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Intelligent Modeling of Human Driver: A Survey

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Abstract—**The control strategy of human operator is naturally dynamic, stochastic and nonlinear. It also changes gradually through the time. Therefore, human driver modeling is a very difficult task. The driver model must be accurate and robust enough to give valid human behaviours under varying conditions, otherwise the model will most probably fail. This means the model has to have some intelligence similar to the human driver. In this paper, human driver modeling was analyzed from an intelligent control perspective.**

I. INTRODUCTION

THERE are many reasons for human driver modeling such as vehicle following [1]-[3], road following, collision avoidance [2], lane keeping on a curving road [4]-[6], etc. Also, human driver model can be used in closed loop simulations interacting with the vehicle as a controller to test the engine (Fig. 1). A human driver has two major functions while controlling the vehicle [7]. These are;

- Longitudinal control
- Lateral control

In longitudinal control, the setting of the accelerator pedal and the brake pedal are determined and suitable gears are chosen. Decisions are based on the distance between the leading vehicle and the approaching velocity. In lateral control case, steering wheel angle is manipulated. The curvature of the road and the planned trajectory are the components that affect the lateral control of the vehicle [8].

In the literature, the lateral and longitudinal controls of vehicle have been generally studied separately as given in the reference [9], [10]. However, human driver model that carries out both lateral control and longitudinal control tasks synchronously is more natural and appealing [9].

The complexity of human driver modeling is caused by the human operator's dynamics involving a variable, random and biased structure. It is almost impossible to obtain the same action from a human operator even if all conditions are identical. Due to all these complications, modeling is difficult and time consuming. Several organizations having different establishment reasons, such as Prometheus (PROgraMme for a European Traffic with Highest Efficiency and Unprecedented Safety) in Europe, PATH Research (Partners for Advanced Transit and Highways), ALVIN (Autonomous Land Vehicle In a Neural Network) in the USA and ARTS, ASV in Japan have been working on human driver modeling. For instance, the objectives of Prometheus are;

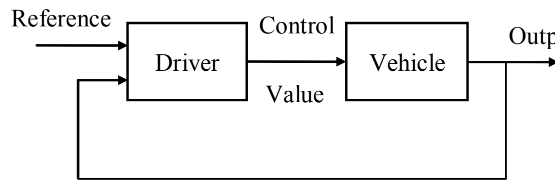

Fig. 1. Closed-loop block diagram of human driver.

- Traffic safety (Preventing crashes)
- Diminishing environmental pollution (Noise and fuel control)
- Diminishing human driver load (Intelligent warning systems)
- The arrangement of the traffic flow (Road capacity optimization) [11], [12].

The major purpose of these human driver modeling studies is to decrease the number of accidents. Fenton [13] stated that the cost of the accidents per year is about 70 billion dollars. It has also been estimated in the same study that the traffic would have doubled from 1992 to 2010. According to the statistics, generally drivers are responsible for the accidents. However, by the existence of a virtual driver who drives simultaneously with the human driver, unexpected situations could be detected earlier and the human driver could be warned accordingly to prevent probable accidents. In the near future, it is expected that the virtual driver will drive the car alone, without a need for a human driver.

II. HUMAN DRIVER MODEL

Shim *et al*. [5] developed a visual data processing method for the road ahead of the vehicle by using Neural Networks (NNs). According to this method, neural network extracts the radius of the road from the visual data and provides it to the human driver model as an input. Curve radius is the main variable affecting the steering wheel action which is an output component of the human driver model. It is necessary to get the correct description of road in order to apply the human driver model to different types of roads.

Macadam and Johnson [6] obtained steering wheel angle by using time delays of sensor data as inputs. In order to attain the time dependent derivation data, time delayed

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sensor information was fed to NN and the training was realized. The important point here is that the road information, which is approximately same as the driver's perception, was given to the model. Since the driver model is highly complex and not linear, a feed-forward type neural network was used for modeling in [6].

However, the model was constituted as single input-single output which are sensor data and steering wheel angle respectively. Steering wheel angle data were obtained from both simulator and the real road driving. In the same study, Fujioka and Takubo [14], Kornhausser [15], Lubin *et al.* [16] mentioned about obtaining neural network models by using simulator data in order to constitute a human driver model. By following the same method, Neusser *et al*. [17] used optical sensor data as input and they constituted a neural network model by using real road data.

