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Short Paper

A Lane Departure Warning System Based on Virtual Lane Boundary

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A lane departure warning system (LDWS) should give as much warning time as possible, while triggering few, if any, false alarms. In this paper, a virtual lane boundary based LDWS (VLWM) is proposed to approach this goal. VLWM allows the driver to drift beyond the physical lane boundary by adding a virtual lane boundary. Accounting for the driving habit of the driver, lane geometry, and the local driver behavior changes, the virtual lane width is determined using a fuzzy-logic inference method. When the vehicle is predicted to exceed the virtual lane boundary, an alarm is triggered. Real world driving data are used to test the LDWSs. Compared with time-to-lane-crossing (TLC) based method, the VLWM has a much lower false alarm rate, while their warning time is almost similar. Meanwhile, VLWM has a much longer warning time than the roadside rumble strip (RRS), while the false alarm rate is almost as low as that of the RRS.

Keywords: lane departure warning system (LDWS), virtual lane boundary, fuzzy-logic inference, computer vision

1. INTRODUCTION

Nowadays, an important social and economic problem is traffic safety. In 1999, about 800,000 people died globally in road related accidents, causing losses of around US $518 billion [1]. A considerable fraction of these accidents is due to single vehicle lane departure crashes that are mostly caused by inattention, drowsiness, intoxication, incapacitation, unintended steering wheel motions or utilization of cell phones [2]. In this condition, some lane departure warning systems (LDWS) are developed to aid the driver in avoiding or mitigating lane departure crashes through warnings to the driver [2-4]. A warning system should give as much warning time as possible, while triggering few, if any, false alarms.

Currently, the most common approach to preventing lane departure is the use of roadside rumble strips (RRS) on road shoulders. When a vehicle drifts off the road, its tire hits the RRS, which vibrates the vehicle, and makes a loud noise, alerting the driver to take corrective action. However, RRS does require an infrastructure and does not exist on a majority of roadways, and adding RRS can be expensive. Furthermore, RRS pre-

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sents a difficult issue to determine the rumble-strip distance threshold. Placed too close to the road boundary guarantees that no lane departures will be missed, yet it increases the frequency of false alarms. Placement further from the road edge reduces false alarms, but decreases the effectiveness of the warning in terms of driver response.

An alternative approach is TLC based method, and when the TLC is below a specified threshold an alarm is triggered. TLC, first proposed by Godthelp [5], is defined as the time predicted before a specified location on the vehicle will cross the lane boundary. In general, TLC based method provides more warning time than RRS, because warnings are triggered when a driver is *predicted* to be in danger. However, this prediction can be wrong, and therefore, the false alarm rate is generally much higher than with RRS. So, RRS has a low false alarm rate, but a short warning time. Conversely, TLC based method, as it is normally implemented, has a much higher false alarm rate than RRS, with a longer warning time.

The first step to develop an onboard LDWS is a robust detection of lane boundaries. Numerous methods have been developed to estimate the lane shape and the vehicle position in the lane. They can be classified into region-based methods and edge-based methods. For a thorough review on lane detection methods, we refer the readers to reference [6].

Based on some kind of lane boundary estimation, some authors have worked on lane departure warning systems. These methods can be classified into TLC based methods [3, 7], vehicle heading direction based methods [4, 8-10], and methods that are based on onboard electronic implementation of the static rumble strip [11-13].

TLC based methods have long warning time, but they usually have high false alarm rates. Vehicle heading direction based methods would fail in curved roads with dashed lane markings, and these methods don’t present their warning time. For electronic rumble strip based methods, the offsets of the rumble strips are difficult to be determined.

Some lane departure warning systems (Supplied by AssistWare Corporation [14], and Iteris Corporation [15]) have recently become commercially available for heavy truck applications. They use computer vision and highly specialized algorithms to detect lane markings, and when necessary the systems generate a warning to the driver. But these systems cannot adapt themselves to the driving habits of the drivers.

