DISCRIMINATING SUBSEQUENT LANE-CROSSING AND DRIVER-CORRECTION EVENTS USING TRAJECTORY MODELS OF LATERAL SLOPES

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ABSTRACT

In this paper, we propose a new framework to discriminate the initial maneuver of lane-crossing event from driver-correction event, which is the primary reason for false warnings of the Lane Departure Prediction Systems. The proposed algorithm validates the beginning episode of the trajectory of driving signals whether it will cause a Lane Crossing Event or not, by employing driver behavior models of Directional Sequence of Piecewise Lateral Slopes (DSPLS) representing lane-crossing and driver-correction events. The framework utilizes only common driving signals, and allows adaptation scheme of driver behavior models to better represent individual driving characteristics. The experimental evaluation shows that the proposed DSPLS has detection error as low as 17% Equal Error Rate. Furthermore, the proposed algorithm reduces the False Alarm rate of the original Lane Departure Prediction System from 38.8% to 6.1% with less trade-off for the prediction accuracy.

Index Terms— Lane Departure Prediction, Driver Correction, Lateral Slopes, Driver Behavior Model, Driver Model Adaptation

1. INTRODUCTION

Traffic accident is one of the major concerns around the world. According to the World Health Organization (WHO), more than one million people are killed on the roads each year. There are a number of contributing factors and causes of traffic accidents ranging from driver behavior to mechanical failure and road design. One of the accident causes is unintentional lane departure from a driving lane to the others. In Japan, 38.9% of single-vehicle crashes involve unintentional lane departure [1]. In USA, road departure problem accounts for 41% of all vehicle fatalities. Similarly, 36% of car accidents in European highways are caused by unintentional lane departure. Several researchers have proposed a variety of ideas and technologies to predict and/or detect unintentional lane departure events to warn a driver about such events or automatically adjust the vehicle systems in order to prevent or mitigate the consequent traffic accidents. Some technical solutions have been proposed, such as Lane Departure Warning System (LDWS), which is a system developed to warn a driver when a vehicle begins to deviate from its driving lane (unless a turn signal on that direction is activated), and Lane Keeping Assistance System, which assists driver's steering maneuver to keep a vehicle within its driving lane, etc.

In this paper, we study Lane Departure Prediction System (LDPS) which is a system developed to warn a driver *before* the vehicle starts to depart for its driving lane [2, 3]. Time to Line Crossing (TLC), which is defined as the time duration available for a driver before any parts of vehicle cross the lane boundary, is a simple and yet powerful indicator for predicting a forthcoming unintentional Lane Crossing Event (LCE). Nevertheless, one drawback of TLC-based indicator is excessive false alarm; the earlier warning time of LCE, the higher false-alarm rate. One of the causes of false-alarm events is due to the subsequent driver-correction maneuver of lateral position. Such intentional driver-correction event may begin slightly before or after the prediction time and has its effect afterward. At the prediction time, although the TLC-based condition is satisfied for warning, the vehicle merely goes close to the lane marking and return, but will never cross the lane boundary. Excessive false alarm is one crucial issue for developing the LDPS products, because it is annoyance to a driver and will discourage the driver from using it.

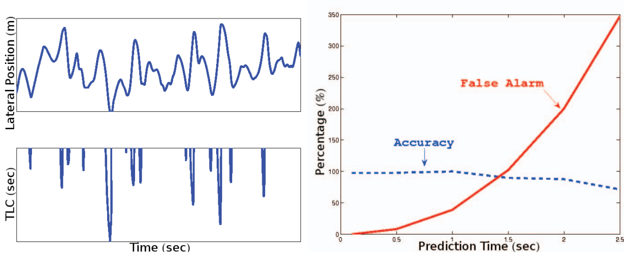
In order to allow LDPS to offer longer available time for a driver to respond to an alarm signal in order to avoid unintentional LCE without increasing annoyance level of excessive false alarm, we proposed a technique to prevent false warnings by validating the warning candidates obtained from TLC-based indicator whether the upcoming event actually is unintentional LCE or deliberate Driver-Correction Event (DCE). The key idea is to employ driver behavior model of 'Directional Sequence of Piecewise Lateral Slopes' (DSPLS), which encodes directional movement of vehicle's lateral position with its corresponding driving signals within each small episode. The proposed technique utilizes trajectory of driving signals at a prediction time as an initial episode of subsequent sequences of lateral trajectory. Consequently, the likelihood ratio of subsequent LCE and DCE generated by such initial trajectory are compared against a pre-defined threshold for a decision making. The proposed technique involves two sets of DSPLS driver behavior models: 1) driver-independent models and 2) driver-dependent models. Driver-independent models are obtained off-line from the driving signals of development data. Driver-dependent models are adapted on-line from driver-independent models using individual driving signals. Finally, driver-dependent models are used to validate the LCE warning candidates. In this study, Gaussian Mixture Model (GMM) framework is used as our core driver behavior model, as well as Maximum-A-Posteriori (MAP) adaptation technique for driver model adaptation.

