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Comprehensive Driving Behavior Model for Intelligent Transportation Systems

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Abstract

This paper presents a novel approach of modeling human driving behavior in a more realistic way that can be effectively utilized in realizing intelligent transportation systems to ensure efficient, safe, secure and human-friendly vehicle control and transportations. A number of supporting systems based on individual driving behavior are identified. The proposed comprehensive driving model approximates complete behavior of individual drivers focusing not only the ideal steady and transient driving styles but also their natural variations. Simulation results and observations from real driving scenario illustrate the significance of the proposed model and its scopes.

I. Introduction

The most significant drawback of the modern road transportation systems is the increasing trend of accidents and casualties. Therefore, the demand for the development of a safe, efficient and human-friendly transportation system has been increased. It is expected that intelligent transportation systems (ITS) through the advancement in new sensing and information technologies of next decades provide solutions of such demand. It is necessary to analyze human driving behavior in developing any user friendly vehicle control system so that it matches with the style and preferences of a driver.

The human driving behavior is very complex as it is often influenced by psychological and physical factors [1]. Researchers have proposed a number of approaches to approximate driving actions in various situations. Most of their models represent the car following behavior of a driver. Since the human driving behavior can be considered as a mapping from driver's sensory information to the operations of driver such as acceleration, braking and steering, both linear controller models and non-linear models have been proposed [2],[3]. Some linear-driving model focuses only stopping, or starting behavior [4]. But the non-linear model such as neural network, Neuro-Fuzzy, etc, can represent both the steady and transient behavior of a vehicle driver [5]. Some driving models mainly focus other situations such as behavior at emerging situations, lane keeping, and steering control. The linear driving models are simple, and they enable us to grasp the physical characteristics of the driving behavior intuitively. But, they often mislead us to wrong understanding due to the high nonlinearity included in human driving behavior [4]. Driving behavior varies widely from person to person. Even for the same situations, a driver drives a car with variations from time to time. Most driving behavior models represent the mean values of range clearance, acceleration and braking without considering their variations.

This paper identifies some supporting system for ITS and introduces a more realistic modeling approach of individual driving behavior for realizing those systems. The longitudinal motion of a car in human driving is modeled using non-linear approximation techniques, recent statistics, and road based history to represent the driver's mean actions, and variations in both steady and transient, and with or without the presence of a preceding car. The new modeling approach is explained using an example model, simulation results, and observations from real driving scenario. The applications of such systems in developing safe and human friendly vehicle control system are sorted out.

II. Driving behavior model for ITS

Intelligent Transportation systems are the solutions of various contemporary problems in transportation. The model of individual driving behavior is essential in designing a number of systems in ITS that are designed to interfere human driver in some ways to and efficient travel on the road [6]. Such assisting systems would not be accepted by drivers if they fail to match their preferences, skills and styles, or simply with their behavior [7]. In our findings, the following supporting systems that reflect the preferences of individual drivers would be very demanding in ITS.

A. *Adaptive Cruise Control*

Adaptive Cruise Control (ACC) system assists a driver on highways by automatically adjusting the speed and range clearance when there is a little change in speed of the preceding car. The action of an ideal ACC system may not match the natural action of every driver. The driver may feel discomfort when the ACC system interfere him. Researchers have now been investigating the acceptability of such ACC vehicles [3]. It is obvious that an ACC system with exact speed adjusting styles of the driver will be more comfortable.

B. *Collision Avoidance*

Collision avoidance systems provide warning to a driver or brakes a car in an emerged danger [7][8]. They usually provide the same level of assistance to all drivers regardless of their driving styles and preferences. It is obvious that levels of assistance desired by drivers vary widely, since driving behavior of a beginner, an expert, a young and an old person are not the same. A typical assist system may not be accepted due to mismatch with their requirements. Such system may seem appropriate to only some drivers, noisy for providing unwanted interfere to some others, and insufficient assistance to the others. The collision avoidance system only based on individual driving behavior can be appropriate to them.

C. *Driving performance monitoring*

It is desired that a driver be defensive on the road to ensure a safe driving environment. It is almost impossible to monitor all drivers on the road networks of a country whether they are over-speeding or violating traffic rules. Only an on-line behavior monitoring system can evaluate a driver in this regards. The skill up process of new drivers takes time. A monitoring system can ensure that the process is smooth and complying with traffic laws.

