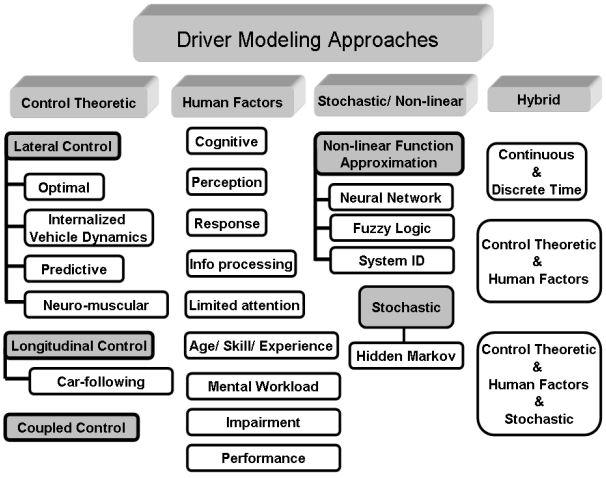

Figure1. A schematic grouping of driver modeling approaches

Other noticeable and widely known control theoretic models for lateral control can be listed as McRuer's model [7] containing anticipatory, compensatory and precognitive control for better representation, and MacAdam's optimal preview control model [8]. The common property of these models is that all of them agree with cross-over model [9] which can explain single loop manual tasks performed by humans. The advantage of control theoretic models is that they give a physical/causal relationship between the input and output variables. In this aspect, the control theoretic models may give insight into driver behaviour. Although some of them ignore the non-linearity, they provide a sound mathematical framework in analyzing driver behaviour in control level. However useful they may be, it should be noted though that most of the control theoretic models are designed to be used in improving vehicle dynamics and handling quality, but not for explaining driver behaviour or design of co-operative systems. These driver models have low fidelity in reproducing driver control commands that have similar characteristics to a real driver in time-domain. The main reason of this infidelity is that these models are designed for tracking the center of the lane or road-median almost perfectly, whereas a real driver would deviate from the median more as demonstrated by [10]. The human driver allows the lateral position error to build up until it reaches a threshold that driver perceives it as a deviation and makes correction. This is known as

complacency, and it is also related to the fact that most of the sensory input that driver uses is not instant measurement of the lateral position but visual cues and vestibular feedback. In order to perceive and process this feedback takes time and it is not instantly used by the driver but delayed. A similar behaviour is observed also in longitudinal control while car-following and was taken into account in Lubashewsky's rational driver model [11]. Since the existing control theoretic models cannot account for complacency, [10] used driver simulator data to identify lateral control model of the driver using system identification tools and ARX models. In [12] driver steering model was identified with particular interest in structured and unstructured model uncertainty. Their work is important as they imply that the structured uncertainty can be used to monitor driver and use adaptive control framework to address the risk from driver performance deterioration whereas the unstructured certainty coming from unmodelled nonlinearity can be addressed by robust control. The non-stationary, uncertain and non-linear nature of driver behaviour was understood by other researchers too. In [13] cascaded Neural Networks (NN) are used with some flexibility employing Extended Kalman Filters (EKF) for update and variable activation in newly added neuron layers. HMM is used to measure the stochastic similarity [14] between the model output and real driver data. This measure is reported to be better than mean square error since the nature of driving is stochastic and we should be looking for main trends in the data not the exact match in numerical sense. In fact, Markov Chains were used to sequence a bank of Kalman Filters for predicting driver actions using preparatory input actions [15]. Hidden Markov Models (HMM) were used to learn human action and transfer human skills for tele-robotics applications [16]. HMMs has later proved to be a very convenient tool in modeling driving control inputs or observed vehicle dynamics and it is widely used to model driver behaviour in several frameworks. In [17] HMM framework is used to recognize different driver maneuvers and [18] used a similar framework for a top to bottom approach in search for 'drivermes', the meaningful smallest unit of driving signals. In our previous studies, HMMs were used to recognize maneuvers and detect the driver distraction or driver faults using a hierarchical approach [19, 20]. Although HMMs are very powerful and can reproduce the driver behaviour with high stochastic fidelity, we lack the capability of explaining the physical/causal meaning of the resulting models.