In this paper, a lane departure warning system (LDWS) is developed to detect when the vehicle begins to drift from the road. The block diagram of the proposed LDWS is shown in Fig. 1. The LDWS uses a velocity sensor and a camera to determine the vehicle’s state relative to the lane and the local structure of the lane ahead. A decision module interprets these states to determine if the vehicle is in danger of drifting out of the

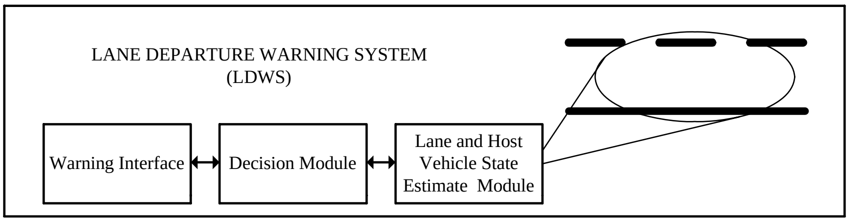


Fig. 1. The block diagram of the proposed lane departure warning system (LDWS).

travel lane. If so, the system provides a warning to the driver. To overcome the demerits of RRS and TLC based methods, a virtual lane boundary based lane departure warning method is developed (In this paper, VLWM is used to stand for virtual lane boundary based lane departure warning method). The virtual lane width is determined by a fuzzy logic based method. Compared with RRS, the VLWM has a much longer warning time, with a false alarm rate similar to the RRS. Meanwhile, VLWM has a much lower false alarm rate than the TLC based methods, while the warning time is almost as long as that of the TLC based methods.

The methods in [12] and [13] use fuzzy logic reference, also. They are electronic implementations of the static rumble strip, using the lateral position and velocity of the vehicle as inputs to estimate the offset of the rumble strip. Their performances are similar to those of TLC based methods.

The rest of this paper is organized as follows: Section 2 describes the used lane geometry and vehicle state estimate method. Section 3 presents the virtual boundary based lane departure warning method (VLWM). Experiment results are provided in section 4 and section 5 gives the conclusions.

2. LANE GEOMETRY AND VEHICLE STATE ESTIMATE

In order to determine if the vehicle is in danger of departing the road, a LDWS must accurately and reliably estimate the vehicle's position and orientation relative to the road, and the geometry of lane ahead.

This study uses our previous developed lane detection and tracking method to estimate the lane geometry and the vehicle position and orientation within the lane [16]. A camera mounted on the vehicle acquires visual information about the road, and the desired information is extracted from the acquired images by means of computer vision technology in real time. Video sequences are obtained at 25 frames per second.

Firstly, a deformable template model of the projective projection of the lane boundaries is used assuming that the lane boundaries are parabolas in the ground plane. Then, the lane detection problem is formulated as a maximum a posteriori (MAP) estimate problem. Due to the non-concavity of the function involved, a Tabu (Taboo) search algorithm is used to obtain the global maxima. The model parameters calculated completely determine the position of the vehicle inside the lane, its heading direction, and the width and curvature of the lane. The lane detection result in the first frame is used to initialize a lane tracker. The lane shape and vehicle position in the sequence of consecutive images are recursively estimated using a particle filter, which has multiple hypotheses capability and can perform nonlinear filtering. Fig. 2 shows some of results of the

Fig. 2. Some of results of the used lane detection algorithm.

used lane detection algorithm. The lane detection and tracking approach can handle the situations where the lane boundaries in an image have relatively weak local contrast or where there are strong distracting edges.

Because this paper focuses on the construction of a lane departure warning model, it does not address the lane detection algorithm in details. We refer the readers to reference [16] for details on the used lane detection and tracking method. The state outputs and accuracies of the used lane detection and tracking method are given in Table 1.

Table 1. The outputting state range and accuracy of the used lane geometry and vehicle state estimate method.

State variable	Range	Accuracy	Units
Lateral offset (d)	[-240,240]	3	centimeters
Lateral velocity (v_l)	[-200,200]	3	centimeters/second
Lane width (W)	[280,420]	3	centimeters
Lane curvature (C)	[-0.01,0.01]	0.0001	1/meter
Heading direction (θ)	[-45,45]	0.5	degrees
Velocity (v)	[0,50]	0.15	meters/second

3. VIRTUAL LANE BOUNDARY BASED LANE DEPARTURE WARNING METHOD

3.1 Virtual Lane Boundary Based Lane Departure Warning Method

In this study, we develop a virtual lane boundary based lane departure warning method (VLWM). This model allows the driver to drift past the physical lane boundary before being alerted to possible danger. This is a more realistic model of driver behavior, as certain drivers tend to drift beyond the lane boundary during normal driving. Allowing this drifting to occur reduces the number of false alarms.