This paper is organized as follows. The TLC-based LDPS is reviewed in Section2. Section 3 discusses the proposed DSPLS framework, followed by driver behavior model training and adaptation in Section 4. An experimental evaluation of DSPLS framework is described in Section 5. Finally, Section 6 concludes this paper.

2. LANE DEPARTURE PREDICTION SYSTEM (LDPS)

One common indicator used to predict vehicle position before Lane Crossing Event (LCE) occurs is Time to Line Crossing (TLC). Several research studies have shown high correlation between TLC value and driver performance [4, 5]. TLC can be calculated from various assumptions of vehicle dynamic, geometric formula, and available information. Nevertheless, there is no clear experimental validation demonstrates whether which assumption or model is the best TLC representation. In our study, we employ the standard model (i.e., straight road and straight vehicle trajectory) as our reference due to its smooth and good characteristics. One estimation of TLC is the ratio of lateral distance to lateral velocity, or the ratio of the Distance to Line Crossing (DLC) along vehicle path to the vehicle forward velocity [3] as: $tlc = y_l/(v \sin\phi)$, where y_l is a lateral distance from lane boundary to vehicle's reference (meters), v is vehicle speed (meters per second), and ϕ is vehicle relative yaw angle (radians).

In general, TLC value decreases as the vehicle moves closer to the lane boundary and equal to zero at LCE. Therefore, a threshold can be set based on a desired available warning time, and an alarm signal is activated when a TLC value starts to be smaller than the threshold. Fig. 1-(a) shows a plot of lateral position (top) and corresponding estimated TLC (bottom). In addition, Fig. 1-(b) shows the prediction performance of TLC-based LDPS as the warning time increases from 0.1 to 2.5 seconds. As we can see, while the accuracy drops from 100% to 71%, the False-Alarm (FA) rate increases from zero to 346% approximately.



(a) (b)

Fig. 1. (a) A trajectory of lateral position with lane boundary as the Y-axis (top) and corresponding TLC values between 0-5 seconds (bottom); (b) Performance of TLC-based LDPS as the prediction time (warning time) increases.

3. DIRECTIONAL SEQUENCE OF PIECEWISE LATERAL SLOPES (DSPLS)

Let us consider a vehicle trajectory movement obtained from its lateral position, which is an orthogonal distance from the lane boundary to the vehicle's gravity center. We segment the lateral trajectory and its corresponding driving signals into small equal segments of length T seconds (e.g., T = 1.0 sec), as shown in Fig. 2. Subsequently, we compute a linear slope of lateral trajectory of each segment, $slope_N$, using linear regression fitting. Such piecewise linear slope of trajectory represents an absolute direction of vehicle movement within each segment, relatively to the curvature of lane boundary. Let us categorize each N-th segment into one of the following three classes based on the estimated linear slope of its lateral trajectory:

- L_N: vehicle is moving to the *Left* direction relatively to its lane boundary, when
$$slope_N > \epsilon, \tag{1}$$
- P_N: vehicle is moving relatively *Parallel* to its lane boundary, when
$$|slope_N| \le \epsilon, \tag{2}$$

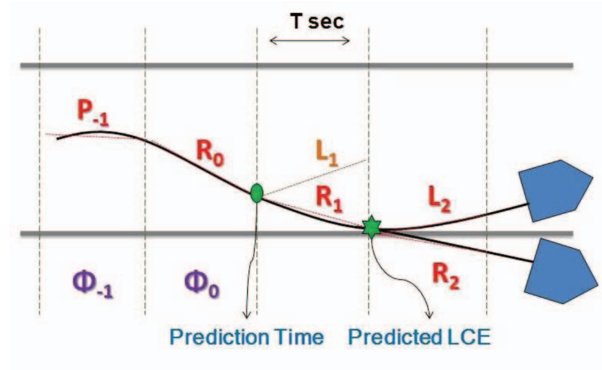


Fig. 2. Directional Sequence of Piecewise Lateral Slope (DSPLS) of Lane-Crossing and Driver-Correction Events.