In addition to mathematical approaches a large group of driver models are derived in human factor engineering. These models consider cognitive, perceptual, and neuro-muscular limitations of human. These models provide very important insight into driver behaviour especially explaining some of the uncertainty, delay and non-linear characteristics. In addition to this, the control theoretic and stochastic models tend to use measured (i.e. observable) data and they often stay in the control level modeling. The tactical and strategic levels in Michon's hierarchical model [21] cannot be modeled with control theoretic or stochastic approaches. [22] proposed ACT-R cognitive model of the driver modeling the information processing and inherent delays of the human cognitive system. As it can be seen, the models derived from human factor engineering are very useful; however, they do not represent a full driver model. Therefore, combined model structures including control aspects, stochastic processes and cognitive capabilities are proposed. These models can be described as 'hybrid' models. This approach is relatively new and very promising for obtaining comprehensive models. For example, [23] described human perception process by a discrete event technique the execution part is modeled by general predictive controllers and the velocity control is represented by a finite state machine to reveal its discontinuous control dynamics. In [24], researchers used a controller switching model for modeling collision avoidance maneuver employing piecewise polynomials. Furthermore [25] used similar approach for modeling vehicle following task dividing the car following control into four different modes. Another model using switching control is used by [26] employing simple control laws and defining the switching rule by a knowledge base.

In this paper, a hybrid driver model combining stochastic, control theoretic and human factor approaches is proposed. The main aim is to obtain a comprehensive driver model including all available knowledge and state-of-art methods in driver modeling for development of human-centric active safety.

Proposed Driver Model

The proposed driver model includes a stochastic longitudinal velocity control model coupled with a realistic control theoretic lateral model based on [5]. Although the lateral model is based on a limited

control theoretic model the complacency phenomena is represented by delaying the position feedback to represent the human limitation. The vehicle model used in Hess model is updated by the velocity supplied by longitudinal model therefore coupling the control strategies. This approach is more realistic than assuming the vehicle longitudinal velocity constant in the lateral model. The main aim of the model is to obtain a driver-adaptable (tunable) and realistic lateral control model coupled with longitudinal dynamics to use in DAS and AVS development. In next sections longitudinal, lateral control strategies are given and finally the full driver model is explained.

Longitudinal Control Strategy

Longitudinal control strategy of driver is inherently discontinuous since the control is achieved by changing between gas and brake at discrete times. In addition to this, the underlying control rule cannot be easily revealed without including the micro-traffic context (i.e. car following, congestion or free driving). For this reason a stochastic modeling approach such as HMM can help us learn the velocity control of driver from observations.

HMM is a naturally suitable tool to model driver behavior for the following reasons:

- HMMs can model the stochastic nature of the driving behavior, providing sufficient statistical smoothing while offering effective temporal modeling,
- The variations in the driving signals across the drivers can be modeled (driver identification) or suppressed (driver-independent route models) according to the requirements of the desired task.

HMMs can be characterised by:

(1) A set of distinct states $S=\{S_i\}$ with q_t denoting a state at time t, with number N

(2) The initial state distribution $\Pi=\{\Pi_i\}$

(3) The state transition probability distribution $A=\{a_{ij}\}$

(4) Each state can produce one of M distinct observation symbols from the set $V=\{V_i\}$

(5)The observation probability distribution function in state j, B_j

Therefore, HMMs can be written in the form of a vector $\lambda=\{N,M,A,B,\Pi\}$. For further information, readers should refer to [27].

In modelling velocity control behaviour of human driver by HMM we used a topology seen in Figure 2. This model represents three states in velocity control: constant, increasing and decreasing. The transitions between any of the two the states out of three are possible and a dynamic variable indicated as *d* can be retrieved as the model stays at one state in certain time. These waiting times can account for certain control strategy in speed control adopted and the state transition probabilities give insight into how several control strategies are switched to obtain a plausible speed control. The emission output of each state is represented by a continuous function to model the speed profile with parameters of a line.

