

Driver Behavior Analysis and Prediction Models: A Survey

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Abstract- In today's life, every human is in hurry to reach their destination like home, office, college, shopping mall, restaurant, etc as quickly as possible. To reach their destination quickly people use vehicles on road use and drive them in faster mode which results in road accidents. Driver behavior is a major cause for the road accidents. To address this problem, driver behavior analysis and prediction models need to be developed. In this paper we have discussed some of existing driver behavior models. These models are classified as two types: Driver behavior analysis and driver behavior prediction models. In this paper we have carried out a detailed survey about the driver behavior analysis models and the driver behavior prediction models.

Keywords- CA=Collision Avoidance, OBD= On Board Diagnostic, ANFIS= adaptive neuro fuzzy inference system, NHTSA=National Highway Traffic Safety Administration

I. INTRODUCTION

Currently, in tune with economic growth in every county, the numbers of the vehicles increase every year. At the same time, the number of non-expert drivers also increases rapidly. Since most novice drivers are unskilled, unfamiliar with the vehicle conditions and no awareness of traffic rules and regulations, drivers' personal factors have become the main reasons of traffic accidents [1]. Understanding, analyzing and modeling human driver behavior 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 [2]. This survey has been conducted to collect various driver behavior analysis and prediction models. The driver behavior analysis models will give us details about the users driving styles and patterns and driver behavior prediction models will give us details about the driver's driving information; whether it is safe or not. The contribution of this paper is twofold. At first, we explore the different driver behavior analysis models in detail. The results show that the driver behavior analysis models significantly differs for different vehicle drivers. The second contribution is about the driver behavior prediction models. In this paper section II introduces survey details and the section III concludes with a discussion of the methods used in this paper.

II. DRIVER BEHAVIOR ANALYSIS AND PREDICTION MODELS

This survey has been conducted to collect various driver behavior analysis and prediction models.

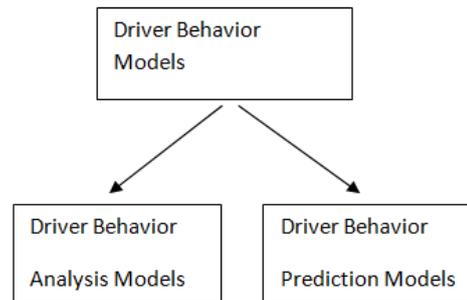


Fig-1: Classification of Driver Behavior Models

The Fig-1 is giving the classification of driver behavior models.

A. Driver Behavioral Analysis Models

A driver behavior is the set of actions, he/she would perform to ensure both the safety of people and compliance to the driving regulations [3].

1) *Based on Vehicle OBD information and AdaBoost Algorithm:* Shi-Huang Chen, Jeng-Shyang Pan, and Kaixuan Lu in [4] proposed a novel driving behavior analysis method based on the vehicle on board diagnostic (OBD) information and Ada Boost algorithms which collects vehicle operation information, including vehicle speed, engine RPM, throttle position, and calculated engine load, via OBD interface. Then the method makes use of Ada Boost algorithms to create a driving behavior classification model, and eventually can determine whether the current driving behavior belongs to safe driving or not .

2) *HMM based analysis model:* Nobuyuki Kuge, Tomohiro Yamamura and Osamu Shimoyama, Andrew Liu in [5], proposed a driver behavior recognition method using hidden Markov models (HMMs) to characterize and detect driving maneuvers and place it in the framework of a human behavior cognitive model. HMMs-based steering behavior models for emergency and normal lane changes as well as for lane keeping were developed using a moving base driving simulator. Analysis of the proposed models after training phases and recognition tests showed that driver behavior modeling and recognition of different types of lane changes is possible using HMMs.