Existing studies in the literature until today have focused on only one type of mission such as lane-keeping, driving on a road with a certain radius at constant speed, etc [5], [6]. One of these scenarios was double lane changing with constant velocity and another one was driving on an S-curve with same radius at both sides. Since there is no effect of velocity in the human driver model, the vehicle velocity was kept constant in order to have successful simulations. Therefore, the model was far from reality and extremely limited.

Hess and Modjtahedzadeh [4] developed a human driver model for predicting the driver steering response. Their driver-vehicle model has low frequency driver compensation and high frequency driver compensation which is called as "structural model of human operator". Since human sensing has some limitations on processing its actions, an effective time delay was added on their model. It is important to realize that driver-vehicle model should exhibit three notions:

- The bandwidth of aggressive steering tasks
- Neuromuscular system model
- The desirable open-loop return ratio

Desirable open-loop return ratio indicates that large magnitudes in low frequencies for good tracking and small magnitudes at high frequencies for low sensitivity to uncertainty. Detailed information about the human driver's lead in low frequency can be found in [18] and low amplitude high frequency component information which can be attributed as the driver remnant can be found in [19], [20]. Cross over frequency was chosen as 1 Hertz for open-loop return ratio [4].

Human operator's band width does not exceed a few Hertz as stated in many studies in the literature [18]-[21]. The input-output data, obtained from real human driver in a research project by the authors, do not include any frequencies over 2 Hz as seen in Fig. 2, except some maneuvers, and it is consistent with the human driver modeling literature [22]. Based on this information, it is adequate to choose the sampling frequency of 10 Hz in order to preserve the highest-frequency component [12], [23].

Huang *et al.* [3] designed an automated driving system and a human driver model. They simulated the automated and manual vehicles in ambient traffic together. For this reason, human driver model was developed for pure longitudinal and pure lateral control. Lateral control focuses on lane changing while longitudinal control focuses on velocity keeping, velocity tracking, weak spacing and strong spacing control. To construct an automated driving system, some mixed longitudinal and lateral control actions were also considered in emergency situations such as hard braking, sudden lane change or trajectory planning. Proposed human driver model must obviously be capable of predicting actual human driver attitudes in order to handle all possible conditions and must manage vehicle following, lane change and driver aggressiveness. Driver aggressiveness indicates the frequency of lane changes.

One of the most important inputs in human driver modeling is the road data. But, the way of giving the road data to the model is an important point. Two different suggested solutions are giving either the look-down or the look-ahead. While the look-down is related to the measurement between the front of the vehicle and the lane, the look-ahead is about giving some forward points within the human driver's sight. The most important criterion here

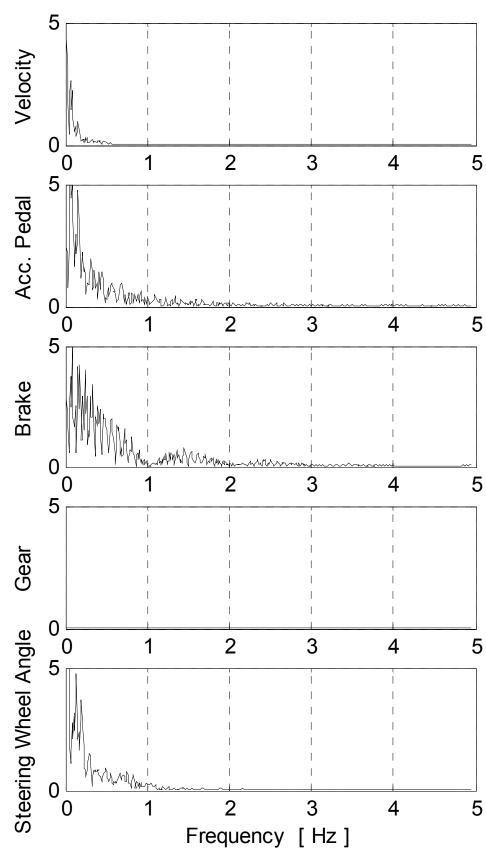

Fig. 2. Frequency band of human driver input-output data.

is providing the information to the model about the human driver's lead depending on the velocity of the vehicle.

Pilutti and Ulsoy [18] showed in their study that in reality a human driver has a lead of 40 dB/dec. When the speed is low, the "look-down" method is adequate to provide the human driver's lead. The look-ahead distance increases as vehicle speed increases and decreases as vehicle speed decreases like the actual human driver [21]. If certain constant distances are taken as look-ahead distance, the above adaptation can not be done. In look-ahead, if "time data" is given to the model as input instead of "distance", more accurate human driver models can be obtained.