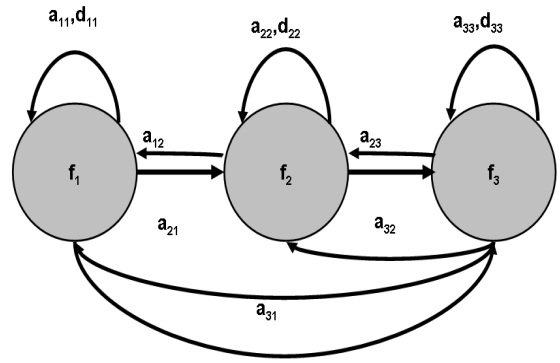

Figure 2. HMM topology for velocity control

Lateral Control Strategy

The lateral control strategy of driver is modeled using a modified control theoretic model based on Hess's work [5]. Two improvements to this model are:

(1) introduction of a dead zone which filters out the lateral position errors below a certain threshold band accounting for complacency of drivers

(2) replacement of the constant velocity LTI model of lateral vehicle dynamics model with LTV model updating the speed and recalculating the model with the inputs from longitudinal velocity model.

The modified lateral driver model and complacency term is shown in Figure 3. Some of the constants seen in the block diagram of lateral driver model are taken from [5], however, the tuning parameters of ω_c (cross over frequency) and time constants T_1, T_2 and T_3 are explored in a range to better fit the model to real driver steering signals. In addition to this, the complacency term dead-zone band changes from one driver to another. Some drivers are more sensitive and correct the errors more often while others let the

lateral position error to accumulate. This band can be related to experience and one's confidence in their driving skills.

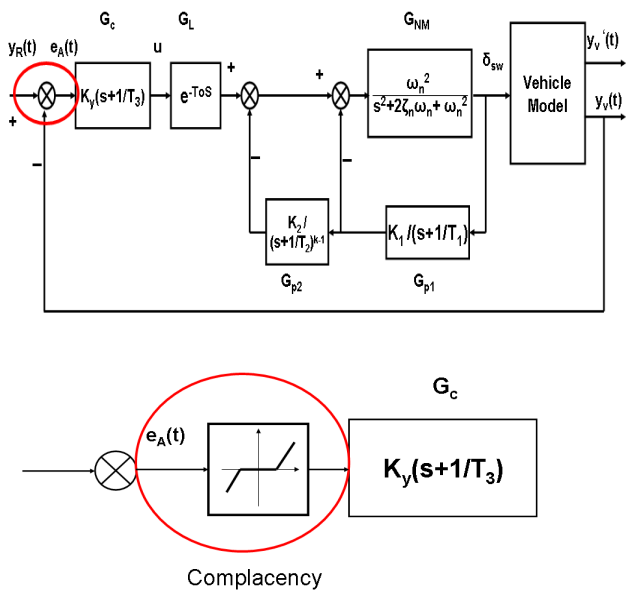

Figure 3. Driver model for lateral control

The vehicle model used is known as 'bicycle model' [28] for calculating the lateral dynamics of the vehicle and linearized at a constant longitudinal velocity. In order to obtain more realistic behaviour from this model, it is updated by changing longitudinal velocity at discrete time steps. Therefore the resulting vehicle model is a hybrid system containing a set of linear-continuous time, time-invariant models of vehicle switched by a discrete update driven by longitudinal speed changes. As a consequence the resultant model is non-linear and closer to realistic vehicle response. The model inputs are steering wheel angle, longitudinal vehicle velocity and outputs are lateral acceleration and side slip angle. The lateral acceleration output of this model is used to calculate the lateral speed and finally lateral position of the vehicle employing numerical integration by trapezoids. The variables of model are given in Table 1.