- R_N: vehicle is moving to the *Right* direction relatively to its lane boundary, when
$$slope_N < -\epsilon, \tag{3}$$

where ϵ is a pre-defined threshold (e.g., 0.01). Furthermore, each segment is associated with its observations (Φ_N), which can be obtained from the corresponding driving signals (e.g., steering-wheel angle, yaw angle, etc.) Therefore, a trajectory of vehicle movement can be represented as a sequence of lateral slopes of consecutive segments, namely Directional Sequence of Piecewise Lateral Slopes (DSPLS).

Suppose that we segment the lateral trajectory and its observations into the same length as the available warning time predicted by the TLC indicator. Thus, the lateral trajectory during the LCE prediction is comprised of three trajectory segments as: 1) $N = 0$, for the segment right before the prediction time, 2) $N = 1$, for the segment between the prediction time and the predicted LCE, and 3) $N = 2$, for the segment right after the predicted LCE. Fig. 2 illustrates a lateral trajectory on a straight road and its corresponding assigned slope class of each segment. From this figure, a sequence of lateral slopes before the prediction time is $\{..., P_{-1}, R_0\}$, and the LCE is expected on the right T seconds after the prediction time–obtained from the TLC parameter. In this figure, the two solid lines of lateral trajectories can be labeled as DSPLS sequences of $\{R_0, R_1, L_2\}$ and $\{R_0, R_1, R_2\}$ for DCE and LCE, respectively.

Given the driving signals Φ_0 observed during the last segment right before the prediction time (i.e., Φ_0 represents the observation of initial trajectory for the upcoming movement), the validation of TLC-based LCE candidates can be performed by hypothesis test between the following two hypotheses:

H0 (LCE): Φ_0 will cause a DSPLS representing LCE.

H1 (DCE): Φ_0 will cause a DSPLS representing DCE.

Thus, the hypothesis test to decide the occurrence of LCE is given by:

$$\frac{p(\Phi_0, H0)}{p(\Phi_0, H1)} \begin{cases} \ge \gamma & \text{Lane-Crossing Event} \\ < \gamma & \text{Driver-Correction Event,} \end{cases} \tag{4}$$

where γ is a pre-defined threshold. Therefore, our challenge is to determine the technique to compute the joint probabilities of these two hypotheses.

Let us again consider a lateral trajectory as shown in Fig. 2. When TLC value is less than a desired threshold δ, the LCE occurrence will be expected at δ seconds after the prediction time. At the prediction time, the lateral trajectory during the latest segment is moving to the right direction, R_0, as we expect LCE on the right. Consequently, the LCE will really occur if the driving signals Φ_0 observed at R_0 lead to the DSPLS pattern $\{R_0R_1R_2\}$. On the other hand, LCE will not really occur if the observation Φ_0 will lead to the DSPLS of either $\{R_0R_1L_2\}$ or $\{R_0L_1\}$ pattern. Therefore, the probability of LCE occurrence following the observation Φ_0 can be computed as a joint probability $p(R_0R_1R_2, \Phi_0)$. Similarly, the joint probabilities $p(R_0R_1L_2, \Phi_0)$ and $p(R_0L_1, \Phi_0)$ represent events belonging to the composite hypothesis. Thus, the hypothesis test can be performed as:

$$\frac{p(\Phi_0, LCE)}{p(\Phi_0, DCE)} = \frac{p(R_0R_1R_2, \Phi_0)}{p(R_0R_1L_2, \Phi_0) + p(R_0L_1, \Phi_0)}. \quad (5)$$

By using Bayes' rule, the above equation can be computed as the likelihood ratio [6]:

$$\frac{p(\Phi_0|LCE_R)}{p(\Phi_0|DCE_R)} = \frac{p(\Phi_0|\Gamma(R_0R_1R_2))P(RRR)}{p(\Phi_0|\Gamma(R_0R_1L_2))P(RRL) + p(\Phi_0|\Gamma(R_0L_1))P(RL)}, \quad (6)$$

where, $p(\Phi_0|\Gamma(R_0R_1R_2))$ represents a conditional probability of Φ_0 generated from a generative model $\Gamma(.)$ of DSPLS pattern $\{R_0$-$R_1R_2\}$, and $P(RRR)$ represents a prior probability of a slope sequence $\{RRR\}$ occurrence, which can be obtained from the ratio of frequency count of such sequence to all possible sequences. A similar equation can be obtained for the LCE expected on the left as:

$$\frac{p(\Phi_0|LCE_L)}{p(\Phi_0|DCE_L)} = \frac{p(\Phi_0|\Gamma(L_0L_1L_2))P(LLL)}{p(\Phi_0|\Gamma(L_0L_1R_2))P(LLR) + p(\Phi_0|\Gamma(L_0R_1))P(LR)}. \quad (7)$$