There are two parameters in the VLWM algorithm: lookahead time, T, and virtual lane width W_v beyond the physical lane boundary. The lookahead time is how far in the future the system is willing to predict future vehicle state. The virtual lane width is a distance beyond the physical lane boundary, which the driver is allowed to occupy. A warning is not triggered when the vehicle is predicted to exceed the physical lane boundary. Rather, it is triggered when the vehicle is predicted to exceed the virtual lane boundary, at time T from now, which is usually beyond the physical lane boundary. If the following relation is true, then an alarm is triggered:

$$L_p > L_v \tag{1}$$

where L_p is the predicted vehicle lateral position, and $L_v = W_v$, is the virtual lane boundary. Fig. 3 shows the sketch of the lane. After the states v, v_l, C, d, μ, W are determined by the method presented by section 2, the location L_p of the host vehicle in time T can be determined (see Fig. 3). There are many ways to compute the predicted lateral position L_p, this paper uses a 1st order kinematic approach, where

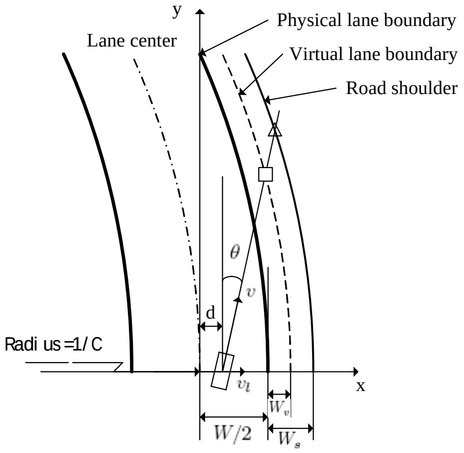


Fig. 3. Projected vehicle path for the vehicle lateral position calculation.

$$L_p = \begin{cases} d + Tv_l - \dfrac{W}{2}, & v_l \geq 0, \\ -d - Tv_l - \dfrac{W}{2}, & v_l < 0. \end{cases} \tag{2}$$

Other models are possible, such as 2nd order models which use lateral acceleration information, or data-centric approaches such as memory based learning which use a distribution of actual future lateral positions calculated using training data.

The decision-making part of the VLWM system requires some inputs and produces an adjustment to the W_v to adapt to the driver behaviors. Driver behavior does change with road geometry, and driver behavior does change over time. Accounting for behavior changes due to road geometry and time results in a more complete alarm decision model, which may improve lane departure warning system performance. Here, we model the driving habit, the curve-cutting behavior, and the local behavior of the driver.

Different drivers have different driving habits. The “loose” drivers have a larger spread in lateral position than the “tight” driver, indicating that the “loose” driver weaves more than the “tight” driver. It is a difficult task to model the driver habit. Here, the long-time lateral position standard deviation δ_m of the vehicle in the lane is used to reflect the driver habit.

Curve-cutting is a behavior in which drivers tend to shift toward the inside of a curve. Reference [17] has shown that when people negotiate curves, their eyes tend to focus on the inside of the curve. Also, when traversing a curve, if the driver starts at the outside, shifts inwards, and then back out, the radius of curvature is maximized and lateral forces are minimized, resulting in a smoother drive. Curve cutting behavior can cause additional false alarms, particularly if exceeds the lane boundary. It is possible to account for this by temporarily increasing the virtual lane boundary on the direction toward the inside of the curve, allowing the driver more freeways.

It is possible to adapt to local deviations by looking at a lagged (by the window size) moving average of the vehicle’s lateral position. By doing so, a warning system would know when the driver's behavior has changed, although it could not infer the reason for that change. When the driver is hugging one side of the lane, the narrow virtual lane could generate false alarms. This shift in lateral position could occur for many reasons: construction zones, passing trucks, a narrow shoulder on the opposite side, driver behavior, etc. If we assume that all such short term changes are due to external circumstances or decisions made by the driver, rather than to inattention or drowsiness, the alarm decision model can be modified to allow the driver more latitude in these circumstances.