Table1. Variables of vehicle model

Symbol	Meaning
c_f or c_r	cornering stiffness coefficients for front and back tire
J	Yaw moment of inertia about z-axis passing at CG
m	Mass of the vehicle
r	Yaw rate of vehicle at CG
U	Vehicle speed at CG
y_c	Lateral offset or deviation at CG
τ	Wheel steering angle of the front tyre
α_f or α_r	Slip angle of front or rear tyre
β	Vehicle side slip angle at CG
ρ_{ref}	Reference road curvature
ψ	Yaw/ heading angle
ψ_d	Desired yaw angle
ω	Angular frequency of the vehicle

The equations of motion using the variables given in Table 1 are presented in equations (1-2).

$$\begin{bmatrix} \dot{\beta} \\ r \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \beta \\ r \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \end{bmatrix} \tau \qquad (1)$$

Where, in a format $\dot{x} = Ax + Bu$,

$$\dot{x} = \begin{bmatrix} \dot{\beta} \\ r \end{bmatrix}, \; A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, \; B = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}, \; u = \tau$$

And in the output format, $y = Cx + Du$

$$\begin{bmatrix} a_s \\ \beta \\ r \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \beta \\ r \end{bmatrix} + \begin{bmatrix} d_1 \\ 0 \\ 0 \end{bmatrix} \tau$$

Where, $y = \begin{bmatrix} a_s \\ \beta \\ r \end{bmatrix}, C = \begin{bmatrix} c_{11} & c_{12} \\ 1 & 0 \\ 0 & 1 \end{bmatrix}$ and $D = \begin{bmatrix} d_1 \\ 0 \\ 0 \end{bmatrix}$.

The elements of the matrices are given explicitly here:

$$a_{11} = -(C_f + C_r)/mU,$$
$$a_{12} = -1 + [(h_r C_r - h_f C_f)/mU^2]$$
$$a_{21} = (h_r C_r - h_f C_f)/J, \; a_{22} = -(h_f^2 C_f + h_r^2)/JU$$
$$b_1 = C_f/mU, \; b_2 = h_f C_f/J$$
$$c_{11} = -[(C_f + C_r)/m] + [l_s(h_r C_r - h_f C_f)/J]$$
$$c_{12} = [(h_r C_r - h_f C_f)/mU] - l_s[(h_f^2 C_f + h_r^2 C_r)/JU]$$
$$d_1 = [(C_f/m) + l_s(h_f C_f/J)] \qquad (2)$$

Combined Full Driver Model

As mentioned before, the lateral and longitudinal models are coupled via the update of vehicle model using the velocity outputs of HMM model for driver velocity control. HMM model uses 1-2 sec history of velocity from CAN-Bus to predict the future sequence. Therefore the vehicle model in lateral driver model is updated before the driver input to this model reaches for new calculation of lateral position. The longitudinal and lateral control strategies are closely related in a two-way relationship:

(1) In higher speeds, the driver is expected to correct the steering wheel with smaller magnitudes.
(2) In sharp turns, the driver might prefer to reduce the longitudinal speed and during the lane change towards a faster lane the speed should be increased to avoid interference with the upcoming traffic.

The combined model has non-linear and stochastic properties together and accounts for the complacency of human driver. The next session reports on model verification using real CAN-Bus data.

Selected Model Verification Results

In model verification, CAN-Bus data is used to assess the model in its fidelity to reproduce steering wheel angle and vehicle speed commands. The model was able to reproduce the expected signals with some drawbacks and advantages:

(1) The steering wheel angle contained a high frequency term
(2) The identification ok K and T parameters in lateral control require several iterations. However, once it is set, these parameters can represent driver characteristics or status.