3) *Driver steering Models:* Malin Sundbom, Paolo Falcone and Jonas Sj Oberg in [6] proposed the PrARX modeling framework is applied to describe the driver's lateral behavior. The parameters of a two-mode model are identified and names are given to the modes according to

the expected output from each mode. Mode one is aggressive driving, describing a driver with a behavior typically perceived as aggressive, eg. higher acceleration in curves and more lateral movement compared to a more standard driver. Mode two represents normal driving, i.e. it models the behavior of a driver with moderate curve acceleration and lateral movement in the lane. The model is validated on data collected on a test track using two different driving styles. In this section, a two-mode PrARX model is used to model the steering behavior and classify the driving style of a car driver. The driver here is assumed to drive in two modes, corresponding to normal and aggressive driving styles, respectively, and the steering angle δ is described by

$$P_i(\phi_t) = \frac{e^{\eta_i^T \phi_t}}{\sum_{j=1}^s e^{\eta_j^T \phi_t}},$$

where $P_i(\phi_t)$ is the probability that the driver is operating in mode i . $i = 1, 2$. ϕ_t is a regressor vector, which consists of measurements from the in-vehicle sensors.

Guoqing XU, Li Liu, Zhangjun Song in [7] proposed a hybrid model based on Bayesian network and multiple classifier of SVM to analyze and recognize the driver behavior. The limited and observable features of driver behavior are extracted. In addition, the relationship between the features of driver behavior and the effect of data loss on the model are analyzed.

4) *Design and Implementation of Driving Behavior Analysis System* : Yi Han, Yuan Yao, and Haiyang Liu in [8] proposed a new driving behavior analysis system. The hardware system combines a Driving Force Pro and two computers. The software system includes open source 3D engine-Speed Dreams, the Monitor program and the Data Analysis program. When drivers drive on this system, not only can the driving data be real-time collected and recorded, but also can the driving data be analyzed and the drivers' operation characteristics be given out. The driving data is preprocessed by using some data processing algorithms, such as smoothing, noise reduction, and derivation. The preprocessed data is analyzed by data mining algorithms. The analyzed results include braking speed, steering speed, and response time.

B. Driver Behavioral Prediction Models

A driver's intended actions (the future behavior) can be inferred from a number of sources such as the driver's current control actions, their visual scanning behavior and the traffic environment surrounding them [9].

1) *Probabilistic Model*: Jason Hardy, Frank Havlak and Mark Campbell in [10] presents an algorithm for propagating a system state distribution through a two stage model consisting of both a GP regression model and a parametric system dynamics model (Fig-2) and also presents a novel on-the-fly reduction method that greatly reduces the required computation time with minimal effect on accuracy.

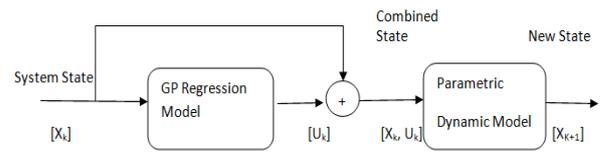


Fig-2: The two stage system consisting of a GP regression model combined with a parametric system dynamic model

2) *Improved Driver Behavior Model*: Pongtep Angkitrakul, Chiyomi Miyajima, Kazuya Takeda in [11] proposed a stochastic driver behavior modeling framework that takes into account both individual and general driving characteristics as one aggregate model. Regular patterns of individual driving styles are modeled using Dirichlet process mixture model and a non-parametric Bayesian approach. The developed framework automatically selects the optimal number of model components to fit sparse observations of particular driver's behavior. General or background driving patterns are also captured with a Gaussian mixture model using a reasonably large amount of development observed data from several drivers. By combining both the aggregate driver-dependent model, the probability distributions can better emphasize driving characteristics of each particular driver and also backing off to exploit general driving behavior in cases of unmatched parameter spaces from individuals' training observations. The proposed model was employed to anticipate *pedal operation* behavior during car-following maneuvers several drivers involve in this operation.

