Lane Change Detection With Smartphones: A Steering Wheel-Based Approach

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ABSTRACT Lane change is a valuable piece of traffic information. An abnormally high number of lane changes on a road section typically suggests that some lanes are blocked due to traffic incidents. Currently, the lane change information of vehicles on an urban road is typically obtained from over-roadway fixed sensors such as surveillance cameras. However, using fixed sensors has limitations in terms of cost and coverage. It is more effective to collect the lane change information directly from each individual vehicle. In addition, lane changing behavior of a driver can help assess his driving risk. One convenient way to detect a lane change directly from each vehicle is to take advantage of sensors on smart mobile devices such as smartphones. In this paper, we explore a new way to identify a lane change event based on a pattern of steering wheel angles detected by a smartphone. This is distinguishable from all of the existing steering wheel-based lane change detection methods, which need to retrieve the steering wheel angle signal from the On-board Diagnostic (OBD) port of the vehicle via the Controller Area Network-Bus (CAN-Bus). In addition, unlike others, our method does not require a lot of complex features to make an accurate detection. In fact, we demonstrate that a high level of accuracy can already be attained with a single simple feature called rotation span. Results show that the proposed detection method performs very well both in terms of precision and recall.

INDEX TERMS Lane change detection, hidden Markov model (HMM), mobile sensing.

I. INTRODUCTION Lane change is a valuable piece of traffic information. On a macroscopic level, it helps identify anomalies such as accidents and blockages in the traffic stream [1]. When an accident occurs, some lanes will be blocked. As a result, the vehicles certainly need to switch lanes in order to avoid the blockage. This creates an abnormally high number of lane changes at the accident site, which allows us to identify and locate it automatically. On a microscopic level, the lane change information of an individual vehicle helps reflect the driver’s behavior. For instance, an aggressive driver typically overtakes and changes lanes a lot more frequently than a safe driver. This microscopic lane change information is beneficial, especially for an insurance application. Along with other indicators, the lane change information can be used for risk assessment, allowing an insurance company to charge an appropriate premium for each individual driver.

Currently, the lane change information of vehicles on an urban road is typically obtained from over-roadway fixed sensors such as surveillance cameras. A vision-based algorithm can be used to count the number of times that the vehicles in the camera scene switch lanes [2]. However, using fixed sensors has limitations in terms of cost and coverage. It is expensive and impractical to blanket the entire road network with fixed sensors. Moreover, data in the area where there is no sensor installed cannot be collected.

The limitations of using fixed sensors, however, can be circumvented by utilizing vehicles as mobile sensors. One of the most effective ways to turn ordinary vehicles into mobile sensors is to use smart mobile devices such as smartphones, smartwatches, and wearable sensors. Most smart mobile devices, especially smartphones, are already equipped with a variety of built-in sensors such as global positioning system (GPS) receivers, cameras, accelerometers, and gyroscopes. These sensors can be exploited for traffic sensing and lane change detection. In fact, a number of smartphone-based lane change detection methods have been proposed [3]–[8].
Other maneuvering types such as left turns, right turns, and U-turns are also considered in [8]. These methods mainly detect the lane change events from the acceleration sensed by the accelerometer and from the angular velocity sensed by the gyroscope on a smartphone. However, none of these smartphone-based methods has detected the lane change events from the steering wheel angle.

In this paper, we explore a new way to detect a lane change event with a smart mobile device, where we particularly experiment with a smartphone. Our detection method identifies a lane change event from a pattern of steering wheel angles measured by a smartphone. Nonetheless, it is also applicable to other types of mobile devices as long as they are able to measure the steering wheel angle. Although many steering wheel-based lane change detection methods exist (e.g., [3], [9]–[11]), all of them have to rely on retrieving the steering wheel angle signal from the vehicle’s On-board Diagnostic (OBD) port via the Controller Area Network-Bus (CAN-Bus). This poses quite a few limitations. First, a new equipment is required to retrieve the steering wheel angle signal from the vehicle. Second, unless an additional processing unit is installed on the vehicle, the steering wheel angle signal needs to be processed off-line for lane change detection. Using a smartphone helps overcome these limitations since it can both measure the steering wheel angle and process it. Moreover, most users already own a smartphone, so this creates no additional burden. There are also a few existing works that use sensors on a smartphone and a smartwatch in estimating the steering wheel angle [12], [13]; however, their main purposes are not for lane change detection, and lane change detection methods are not discussed in these works. To our knowledge, through an extensive literature survey, there is no steering wheel-based lane change detection method that makes use of the sensors on a smartphone.