3.2 Fuzzy-logic-based Virtual Lane Boundary Width Determination

Determination of the width of the virtual lane is the key of the proposed LDWS. By adjusting the width of the virtual lane, we aim to approach the goal that the proposed method has low false alarm rate and long warning time. So, the decision-making part of the VLWM system is required to take the road construction, the curvature *C*, the lateral position standard deviation δ_m, the local lateral position mean M_p inputs and produce the width W_v of the virtual lane boundary. Here, a supervisory approach using a rule-based system is selected. The selection of a rule-based system is guided by the need to express heuristics and human expertise employed during driving.

Table 2. Rules used to determine the virtual lane width for VLWM system.

				$1/C$		
				small	medium	large
δ_m	small	M_p	small	M	S	S
			medium	M	M	S
			large	L	M	M
	medium	M_p	small	M	M	S
			medium	L	M	S
			large	L	L	M
	large	M_p	small	L	M	S
			medium	L	L	M
			large	L	L	L

The rules of human expertise can be summarized in a rule set, as shown in Table 2. The rules are reformatted as IF-THEN rules, *e.g.*,

IF (δ_m is small) and (M_p is large) and ($1/C$ is medium) THEN (W_v is medium).

These rules represent the heuristics of how the VLWM behaves. At any point in the input space, only one of the rules is active. In this meaning, the rule base is simply a set of linguistic descriptions. The rule base forms the input/output structure of the fuzzy-logic system, and enables us to develop the input and output membership function.

The input variables consisting of $1/C$, δ_m, and M_p, are fuzzified in order to be treated by the fuzzy rule base. For each input, there are three input membership functions representing the fuzzy set small, medium, and large. The input space *U* is simply the expected working range to be included in the fuzzy set. The range for the lane radius $1/C$ is described by the set notation as $U_{1/C}$ = [400, 1200]. The lower bound is decided by according to the construction design standard of highway. Defining the upper bound to be 1,200m is because the curve-cutting behaviors usually happen when the radii of the lanes are small. For the lateral position standard deviation δ_m, U is defined as $U_{\delta m}$ = [0.15, 0.45]. This range is selected by taking into account the ranges of the lateral position deviations of a great deal of drivers. δ_m is calculated using long time of driving data of a driver, typically 10 hours of data. Ideally, the mean of the lateral position should be about zero. When the lateral position of the vehicle is about 0.8m, the wheels of the vehicle will cross the lane edge. So, U is defined as U_{Mp} = [0, 0.8] for the average of the vehicle lateral position in the short time segment. M_p is calculated using the recent 6s' dada of lateral position.

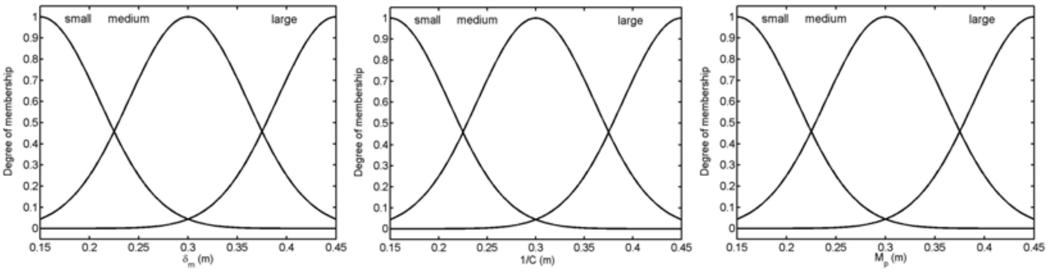


Fig. 4. VLWM input membership function for $\delta_m(\mu_{small}, \mu_{medium}, \mu_{large})$, $1/C(\mu_{small}, \mu_{medium}, \mu_{large})$, and $M_p(\mu_{small}, \mu_{medium}, \mu_{large})$.

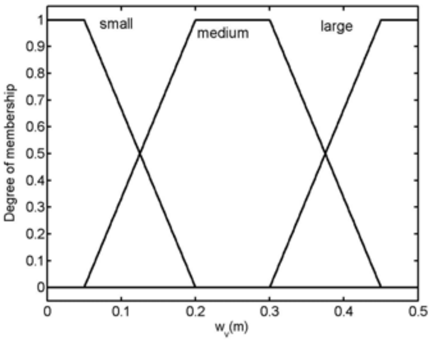


Fig. 5. VLWM output membership function for $W_v(\mu_{small}, \mu_{medium}, \mu_{large})$.