3) Acceleration Model

a. Car following Models

i. *GMM*: Pongtep Angkitrakul, Chiyomi Miyajima, and Kazuya Takeda in [12] presented and developed Gaussian mixture model (GMM) framework for driver behavior modeling. This framework is employed to anticipate car-following behavior in terms of pedal control operations in response to the observable driving signals such as the *following distance* to the leading vehicle and the own vehicle velocity. This driver modeling allows adaptation scheme to enhance the model capability to better represent particular driving characteristics of interest (i.e., individual driving style) from the observed driving data themselves. The adapted driver models showed consistent improvement over the unadapted driver models in both short-term and long-term predictions.

Chiyomi Miyajima, Katsunobu Itou in [13] model such driving behaviors as car-following and pedal operation patterns. The relationship between velocity and *following distance* mapped into a two-dimensional space is modeled for each driver with an optimal velocity model. This modeling is approximated by a nonlinear function or with a statistical method of a Gaussian mixture model (GMM). Pedal operation patterns are also modeled with GMMs that represent the distributions of raw pedal

operation signals. The spectral features extracted through the spectral analysis of the raw pedal operation signals.

ii. *Optimum Velocity Model:* Prof. Tom V. Mathew in [14] The concept of the proposed model is that each driver tries to achieve an optimal velocity based on the distance to the preceding vehicle and the speed difference between the vehicles. This was explored recently as an alternative possibility in car-following models. The following formulation is based on the assumption that the

desired speed $v_{ndesired}^t$ depends on the distance headway of the n -th vehicle. i.e. $v_{ndesired}^t = v^{opt}(\Delta x_n^t)$ where v^{opt} is the optimal velocity function which is a function of the instantaneous distance headway Δx_n^t . Therefore α_n^t is given by

$$\alpha_n^t = [1/\tau][V^{opt}(\Delta x_n^t) - v_n^t]$$

where $\frac{1}{\tau}$ is called as sensitivity coefficient. In short, the driving strategy of n -th vehicle is tries to maintain a safe speed and which in turn depends on the relative position rather than relative speed.

ii. *Neural network (NN) model:* Tom V. Mathew, K.V.R. Ravishankar in [15] proposed to predict the following behavior for different lead and following vehicle-type combinations. Performance of the model is observed and collected using data collected for six vehicle-type combinations. A multilayer feed-forward Back propagation network(MLFF-BPN) is used to predict the vehicle-type dependent following behavior by incorporating the vehicle-type as input to this model and then, this model is integrated into a simulation program to study the macroscopic behavior of the model.

iii. *GHR Model:* Alireza Khodayari, Ali Ghaffari, Reza Kazemi in [16] The first formulation of this model was developed in 1958 at the General Motors Research Laboratory in Detroit. The Gazis–Herman–Rothery (GHR) model considers acceleration as a function of the following three variables: 1) the velocity of the LV; 2) the relative velocity and the relative distance between the LV and the FV; and 3) the driver’s reaction time. Subsequently, many works have been done to develop and improve the performance of these models

iv. *Fuzzy Logic Models:* Alireza Khodayari, Ali Ghaffari, Reza Kazemi, Fatemeh Alimardani, Reinhard Brauningl in [17] an improved adaptive neuro fuzzy inference system (ANFIS) model is proposed to simulate and predict the car-following behavior based on the reaction delay of the driver vehicle unit. In this model, the reaction delay is used as an input and other inputs and outputs of the model are chosen with respect to this parameter. Using the real-world’s collected data, the performance of the model is evaluated. This model also compared with the responses of existing ANFIS car-following models. The simulation of this model results show that the proposed model has a very close compatibility with the real-world data and also reflects the situation of the traffic flow in a more realistic way. The

comparison shows that the error in the proposed model is very smaller than the error in other models.

Toshihisa Sato and Motoyuki Akamatsu in [18] introduce two case studies that investigate drivers’ car following behavior using the fuzzy logic car-following model. This model can determine the degree to which a driver controls longitudinal acceleration according to the relationship between the preceding vehicle and his/her vehicle. The fuzzy logic model evaluates the driver’s acceleration and deceleration rates using a rule base in natural language.