The ultimate goal of this study is to find a method that can detect a lane change event highly accurately by using only a single feature derived from the steering wheel angles. This is a clear distinction to the existing studies, which normally require a large number of features in their lane change detection algorithms. A new single-featured steering wheel-based lane change detection method will be introduced in this paper. In contrast to our previous work, where a rule-based detection method was investigated [14], a probabilistic method which detects a lane change event from a time series of steering wheel rotations will be presented here.

The main contributions of this work can be summarized as follows:

1) We introduce a new smartphone-based lane change detection method that takes advantage of the steering wheel rotations. Unlike any existing steering wheel-based lane change detection methods, ours does not rely on retrieving the steering-wheel angle signal from the vehicle’s OBD port. This makes it a lot more convenient for any smartphone user to turn his or her vehicle into a mobile sensor.

2) We demonstrate that our method is able to detect the lane change events with high accuracy, by using only a single simple feature derived from the steering wheel angles. This simple feature, called “rotation span,” enables our method to achieve the similar level of accuracy attained by the more complex methods that require a larger number of features. In fact, in many cases, our method outperforms the more complex ones.

The rest of this paper is organized as follows. In Section II, we thoroughly discuss related work on lane change detection. The proposed lane change detection method is described in Section III. Accuracy of the detection method is discussed in Section IV. Finally, we conclude this paper in Section V.

II. RELATED WORK

Lane change detection has been an important research topic in the field of intelligent transportation systems. A number of studies on in-vehicle lane change detection exist; however, they can generally be classified into three categories:

1) trajectory-based approach
2) vision-based approach
3) pattern-based approach

A trajectory-based approach detects a lane change event from vehicle trajectory trace. This approach relies on positioning sensors such as GPS receivers. With a combination of lane-level geographical information (e.g., lane-level digital map) and a GPS receiver, a trajectory trace can be used to determine whether the vehicle departs from its current lane [15], [16]. Alternatively, if a lane-level digital map is not available, a reference trajectory method can be applied [17]. In this method, however, a database of in-lane reference trajectories for every lane on the road needs to be created in advance. This is typically done by deploying probe vehicles to collect their trajectory traces for each reference lane. Essentially, a trajectory-based approach requires some forms of lane-level reference information, whether it is a lane-level digital map or a database of in-lane trajectories. It requires huge efforts to acquire such information for the entire road network. Performance of a trajectory-based approach depends mainly on the accuracy of the reference information and the accuracy of the GPS, which is subject to factors such as weather and the number of satellites in connection.

A vision-based approach relies on vision sensors such as cameras. Modern vehicles may already have cameras installed from a factory, but smartphone cameras are also a great alternative for the older vehicles. Typically, the lane markings will be tracked, and a lane change event is detected when the vehicle departs from the current lane markings [18]–[21]. However, a vision-based method requires video processing, which is computationally intensive. Moreover, its effectiveness is subject to the visibility of the lane markings. Lane markings that are faded or occluded cannot be detected well. Moreover, weather condition (e.g., snow, rain, and fog) and lighting condition (e.g., shadow and brightness) highly affect the accuracy of the vision-based approach.
A pattern-based approach detects a lane change event based on the patterns observed from the sensed data. The typical data sensed from the vehicle are its acceleration, angular velocity, speed, yaw-rate, and steering wheel angle. A comparison of relevant pattern-based lane change detection methods is given in Table 1. The details are explained here.