The model is capable of reproducing steering wheel angle commands in lane keeping, curve negotiation and lane change profiles. The application of complacency zone in the model was found very useful since it gives the safety margin of the driver in the lateral control task and it is a driver-specific characteristic. In addition to this internal delay due to processing and the gain of feedback from proprioreceptive system are explored. It was observed that increasing the internal delay from 0.15 (nominal) to 1-15 sec interval representing driver distraction caused the error building in lateral position and the vehicle drifted. It was also observed that increasing the gain from proprioreceptive feedback reduces the errors in lateral position tracking. This is also observed during the experiments; the novice drivers relying on only visual feedback have larger errors while the expert drivers depend on the feedback from neuro-muscular system (i.e. thus their gain is higher in that component) and have less lateral positioning errors. The effect of vestibular/proprioreceptive feedback gain is represented from validation experiments performed in Simulink (Figure 4 and 5).

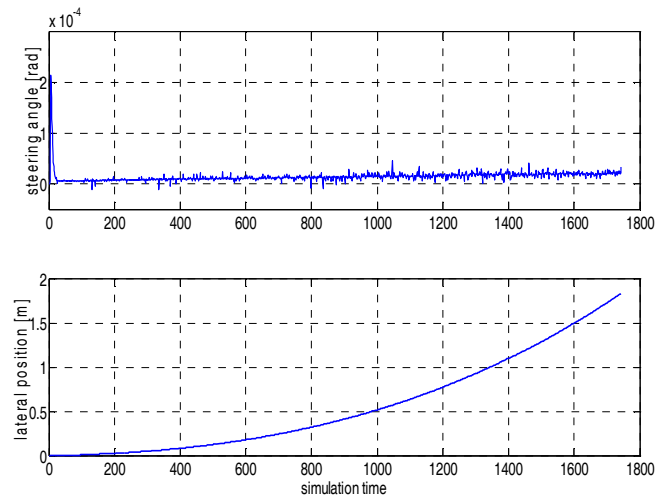

Figure 4. Drift in lane keeping task (max 2 m) with internal delay of 1 sec and proprioreceptive gain of 2.

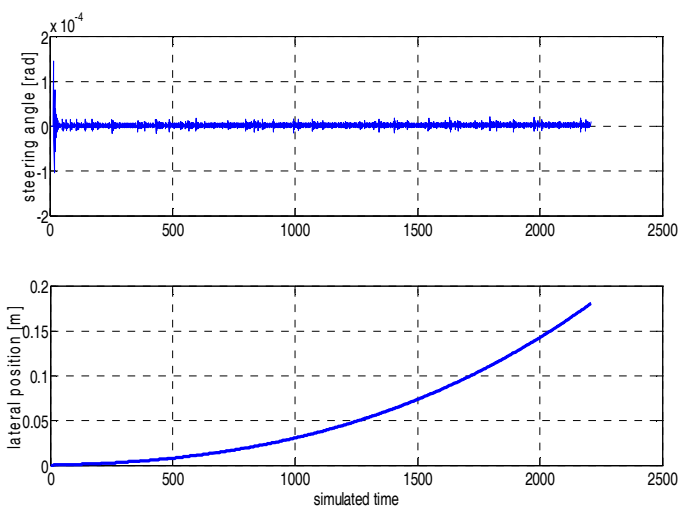

Figure 5. Drift in lane keeping task with an internal delay of 1 sec and proprioreceptive gain of 20.

CONCLUSIONS

In this paper, a hybrid model using a stochastic model for velocity control and a continuous control theoretic model for lateral control are combined. The lateral model is modified in order to represent driver complacency. In addition to that internal processing time is represented by a delay term which can account for distraction since it blocks the processing sources of the driver. Finally the importance of vestibular feedback is shown by observing the drift in using the feedback from this system less (Fig..4) or more (Fig.5). This type of change can represent the difference between novice and expert driver, since the expert driver would trust more on muscle system/learned skills than visual input.

In summary, the proposed driver model can account for human deficiencies or bottlenecks in information processing, complacency. Also, the model can explain the effects of the distraction in a tracking task (i.e. lane keeping) and the experience level (i.e. changing gains in different feedback channels). For these reasons, the model is very convenient to be used in developing human-centric lane assistance/ control systems.

In our future work, the proposed model will be improved and several driver behaviour, performance and characteristics will be linked and added using Hybrid Dynamic Systems and stochastic modeling tools.

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