4) *Gap Acceptance Models:* Andyka Kusuma, Ronghui Liu, Francis Montgomery in [19] In order to capture the gap acceptance behavior on the motorway, the proposed applies an algorithm of driver’s decision-making process. In practice, it was difficult to observe the behavior directly from the field considering that each weaving driver has their own preferences in selection of the available gaps. The vehicle driver may choose an available gap based on their utility usually the driver chooses a highest utility. Applying the likelihood function, this paper finds a beta for the utility function that maximizes the probability for choosing each available gap both in the current and target lane respectively. The Weaving Movement Decision Process model is given in Fig-3.

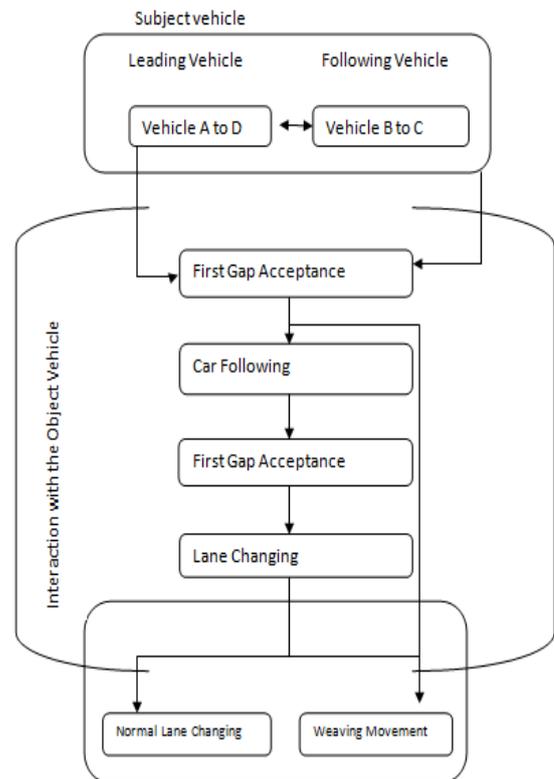


Fig-3: Weaving Movement Decision Process

Haneen Farah, Shlomo Bekhor, Abishai Polus And Tomer Toledo in [20] Passing gap acceptance is an important driving behavior that has important implications on traffic flow and safety in two-lane rural roads. In this study, data that was collected with an interactive driving simulator in a laboratory environment is used to develop a passing gap acceptance model as illustrated in Fig-4.

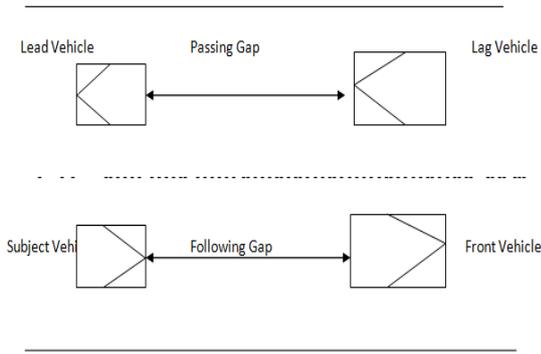


Fig-4: Definition of Passing Gap Acceptance Situation

The model incorporates variables that capture both the impact of the attributes of the specific passing gap that the driver evaluates (e.g. passing gap size, speed of the subject vehicle and the following distance it keeps from the vehicle in front), the infrastructure quality of the specific road section and the personality characteristics of the driver (e.g. gender, age, kilometers driven per month, accident record). The results indicate that all these types of variables significantly affect passing behavior.