The Gaussian-shaped input membership functions used in the VLWM are given in Fig. 4. For $1/C$, δ_m, and M_p, the membership functions μ_{small}, μ_{medium}, and μ_{large} have adequate support across U. It is noted that the expected range of the inputs may exceed or be less than U. Values outside the expected ranges are set to the nearest range extremum. If $1/C < 400$, for example, let $1/C = 400$.

Three output membership functions for one output W_v are specified representing the fuzzy sets small (S), medium (M), and large (L). The trapezoidal membership functions are shown in Fig. 5. For this implementation, the ranges in W_v = [0, 0.5]m.

The VLWM system uses Mamdani-style inference. The inference process is performed in four steps: fuzzification of the input variables, rule evaluation, aggregation of the rule outputs and defuzzification. Fuzzification step takes the crisp inputs, and determines the degree to which these inputs belong to each of the appropriate fuzzy sets. Rule evaluation step takes the fuzzified inputs, and applies them to the antecedents of the fuzzy rules. Because the fuzzy rules have multiple antecedents, a fuzzy operator *AND* is used to obtain a single number that represents the result of the antecedent evaluation. This number is then applied to the consequent membership function. Aggregation of the rule outputs is the process of unification of the outputs of all the rules. This is done by taking the membership functions of all of the rules' consequents, after the rule evaluation process, and combining them into a single fuzzy set by summation operator. Aggregation is done separately for each output variable. Defuzzification, which turns the output fuzzy set into a crisp number, is the last step in the Mamdani inference system. It is actually equivalent to finding the center of gravity (COG) of the fuzzy set in the output range [0, 0.5].

4. EXPERIMENTS

In this section, we test the VLWM's performance and compare the performance of the VLWM with those of the RRS and TLC based methods. Here, we use a large amount of real world driving data to test the LDWS performances. Most previous efforts on lane departure prevention use data which were collected by having subjects drive simulations [12, 18]. The primary advantage of using the real world driving data is that if the goal of lane departure prevention work is to build systems which can work in the real world and prevent single vehicle roadway departures, then the models and algorithms used must be validated on real world data. Most of the current work based on simulation studies, however, leaves real word implementation as a future problem to be solved.

4.1 Experiment Method

LDWS performances are evaluated using two metrics: warning time and false alarm rate. An LDWS should give as much warning time as possible, while having few false alarms.

The warning time is the time between the alarm trigger and the first tire touching the edge of the shoulder. It measures how much reaction time the driver would have to prevent the outside tire from crossing a road shoulder.

In this application, all the lane departure events (explained below) form a validation set of warning V. Warnings from the proposed VLWM would form the evaluation set E. Warnings in E, which coincide with elements in V, are classified as hits H. The set F are those warnings in E, which are not an element of the validation set H. In a similar manner, a miss is classified as the set M comprising the elements in V, which are not an element of H. We denote the false alarm rate as follows: one is the number of alarms per hour which are in $F \cup M$, the other is the ratio of the element number of $F \cup M$ to the element number of the E.

To evaluate a warning system, there have to be positive examples of lane departure events. Since vehicle state during lane change can be similar to vehicle state during lane departures due to unintended steering input or inattention [19]. We choose to use lane changes as surrogate lane departure events because true lane departures which involve an accident are very rare. Even if the data contain a true road departure, it would be difficult to evaluate system performance using just one example of a road departure. In this experiment, about 50 hours of data that are from fifteen drivers are used, and the details of the data used are shown in Table 3. Here, *LCN* represents the lane change number, M_{lp} and δ_m represent the mean and the standard deviation of the lateral position, respectively.

Table 3. Details of the data used in this experiment.