D. *Abnormality Investigation*

Individual driving behavior can be used to monitor the abnormality in driving due to mistakes of a driver or any other external causes. An abnormality recording system can be very useful in investigating the causes of any accidents. Also, analyzing the abnormality record, drivers who are susceptible to accidents can be easily ensure a safe identified, and an adaptive insurance premium can encourage a driver not to violate the driving rules.

E. *Security and Antitheft*

Since the driving behavior of individuals differ to some extent, whenever the car is driven by other person can be easily identified in most cases. That can be effective in reducing car theft.

III. INDIVIDUAL DRIVING BEHAVIOR MODEL

The driving style of a driver differs from that of others even in the same road, environment, weather, and other physical factors. The model of human driving is based upon fundamental premises concerning how a driver senses pertinent information, perceives the meaning of that information, decides on the course of action to take and control vehicle acceleration to achieve a desirable driving situation. A driver has visual capabilities for sensing range-clearance (headway distance) R, range changing rate $R_{DOT} = V_P - V$, and the velocity V, **Fig. 1**. Based upon this basic assessment and desired or set velocity V_D a driver decides the action (acceleration/ braking) V_{DOT} of the subjective vehicle [3][7]. V_D is the speed that the driver chooses to go when R is large in the driver's view.

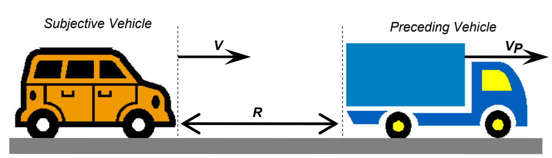


Figure 1. Car following concept in real driving scenario

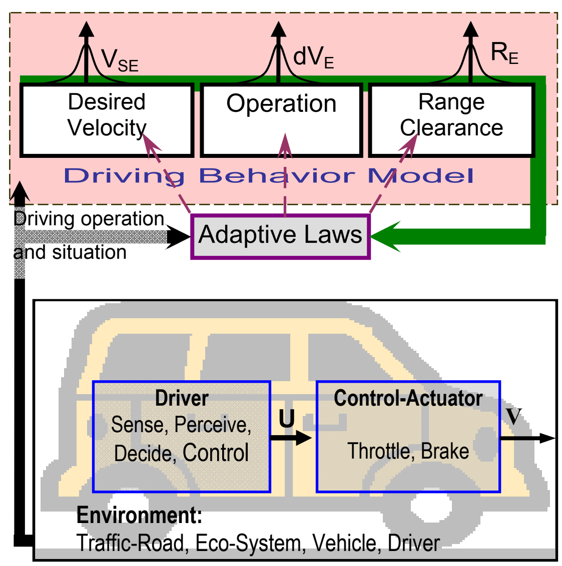


Figure 2. Adaptive driving behavior model

Fig. 2 illustrates the proposed comprehensive model to represent the complete behavior of any individual driver for longitudinal vehicle motion. It approximates the set speed V_{DE}, range-clearance R_E, action (braking or accelerating) dV_E, and their usual variations. The subscript 'E' indicates the estimated values. The model must be adaptive to track recent behavior of a driver. There are some alternative algorithms or techniques to identify or approximate these values and their variations. As an example, here, we present adaptive neuro-fuzzy systems to estimate R_E and dV_E. The Gaussian membership functions are used in the input where as the output singleton membership functions are tuned dynamically [7]. The estimation of R_E is based on the speed of the car, and the estimation of dV_E is based on R_{DOT}, R, V and V_{DE}.

The set speed V_D of a driver depends on road-environment-weather conditions and psychological state of a driver. Therefore V_D should be estimated from the recent statistics (mean and standard deviation) of the driver on a particular point on the road. Here, we present a technique of incremental learning from real data to find the recent mean value of a variable. Eq.(1) shows the weighted mean at any instance, which can be obtained by incremental update using eq.(2).