5) *Lane Change Models:* Tomer Toledo, Haris N. and Koutsopoulos in [21] proposed an integrated lane-changing model that overcomes both these limitations. The model combines mandatory and discretionary considerations into a single utility model. The lane-changing process consists of two steps: choice of target lanes and gap acceptance decisions. A logit model is used to model the choice of target lanes. Gap acceptance behavior is modeled by comparing the available space gaps to the critical gaps. This model requires that both the lead and lag gaps are acceptable. The effect of unobserved driver or vehicle characteristics on the lane-changing process is captured by a driver specific random term. This term is included components of all the models.

Dr. Tom V. Mathew et.al in [22] proposed detailed discussion on Mandatory Lane Change (MLC) Discretionary Lane Change (DLC), Mandatory lane change (MLC) occurs when a driver must change lane to follow a specified path. Assume if a driver wants to make a right-turn at the next intersection then the driver changes to the right most lane, that lane is referred as Mandatory Lane change. Discretionary Lane Change (DLC) occurs when a driver changes to a lane perceived to offer better traffic conditions. The driver attempts to achieve the desired speed, avoid following trucks and avoid merging traffic to change the lane.

6) *Cellular Automation Model:* CA models that incorporate lane changing behavior have been developed to model multilane traffic flow. These models also incorporate conditions that capture the incentive and the safety of lane changing. A typical set of conditions [23] is:

$$g_n(t) < \min(V_n(t) + 1, V_{max})$$

$$g_{n,o}(t) > \min(V_n(t) + 1, V_{max})$$

$$g_{n,ob}(t) > V_{max}$$

$g_n(t)$, $g_{n,o}(t)$ and $g_{n,ob}(t)$ are the number of open cells in front of the vehicle in the current lane, in the other lane and behind vehicle in the other lane respectively. The first two conditions above verify that the driver's speed is constrained in the current lane and that the other lane provides better conditions. The third condition is guarantees that space is available to lane change. The lane change will occur with some probability, If all conditions are met. These lane changing conditions may be symmetric or asymmetric because they are different for the nearside and the offside.

7) *Dynamic Driver Behavior Model:* Guoqing Xu, Li Liu, Yongsheng Ou, and Zhangjun Song in [24], introduces a dynamic model of the driver control strategy of lane-change behavior and applies it to trajectory planning in driver-assistance systems. This model reflects the driver control strategies of adjusting longitudinal and latitudinal acceleration during the lane-change process. This model can represent different driving styles by using different model parameters (driving styles such as slow, careful, sudden and aggressive). They also analyzed the features of the dynamic model and present the methods for computing the maximum latitudinal position and arrival time.

Xiaokai He, Jiajun Hu, Jialiang Lu and Min-You Wu in [25] introduced a new driver behavior model, which mainly focuses on driver lane changing decision making process. The model takes both HMM and cognitive factors into consideration and is easy to implement. After that, a simulator based on this driver behavior model is carried out. With the help of this simulator, the correctness and applicability of the driver behavior model is testified. This paper also demonstrated some researches which take benefits from the newly developed model and simulator.

8) *Collision Models: Rear & Front End Collision Models:* Xiaoqin Yin and Mingxia Wang in [26] proposed a pro-active head restraint model which is a new automotive safety device with both active safety and passive safety characteristics. This model can make a pre-estimation of the occurrence possibility of rear-end collision. Establish an effective safety distance mathematical model is one of the key elements in rear-end collision avoidance system. The related calculation models of safety distance are established based on the running state of front car by means of dynamical and kinematical analysis of vehicle braking process and following process.

Adrian Cabrera, Sven Goyal and Alcherio Martinoli in [27] proposed a new collision avoidance warning system(CWS) T_{lsa} for lead vehicles in rear-end collision. It is a time-based approach and is coherent with the human judgment of urgency and also severity of threats. This system is directly quantifies the threat level of the current dynamic situation, assuming that the required evasive action involves accelerating. Here, warning criteria were

also proposed by considering driver reaction times to artificial warning signals under two possible implementation of CWS using the T_{isa} . Here the effect on decreasing the severity of the accident was studied and the reliability of the system was tested in a realistic simulation framework.