- The first column lists the references for each lane change detection method.
- The second column describes the types of sensors used in each detection method. Basically, three major types of sensors are utilized: 1) smartphone sensors, 2) car sensors (i.e., embedded in the vehicle by manufacturer), and 3) external sensors (i.e., instrumented on the vehicle).
- The third column indicates where the sensors are placed on the vehicle. Smartphones are typically mounted on the windshield, placed on the dashboard or on the console, and put in the cup holder or in the driver’s pocket. Note that none of these methods has considered placing a smartphone on the steering wheel. In contrast, the car sensors are already embedded in the vehicle by the manufacturer. The data from these sensors can be read via the CAN-Bus. Finally, the external sensors such as radars, lidars, and cameras can be installed on the interior and exterior of the vehicle.
- The fourth column describes the source signals used for lane change detection. The commonly used signals are acceleration, angular velocity, speed, and steering wheel angle. It is important to note that none of the methods which use the steering wheel angle for lane change detection has utilized the smartphone sensors.
- The fifth column specifies the number of features that each lane change detection method uses. These features are derived from the corresponding source signals. For example, the features derived from the acceleration signal could be its mean, its extrema values, the temporal gap between two extrema values, etc. These features are important traits of the signal that the detection algorithm uses in decision making. The number of features used in these methods varies from 1 to as many as 42.
- The sixth column indicates the type of algorithms or techniques that each lane change detection method employs. The methods are rule-based (i.e., [3]–[7]), where a lane change event is declared if the observed features follow a predefined set of rules. A few detection methods (i.e., [9], [10]) resort to the hidden Markov model (HMM). Support vector machine (SVM) is considered in [11] and [22] while six classification algorithms are considered in [8].
- The seventh column lists the number of features used in the evaluation of each detection method. Roughly, the number of lane change events in most studies is on the order of a few hundreds events.
- Finally, the last column lists the accuracy of these lane change detection methods.

The third column indicates where the sensors are placed on the vehicle. Smartphones are typically mounted on the windshield, placed on the dashboard or on the console, and put in the cup holder or in the driver’s pocket. Note that none of these methods has considered placing a smartphone on the steering wheel. In contrast, the car sensors are already embedded in the vehicle by the manufacturer. The data from these sensors can be read via the CAN-Bus. Finally, the external sensors such as radars, lidars, and cameras can be installed on the interior and exterior of the vehicle.

A smartphone is affixed to the steering wheel to measure the steering angle.

In our perspective, a lane change detection algorithm should be simple and should require the least amount of resources, so that it is feasible to run on mobile devices like smartphones. In the next section, we introduce a smartphone-based lane change detection method that relies only on a single simple feature derived from the steering wheel angles.

### III. METHODOLOGY

In this section, we describe our lane change detection method. Data collection, lane change characteristics, and the detection algorithm are presented.

#### A. DATA COLLECTION

In order to find a relation between the steering wheel angles and the lane change events, we need to collect the actual field data. In this study, built-in motion sensors such as accelerometer and gyroscope on an iPhone 5s are collectively used to measure the steering wheel angle. The smartphone is affixed on the inside of the steering wheel at the zeroth degree angle as shown in Fig. 1, and thus it does not interfere with the driver’s maneuvering. The zeroth degree angle is calibrated and used as the reference angle for the straight heading. If the steering wheel is rotated clockwise (i.e., to the right), the angle of the steering wheel will become more negative. On the contrary, if the steering wheel is rotated counterclockwise (i.e., to the left), the angle of the steering wheel will become more positive. Note that, unlike [3]–[8], the smartphone senses the motion of the steering wheel rather than the motion and the steering (heading) of the vehicle. Thus, the steering wheel angle measurement is not affected by road elevation.

An iOS application is developed to record the steering wheel angle measurements. In addition, in order to reduce noises, the raw measurements are smoothened by a moving average as follows