Driver	T_D (hour)	LCN	M_{lp}(m)	δ_m(m)
D(1)	3.52	78	0.08	0.24
D(2)	4.10	115	0.08	0.31
D(3)	2.56	82	0.04	0.29
D(4)	3.12	76	-0.05	0.41
D(5)	4.25	158	0.07	0.27
D(6)	2.82	74	0.06	0.37
D(7)	3.56	102	0.09	0.28
D(8)	4.36	109	-0.07	0.30
D(9)	2.84	86	0.01	0.33
D(10)	3.50	93	0.10	0.46
D(11)	3.25	106	0.08	0.44
D(12)	2.80	68	-0.08	0.29
D(13)	3.22	122	0.09	0.33
D(14)	2.65	91	0.16	0.32
D(15)	3.23	115	0.05	0.28
Total	49.78	1475		

When the vehicle is predicted to be beyond the virtual lane boundary, an alarm is triggered. For a given driver, the algorithm is run over all the data for that driver. This results in a set of alarm triggers, *E*. All the lane change events are recorded as the validation set of the alarms, *V*. For each alarm trigger, the neighborhood is searched. If a lane change is found, then it is marked as a true alarm. Otherwise, it is marked as a false alarm. When an alarm is triggered, all future alarms are suppressed until the driver has not been in an alarm state for the previous six seconds. For a lane change, if not an alarm trigger corresponding to it, then a miss happens.

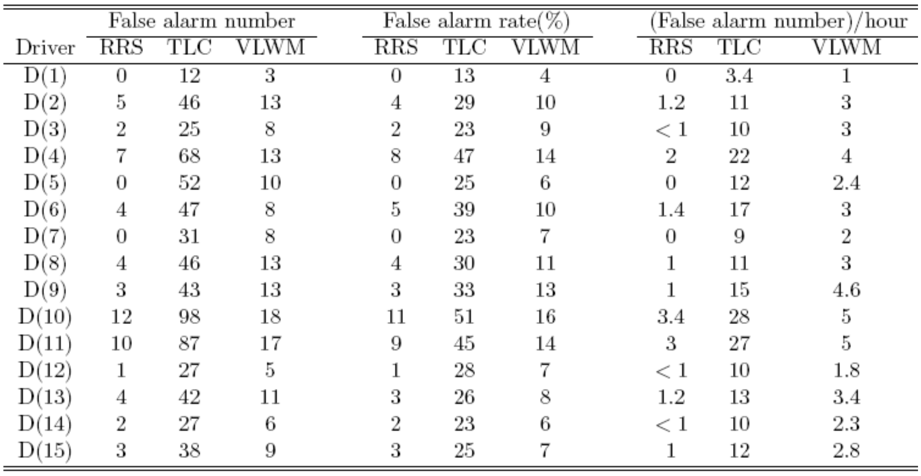
The warning time is calculated as follows: When an alarm triggers, search forward in the data up to a certain point (usually about 4 seconds or so) and see if a lane change is found. If a lane change is found, then find the point where the vehicle's outside wheel first exceeds the (virtual) shoulder width. There are now two points: the alarm trigger point, and the shoulder excursion point. The difference in time between these two points is the warning time.

In this experiment, the width of the host vehicle is 1.80m, and the width of the lanes is 3.6m. For the calculation of the warning time of the RRS, the virtual road shoulder width W_s equals to 0.9m and the infra-structure based roadside rumble strips system is simulated using a warning threshold set 0.3m beyond the physical lane boundary. The lookahead times of the TLC based method and the VLWM are 1.0s.

4.2 Experiment Results

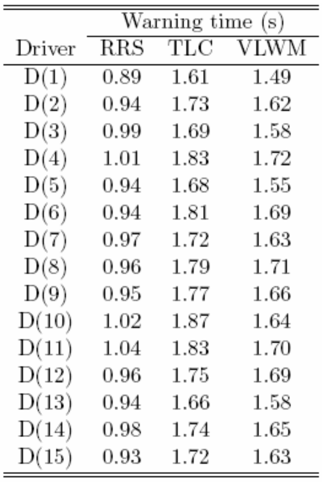
Tables 4 and 5 show how the warning system would perform on the naturalistic datasets. For the RRS, the false alarm is low, except for *D*(4), *D*(10) and *D*(11). Their high false alarm rates imply that they frequently exceed the physical lane boundary by 0.3m during normal driving. The false alarm rate is low, and most likely acceptable. However, the warning time is also low. In all cases, it is less than 1 second. While this is within the boundaries of human reaction time, as shown by [20], it is not much time in which to react to a dangerous situation. A system, which provides more warning time, would be even more effective on a roadway with wide shoulders and even work on roadways with narrow shoulders.