9) *Collision Avoidance Models*: Michael R. Hafner, Drew Cunningham, Lorenzo Caminiti, and Domitilla Del Vecchio in [28] presented algorithms and experimental validation on prototype vehicles for cooperative collision avoidance at intersections based on a formal control theoretic approach. Since the application considered is life critical, algorithms for collision avoidance should have safety certificates. This approach can be applied where vehicles are on known crossing or merging paths, such as at intersections or when a vehicle merges onto a road from a parking lot or on the highway.

10) *Linear Models*: H. Olmuş, S. Erbaş [29] presented a modeling effort using log-linear models to estimate the relationships between driver's fault, carelessness and the traffic variables such as gender, accident time and accident severity. The obtained results provide valuable information in regard to preventing undesired consequences of traffic accidents. square (G^2), and therefore can be used to analyze greater than two-way tables. To determine whether there is a significant difference between the observed and expected frequencies, the likelihood-ratio chi-square (G^2) is computed. The definition of the likelihood-ratio chi-square is

$$G^2 = 2 \sum [O_i \ln(O_i/E_i)]$$

where E_i is the expected frequency and O_i is the observed frequency.

MD Rizal Othman, Zhong Zhang, Takashi Imamura and Tetsuo Miyake in [30] presented a new method for modeling driver operation behavior and that method is based on using the predictor coefficients as feature vectors extracted from driving operation signal by linear prediction analysis (LPA). The distribution of the feature vectors is captured by employing auto associative neural networks model (AANN Model). The performance of the proposed model was evaluated through driver identification process and the results obtained demonstrate that the model can grasp the individual characteristics of the driver.

11) *Point Based Models*: He Crane Huang, Katia M. Harlé, Martin Paulus, Javier Movellan in [31] propose an inverse optimal control approach (Fig-5) to analyze and factorize performance deficits into two components of subjects' behaviors: 1) sensory motor speed and 2) reward-processing. The result of this proposal is a viable computational approach to quantify and factorize the underlying causes of sensory motor deficits in individuals with depression.

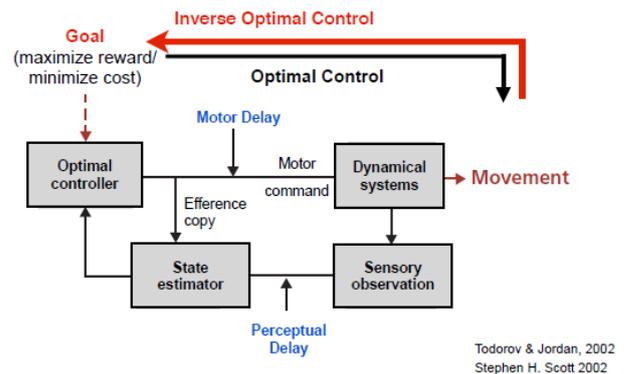


Fig-5: Inverse Optimal Control Approach.

Wuhong Wang, Wei Zhang, Dehui Li, Kiyotaka Hirahara, Katsushi Ikeuchi in [32] analyzed in more detail the Action Point (AP) model and ameliorated AP model by eliminating its deficiency. The main emphasis of this paper is placed on the deduction of the acceleration equations by considering that the following car is subjected in congested traffic flow. The model validation and simulation results have shown that the improved action point car-following model can replicate car-following behavior and be able to use to reveal the essence of traffic flow characteristics.

III. CONCLUSION

A survey has been conducted on driving behavior analysis and prediction models till date. A more precise definition of driver behavior analysis models would focus on various methods to understand the driver behavior, and also give information regarding driver driving information. The driver behavior prediction models give predictions of the drivers' driving nature whether the driving is safe or not. This paper enlightens various behavior models, which may help the researchers to carry out similar research work in this field in future.

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