$$\phi_n = \frac{1}{w} \sum_{i=0}^{w-1} x_{n-i}$$

(1)
| Work | Sensors | Sensors Placement | Source signal | Features | Algorithm/Technique | Total lane change events | Accuracy |
|------|---------|-------------------|--------------|----------|---------------------|-------------------------|----------|
| [3]  | Smartphone:  
  • Accelerometer  
  • Gyroscope  
  • Magnetometer  
  • GPS  
  Car sensors:  
  • Steering wheel angle sensor  
  • Speed sensor | Windshield  
  Cup holder  
  Driver’s pocket | Vehicle orientation  
  Speed | 3 features:  
  • Max deviation of vehicle orientation  
  • Orientation difference  
  • Speed | Rule-based | Over 300 events | Straight road:  
  • 58.33% recall with crowdsourcing  
  • 76.57% precision with crowdsourcing (see [3] for accuracy on curves) |
| [4]  | Smartphone:  
  • Accelerometer  
  • Gyroscope  
  • GPS | Unspecified | Acceleration  
  Speed | 3 features:  
  • Acceleration  
  • Duration of peak acceleration  
  • Speed (for on-curve detection) | Rule-based | 26386 events | Straight road:  
  • 97.08% recall for single lane change  
  • 91.02% recall for sequential lane change |
| [5]  | Smartphone:  
  • Camera  
  • Accelerometer  
  • Gyroscope | Windshield | Acceleration | 3 features:  
  • Extrema of acceleration signal  
  • Time between two extrema  
  • Gap between max and min value | Rule-based | Unclear (226 of mixed events) | 88.5% precision |
| [6]  | Smartphone:  
  • Accelerometer  
  • Gyroscope | Windshield  
  Driver’s pocket | Angular velocity | 3 features:  
  • Angular velocity  
  • Max angular velocity  
  • Duration that the angular velocity is above a threshold | Rule-based | Around 160 events | 93% recall for windshield mounted  
  88% recall for driver’s pocket |
| [7]  | Smartphone:  
  • Accelerometer | Center console | Acceleration | 1 feature:  
  • Acceleration | Rule-based | Unspecified | Unspecified |
| [8]  | Smartphone:  
  • Accelerometer  
  • Gyroscope | Dashboard | Acceleration  
  Angular velocity | 42 features:  
  • Derived from acceleration and angular velocity | 6 classification algorithms | 103 events | Around 98-99% recall with the Naive Bayes method |
| [9]  | Car sensors:  
  • Steering wheel angle sensor  
  • Others that can be obtained via CAN-BUS | Installed by car manufacturer | Steering wheel angle  
  Acceleration  
  Speed  
  Yaw-rate | 11 features:  
  • Derived from steering wheel angle, acceleration, speed, and yaw-rate | HMM | 372 events | Around 88% recall  
  Around 87% precision |
| [10] | Car sensors:  
  • Steering wheel angle sensor | Installed by car manufacturer | Steering wheel angle | 3 features:  
  • Mean values of steering wheel angles in 3 parts of input segment | HMM | 331 events | Around 82% recall  
  Around 84% precision |
| [11] | External sensors:  
  • Lidar  
  • Cameras  
  • Initial measurement unit  
  • GPS  
  Car sensors:  
  • Steering wheel angle sensor | External sensors:  
  • Interior and exterior of the vehicle  
  Car sensors:  
  • Installed by car manufacturer | Steering wheel angle | 11 features:  
  • Derived from steering wheel angle | SVM | 301 events | 96.35% recall  
  87.09% precision |
| [22] | External sensors:  
  • Radar  
  • Cameras  
  • Accelerometers  
  • GPS | Interior and exterior of the vehicle | Acceleration  
  Speed  
  Yaw-rate | 3 features:  
  • Acceleration  
  • Speed  
  • Yaw-rate | SVM | 65 events | Around 90% recall for dangerous lane change detection |
where $\phi_n$ is the $n$th sample of the smoothened steering wheel angle, $x_n$ is the $n$th sample of the raw steering wheel angle, and $w$ is the window size. In this study, the value of $w$ is set to be equal to 10. We have also experimented with other window sizes, but this value yields the best results.

In this study, the field data are collected on urban roads, consisting of straight segments and curves, in Bangkok, Thailand. A driver drives naturally in the traffic stream, and the application records the angle of the steering wheel at every 0.1 second. For each actual lane change event, the instant at which the driver starts making a lane change and the instant at which the lane change is complete are also manually recorded into the application by the driver. The driver simply has to tap the smartphone at the beginning and the end of the lane change event. The timestamps are automatically recorded. We emphasize that this is done for the purposes of data collection in this experiment only. In practice, the lane change will be detected automatically, and it does not require the driver’s attention or interaction with the smartphone.