4. DRIVER BEHAVIOR MODEL

One important step to perform the previously mentioned likelihood ratio test is to compute the probabilities of observation Φ_0 given a particular pattern of DSPLS. In our work, Gaussian Mixture Model (GMM) framework is used as our core driver modeling technique. GMM framework is a powerful stochastic generative model which is successfully used in various applications (e.g., speaker recognition [7], image retrieval [8], etc.) A GMM can be represented as a set of parameters $\{w_m, \mu_m, \Sigma_m\}, m = 1, \ldots, M$, where M is the number of mixture components, μ_m and Σ_m are a mean vector and a covariance matrix of a uni-modal Gaussian *pdf* respectively, and w_m is a linear weight with a constraint $\sum_{m=1}^{M} w_m = 1$. The GMM parameters can be obtained by the iterative Expectation-Maximization (EM) algorithm [9] using training or development data.

The GMM parameters of a desired sequence pattern can be trained from a pool of all the observations belonging to the first episode of such sequence. Fig. 3 illustrates a trajectory of lateral position and its corresponding assigned sequence of lateral slopes (Eq. 1- 3.) For example, to estimate GMM parameters of LLR slope sequence pattern, $\Gamma(LLR)$, we first search for all of the non-overlapped slope sequences LLR (dashed circles) from the training data and then use the observations from the first L-labeled segments (dashes rectangles) to train a GMM model $\Gamma(LLR)$. The other GMM models can be obtained in a similar manner as described.

Although it is necessary for a driver to maneuver a vehicle following the vehicle dynamic principles in order to control a vehicle

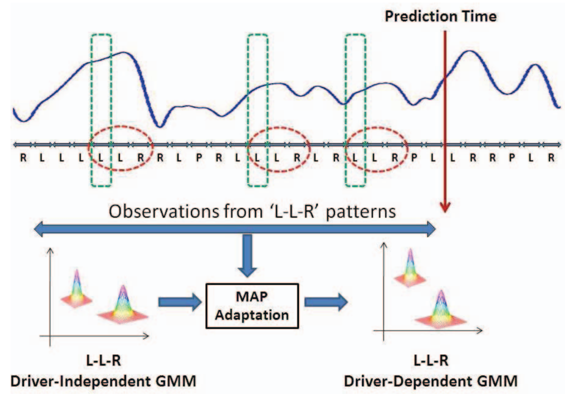


Fig. 3. Illustration of training/adapting sequences for LLR pattern.

movement as desire, it is also acknowledged that the characteristics of driving behavior are varied among individual driver due to a variety of factors such as experience, gender, age, physical and mental states, personality, driving environment, vehicle performance, etc. Moreover, in the beginning, the amount of observation data or driving signals acquired from individual driver are generally sparse which is not sufficient to train a well-defined probabilistic model. Thus, driver model adaptation scheme is favorable for tackling such problem. First, driver-independent models are trained from the large amount of development data as described previously, and then adapted into driver-dependent models using on-line observations from individual driver in a similar manner to the training process. In Fig. 3, the driver-dependent model of $\Gamma(LLR)$ is obtained by adapting the driver-independent version with the observations from the first L-labeled segments of the non-overlapped slope sequence LLR observed up until the prediction time. In our work, we employed the Maximum-A-Posteriori (MAP) adaptation technique [7] to adapt the mean vectors of each GMM (with relevant factor = 19.0). Finally, a set of driver-dependent models are used in the validation process (Eq. 6 and 7).

5. EXPERIMENTAL VALIDATION

5.1. Driving Corpus

The driving corpus was collected using a driving simulator–a desktop type with attachable steering wheel and pedal pads. The vehicle was installed with an adaptive cruise control (ACC) system, which automatically keeps a distance between the driving vehicle and the preceding car. The subjects were asked to keep their vehicle position within the initial driving lane (i.e., no intentional lane changing allowed). The total number of participants was 94 (49 males, 45 females) with the average driving time duration about 45 minutes. The collected data include lateral position, vehicle velocity, steering-wheel angle, vehicle's yaw angle, brake pressure, throttle pressure, etc. All driving signals are synchronized and sampled at 10 Hz. The driving corpus contains reasonable amount of lane crossing events and nearly lane crossing events as a result of driver distraction, drowsiness, mind-wandering, etc.