Table 4. Comparing of false alarm number and false alarm rate of different warning methods.



Driver	False alarm number			False alarm rate(%)			(False alarm number)/hour		
	RRS	TLC	VLWM	RRS	TLC	VLWM	RRS	TLC	VLWM
D(1)	0	12	3	0	13	4	0	3.4	1
D(2)	5	46	13	4	29	10	1.2	11	3
D(3)	2	25	8	2	23	9	< 1	10	3
D(4)	7	68	13	8	47	14	2	22	4
D(5)	0	52	10	0	25	6	0	12	2.4
D(6)	4	47	8	5	39	10	1.4	17	3
D(7)	0	31	8	0	23	7	0	9	2
D(8)	4	46	13	4	30	11	1	11	3
D(9)	3	43	13	3	33	13	1	15	4.6
D(10)	12	98	18	11	51	16	3.4	28	5
D(11)	10	87	17	9	45	14	3	27	5
D(12)	1	27	5	1	28	7	< 1	10	1.8
D(13)	4	42	11	3	26	8	1.2	13	3.4
D(14)	2	27	6	2	23	6	< 1	10	2.3
D(15)	3	38	9	3	25	7	1	12	2.8

Table 5. Warning time comparison between different LDWSs.



Driver	Warning time (s)		
	RRS	TLC	VLWM
D(1)	0.89	1.61	1.49
D(2)	0.94	1.73	1.62
D(3)	0.99	1.69	1.58
D(4)	1.01	1.83	1.72
D(5)	0.94	1.68	1.55
D(6)	0.94	1.81	1.69
D(7)	0.97	1.72	1.63
D(8)	0.96	1.79	1.71
D(9)	0.95	1.77	1.66
D(10)	1.02	1.87	1.64
D(11)	1.04	1.83	1.70
D(12)	0.96	1.75	1.69
D(13)	0.94	1.66	1.58
D(14)	0.98	1.74	1.65
D(15)	0.93	1.72	1.63

While the RRS has a low false rate, which is acceptable for most drivers, the warning time is also low. TLC can provide great warning time. However, as Table 5 shows, this comes at the expense of additional false alarms. The warning time increases by over 80%. The false alarm rate rises dramatically, though. For *D*(4), *D*(10) and *D*(11), there is an alarm about every 3 minutes, which is clearly unacceptable. The lowest alarm rate is equal to the highest alarm rate generated by the roadside rumble strips system.

For the VLWM system, the false alarm rate decreases drastically, especially for driver *D*(4), *D*(10) and *D*(11). They have large lateral position standard deviations. For all the drivers, the false alarm rate is below 5 alarms per hour, which is acceptable. The reduction of the false alarm rate comes at the expense of short warning time. For *D*(10), the warning time of the VLWM is 0.23s shorter than the warning time of the TLC. But the warning time of the VLWM system has a large improvement than the RRS, about 70%, while the false alarm rate is acceptable.

The warning time provided by the system is related to the lookahead time, *T*, and the width of the road shoulder. The wider the road shoulder is, the longer the warning time is. When the system has long lookahead time, the warning time is also long with high false alarm rate.

The developed VLWM has a much longer warning time than RRS, with a false alarm rate similar to the RRS. Meanwhile, VLWM has a much lower false alarm rate than TLC based method, while the warning time is almost as long as that of TLC based method. In a word, VLWM has better performance than the RRS and the TLC based methods.

5. CONCLUSIONS AND FUTURE WORK

In this paper, a new lane departure warning system is developed to overcome the demerits of the roadside rumble strips (RRS) and time-to-lane-crossing (TLC) based methods. When the vehicle is predicted to exceed a virtual lane boundary, an alarm is trigger. Accounting for the driving habit, lane geometry, and the local driver behavior changes, the virtual lane width is determined using a fuzzy logic based method. The experiment results reveal that the proposed VLWM's performance is better than the RRS and TLC based warning methods. It has longer warning time than RRS, while its false alarm rate is lower than that of TLC-based method.

Currently, we are developing an estimate method of driver state, *e.g.*, drowsiness, which can be integrated into the proposed VLWM to improve the performance of the VLWM.

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