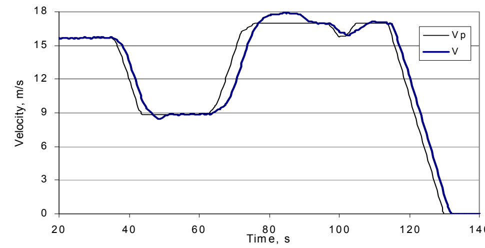
$$M_x^n = \sum_{i=1}^{n} \gamma^{n-i} x_i - \sum_{i=1}^{n} \gamma^{n-i} x_{i+1} \qquad (1)$$

$$M_x^n = \gamma \; M_x^{n-1} - x_n (1-\gamma) \qquad (2)$$

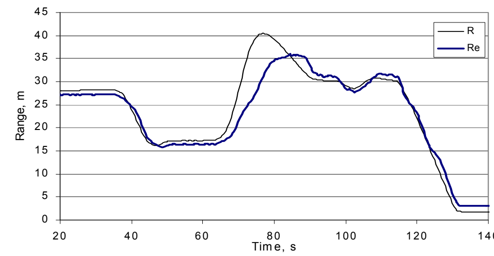
Where $\gamma \in [0,1)$ is the discount or forgetting factor, x_i is the ith data item, and M_x^n is the recent mean up to the nth observation. It is necessary to store only the value of recent mean to update it with next sample. This update rule is used to determine the recent mean and recent mean square deviation of V_D (on a particular point on the road) and fluctuations of R. The estimation of these variables and their usual variations together represent complete driving behavior in longitudinal motion.

IV. Observations and Results

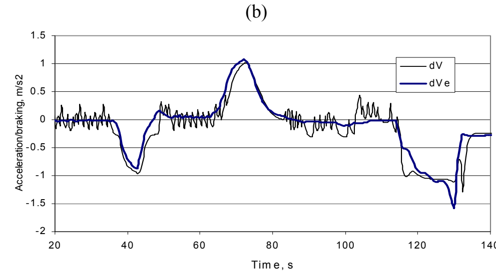
The driving behavior model proposed in this paper has been investigated in two steps. The characteristics of R and V_{DOT} are modeled using two neuro-fuzzy estimators. A simulated driver is chosen which is capable to start, stop and follow the preceding car by controlling both the brake and accelerator very similar to a human driver in generating complex control actions [5]. The driver follows constant time headway with a zero speed range margin. The adaptive fuzzy behavior models are used to learn behavior of different drivers whose desired range-clearance styles are not the same. Their responses contain stochastic noises and random reaction delay.



(a)



(b)



(c)

Figure 3. Driving behavior (a) Velocities of both cars, (b) range-clearance: actual (R) and estimated (Re) values, (c) action: actual (dV) and estimated (dVe) values.

The estimators could approximate mean values of R and V_{DOT} throughout the driving states properly. **Fig. 3** shows the comparison of the estimated values with the actual values in a typical scenario when both cars run at the same steady speed, then preceding car brakes to a lower speed, again speeds up and finally stops. The subjective car follows the preceding car with desired time-headway of 1.8 sec and V_D of 18.0 m/sec. The system could estimate R_E with less than 3.0% error. This error could be reduced further if there were no variation in driving style. The action style dV_E is also estimated for the same driving scenario. Although the actual values are very noisy, even in steady driving, the estimator could correctly approximate the mean values of action dV_E throughout the driving scene.

In most driving models it is assumed that a driver has a fixed set speed V_D if there is no preceding vehicle. Actually, the set speed of every driver is not the same, and it also varies depending on external factors such as road and weather conditions. Therefore it is necessary to incorporate a separate model to approximate V_D of a driver, and then this can be fed to the previous model to estimate the other behavior of the driver. This conclusion is made after a number of observations. The probability distribution of V_{DE} of a driver on different point of a road is shown in **Fig. 4**. The driving data are taken from a Japanese driver on an urban highway in Fukuoka city, who drives a shuttle minibus on the road 3-4 times a day. His mean maximum speed on the straight high way is 79.38km/h with a standard deviation of 1.53km/h, on a sharp bend it becomes 69.6 and 1.78, and on three light bends the values are 76.5 and 1.62. It was observed that many others drive much faster on the same conditions.