5.2. Driving Signals

The driving signals used as observation feature in our work are steering-wheel angle and yaw angle. The yaw angle is the relative angle between a vehicle's heading and road curvature. The steering-wheel angle is bandpass filtered to remove the effects of road curve and high-frequency noise components. Consequently, observation feature of each segment is obtained by concatenating both corresponding steering-wheel and yaw angles into a feature vector (e.g., 20-dimensional feature vector for 1-second segmentation).

5.3. TLC-based LDPS

The driving data from 14 drivers is used in our analysis which contains the total of 49 lane crossing events. A standard computation of TLC is used to predict the LCE that will happen at one second after the prediction time (we will keep one-second prediction time throughout this study). In our analysis, we allow a small margin of time duration between the predicted and actual LCE occurrence to compensate errors from sampled data and non-linearity of road curvature and vehicle velocity. That is, a prediction is considered to be accurate if an LCE occurs after warning, and false-alarm warning is considered if there is no LCE occurrence at all. From experimental data, at one second warning time, the TLC-based LDPS predicted 68 LCE Events, with 49 correct prediction (100% accuracy) and 19 false warnings (38.78% FA).

5.4. LCE and DCE Detection Performance

In this section, we evaluate detection performance of the DSPLS framework in discriminating between beginnings of LCE and DCE. A set of driver-independent GMMs with two mixture components are trained from development data (the remaining data from selected 14 drivers) for each DSPLS sequence (e.g., Γ_{RRR}, Γ_{RRL}, and Γ_{RL} for right LCE; Γ_{LLL}, Γ_{LLR}, and Γ_{LR} for left LCE.) Then, for each driver, the observations–up until each prediction time–of particular DSPLS pattern are used to adapted the driver-independent model. In case of not having enough data for adaptation, we retain the driver-independent mode for that DSPLS model. Fig. 4 shows a Detection Error Trade-off (DET) curve of LCE and DCE detection–at one second prediction. The DET curve shows Equal Error Rate (EER) around 17.08% with some bias of higher false-alarm rate at lower false-rejection rate.

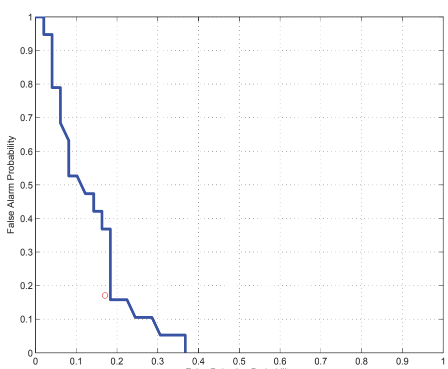


Fig. 4. The DET curve of LCE and DCE detection performance.

5.5. LDPS with DSPLS

In this section, we compare the performance of the proposed DSPLS technique to the original TLC-based LDPS. As mentioned earlier, the original TLC-based system provides 100% accuracy with 38.78% false alarm rate. Once we integrated the DSPLS technique to validate all the LCE candidates obtained from TLC-based system and then compare the log-likelihood score with a fixed optimal EER threshold for a decision making, the proposed technique reduces the false alarm rate to 6.1%, while only reduces the accuracy to 91.8% as a trade-off, as shown in Table 1.

Table 1. Comparison of Accuracy and False Alarm of LCE prediction using TLC and TLC with DSPLS validation.

Methods	Accuracy (%)	False Alarm (%)
TLC	100	38.8
TLC+DSPLS	91.8	6.1

6. CONCLUSION AND FUTURE WORK

In this paper, we have proposed and demonstrated a promising technique to support a lane departure prediction system. The proposed framework validates a warning candidate of a predicted lane crossing event obtained from time-to-line-crossing parameter whether following maneuver will result in unintentional lane departure or deliberate driver correction of lateral position. The algorithm employs Gaussian Mixture Models of Directional Sequences of Piecewise Lateral Slopes representing both lane-crossing and driver-correction events.The framework allows the driver-independent models to be adapted into driver-dependent models using on-line driving signals to better represent individual driving characteristics. The experimental validation using driving simulator data has showed that the proposed framework can discriminate both subsequent events with detection error rate of 17% EER. Consequently, DSPLS reduces false alarm rate of the original LDPS from 38.8% to 6.1% with less trade-off for the accuracy. The proposed framework can be extended to support any lane departure prediction systems. Future work will consider both long-term and short-term driver behavior characteristics for the adaptation framework.

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