Riedel and Wurster [24] stated that the data needed for modeling should be obtained from driving sessions of test drivers, i.e. professional drivers. Human drivers' faults should be kept out of modeling. They also suggested that shape of the road, steering wheel angle, engine speed (RPM), steering wheel moment, tire pattern could be used as inputs and steering wheel angle or moment, accelerator pedal position, the clutch pedal position, and the actual gear could be used as outputs. Input and output components related to various situations can be chosen depending on the problem and simplifications can be made whenever appropriate (Table I). Apel [25] also gave all possible physical variables that can be used for the human driver model. For example, if the simulated driving course is flat, it is not necessary to take the slope as an input.

Three different research areas about human driver were studied in [2] namely vehicle following, road following, and collision avoidance. They designed two separate Neural Network controllers which can be transportable to any vehicle regardless of its dynamics for vehicle following. Nonlinear model descriptions, e.g., NNs do not need the characterization of nonlinear vehicle dynamics. The first NN controller's aim was speed control consisting of seven input variables: the normalized current speed and the normalized current and five past samples of range errors. The second NN controller was trained for steering control consisting of four variables: the normalized current range and the normalized current and two past samples of heading angles. They also tested their controller performance with different data collected from different runs. Practically speaking, experimental verification shows NN is feasible to drive the vehicle.

Nechyba and Xu [26] used Cascaded Neural Networks to model human driver. Initially, there are no hidden units in the network, only direct input-output connections. Firstly, these weights are trained to capture any linear relationship. They fed to previous state information, previous control information and a description of road as input to cascade networks. For a stochastic process, a static error criterion, based on the difference between the trained data and predicted model outputs may be inappropriate. So, human driver model must be verified by the data that is not used in the training stage [27], [28].

TABLE I
INPUT-OUTPUT COMPONENTS AND SOME FUNCTIONS USED FOR DRIVER MODELING [24]

Inputs	Functions	Outputs
Description of the road	Path	Accelerator or Brake Pedal
Engine RPM	Velocity Choice	Steering Wheel Angle
Vehicle Velocity	Driving	Gear
Steering Wheel	Accelerator or Brake Pedal	
Moment	Clutch	
	Speed Limit	

Multiple mental human driver model was studied and analyzed on adaptive cruise control system in [1]. Mental model is an internal mechanism that predicts and computes future responses based on current state within the dynamic environment. Obviously, this model uses the human operator as a template for automation. For this reason, they tried to understand how operators manage tasks and switch from one skill (operator activities) domain to another skill domain. For example, when cruise control must be activated or disabled and how the transition must be. Since the human driver feels the dynamical forces, cruise control which emulates human driver behaviour should be as smooth as human driver.

Many of the human driver models are getting closer to the human driver's performance. However, none of them is expected to reflect the exact human driver [29]. A model consisting of "if-then" expressions in Fuzzy Logic Controller (FLC) that would include all parameters of a human driver would contain approximately 10000-50000 rules that should be identified [30]. Therefore, it will be more useful and easier to constitute a model that accomplishes only the given specific mission, than a model performing every operation that a human driver could. However, intelligent controller techniques, e.g., NN, FLC are the best candidates to the multiple tasks such as both longitudinal and lateral control synchronously.

III. CONCLUSIONS AND FUTURE WORKS

Although the human driver has access to information from many different channels, the constituted model has only the information which is included in the data. Therefore, if a model is extracted from straight course data, it drives and finishes straight courses successfully, but it may not succeed in other scenarios, for instance, parking. To be successful in different scenarios, modules and/or subparts for every different mission need to be prepared and the required module will be called according to the situation.

The interaction of the driver and the vehicle is very complicated due to the human operator characteristics. Because of human's randomness and bias, defining a human operator model with a deterministic model is very difficult. Especially in vehicle driver modeling, the most important stage is determining the input-output components. The advantage that NN or FLC provides is, without changing input-output components, different dynamics can be hidden in the internal mechanism of intelligent controllers.

The models that were constituted until now, were mostly with one output, they had restrictions and were very far from the reality. The driver models in the future studies should combine lateral and longitudinal control and have some specifications in order to be practical. First of all, model should adapt to the driving conditions, it should keep learning while it is running. Model parameters should be changed and made suitable for all conditions. Secondly, model should be independent of training road and maneuvers; so that driving can be achieved easily on any other roads.

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