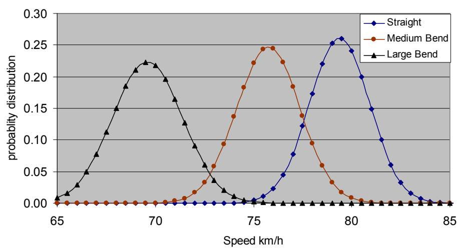


Figure 4. Maximum speed on the same highway in different road curvature.

The set speed V_{DE} of four drivers on the peak of a curved flyover is also observed. The given speed limit on that road is 60km/h, but that flyover has a given limit of 50km/h. **Table 1** shows the variation of recent mean and recent deviation of V_{DE} of four drivers.

TABLE 1: DESIRED SPEED KM/H AT A CURVED FLYOVER

Driver	1	2	3	4
Recent mean	78.05	72.25	73.89	69.1
Recent deviation	2.49	2.91	2.74	2.11

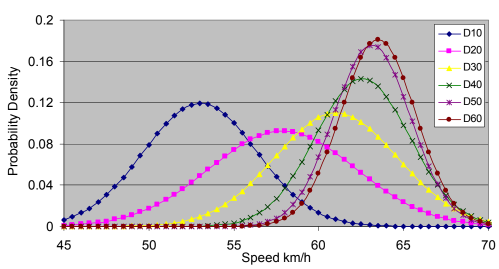


Figure 5. Maximum speed at a curved road in skill up of a new driver.

In case of a skilled driver the variation in set speed for the same physical conditions can be little over the time. It can be easily obtained after taking a large number of samples. But if the speed characteristic varies over time, it is necessary to find the mean and standard deviation of recent driving, as proposed. On the same curved flyover, the speed characteristics of a completely new driver are shown in **Fig. 5**. D10 to D60 represent the probability distribution of desired speeds corresponding to every 10^{th} day when the driver run over the same point. The distribution curves plotted using the recent mean and recent deviation data.

V. CONCLUSIONS

In realization of ITS, several supporting systems for safe and efficient road transportation have been identified. Comprehensive driving behavior model presented in this paper can be utilized to make these systems more comfortable, friendly and widely accepted. Ability of this adaptive model in identifying different driving aspects and their variations has been evaluated. Future research can be extended to develop and evaluate the newly proposed supporting systems over a wide range of drivers in different road terrains and weather conditions.

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REFERENCES

[1] K. Matsunaga, Combined Factors in Traffic Accidents and a Method of Education for Safe Driving, *Society of Automotive Engineers of Japan*, Vol. 54(7), 2000, pp.23-38.

[2] T. Akita, S. Inagaki, T. Suzuki, S. Hayakawa, and N. Tsuchida "Analysis of Vehicle Following Behavior of Human Driver Based on Hybrid Dynamical System Model" in the proc. of 2007 IEEE CCA, pp. 1233-1238.

[3] P. Fancher, Z. Bareket, H. Peng and R. Ervin, "Research on Desirable Adaptive Cruise Control Behavior in Traffic Streams," Phase-2 Final Report, UMTRI, 2003.

[4] J. Kim, Y. Kim, D. Hwang, "Modeling of Human Driving Behavior Based on Piecewise Linear Model," AUTOMATIKA 46(2005) 1–2, 29–37.

[5] J.E. Naranjo, C. Gonzalez, R. Garcia and T. Pedro, "ACC+Stop&Go Manuevers with Throttle and Brake Fuzzy Control," *IEEE Trans. On Intelligent Transportation Systems*, vol.7, no.2, 2006, pp.213-225.

[6] S. Nagiri, Y. Amano, K. Fukui and S. Doi, A Study of a Personally Adaptive Driving Support System Using a Driving Simulator, *Driver Behavior and Active Safety*, Special Issue R&D Review of Toyota CRDL, vol.39 no.2, 2004.

[7] M.A.S. Kamal, T. Kawabe, J. Murata and M. Mukai "Driver-Adaptive Assist System for Avoiding Abnormality in Driving" in proc. of 2007 IEEE CCA, pp 1247-1252.

[8] A. Doi, T. Butsuen, T. Niibe, T. Yakagi, Y. Yamamoto and H. Seni, "Development of a Rear-End Collision Avoidance System with Automatic Braking Control," *JSAE Review*, vol.15(4), pp.335-340, 1994.