Two datasets were collected in this study. For convenience, let us refer to them as Dataset 1 and Dataset 2. The drivers and the vehicles used in collecting these two datasets are different. Dataset 1 was collected by a male driver, driving on a Mazda 2 which is a typical subcompact car. It contains approximately 6 hours of driving time and includes 421 occurrences of lane change events. Out of these, 147 of them are left lane change, and 274 of them are right lane change. The vehicle speed and the duration of each lane change event in Dataset 1 are shown in Fig. 2. Although these samples were collected by a single driver, they cover a wide range of lane change duration and vehicle speed. As observed, the duration of most lane change events varies from 3 seconds to 17 seconds. There is an outlier where the lane change duration is as large as 29 seconds. This extremely long duration can happen when the driver gets stuck half-way in the traffic while trying to complete the lane change. The speed at which the lane change occurs ranges from nearly zero to around 101 km/h.

Dataset 2 was collected by another independent male driver, driving on a Toyota Yaris which is also a subcompact car. It contains approximately 1 hour and 23 minutes of driving time and includes a total of 76 lane change events. Out of these, 28 of them are left lane change, and 48 of them are right lane change. The vehicle speed and the duration of each lane change event in Dataset 2 are shown in Fig. 3. It can be observed that the lane change duration ranges approximately from 4 seconds to 9 seconds while the vehicle speed at which the lane change occurs ranges from around 9 km/h to 67 km/h. The main purpose of Dataset 2 is for evaluating the generality of our lane change detection method. Basically, a lane change detection model will be built based on the samples in Dataset 1. Then, in order to ensure that the model generalizes well on a different driver and a different vehicle, it will also be tested with the samples in Dataset 2. The number of lane change events in the two datasets combine to a total of 497 events. This sample size is larger than those used in most of the existing studies (see Table 1).

Since we only focus on lane change detection, events such as left turns and right turns are pre-filtered as in [10]. In practice, left turns and right turns can be detected easily from a GPS trace. In addition, given a typical traffic on busy urban roads, vehicles can rarely change across multiple lanes at once in real practice. Therefore, we do not consider the detection of such an event. This is not uncommon since none of the studies listed in Table 1 has considered the case of changing across multiple lanes at once, except [4] which only considers this in the highways scenario (i.e., not in the urban roads scenario). Finally, since most lane change events in practice occur on straight road segments, detecting the lane change events on curves is not considered in this paper. Our data still include driving on curves, but without lane changing while driving on them. We also would like to point out that none of the studies listed in Table 1 has considered detecting a lane change event on curves, except [3] and [4] which only consider curves in the non-urban roads scenario.
FIGURE 4. A time series of steering wheel angles during (a) a right lane change event and (b) a left lane change event.

B. LANE CHANGE CHARACTERISTICS

Once the data are obtained, the next step is to identify the pattern in the data that corresponds to a lane change event. In order to gain some initial insights, we first look at the steering wheel angle during a lane change event. A time series of the steering wheel angles during a right lane change event is shown in Fig. 4a and a time series of the steering wheel angles during a left lane change event is shown in Fig. 4b. The horizontal axis illustrates the time in the standard HH:MM:SS format, where HH is the hour, MM is the minute, and SS is the second. In each of these figures, the period during which the lane change occurs is illustrated by the blue dots whereas the period during a normal lane keeping is illustrated by the grey dots. Let us first consider the right lane change event in Fig. 4a. It can be observed that the steering wheel angle during the lane change event has a sinusoidal pattern, which can be dissected into three phases. In the first phase, the steering wheel angle decreases toward a local minimum at around $-40^\circ$, indicating that the driver rotates the steering wheel clockwise to depart from the current lane.

In the second phase, the steering wheel angle increases from the local minimum toward a local maximum at around $38^\circ$, implying that the driver rotates the steering wheel back in the counterclockwise direction. Finally, in the last phase, the steering wheel angle decreases toward the zeroth degree, suggesting that the driver rotates the steering wheel clockwise again to adjust the vehicle orientation in the new lane.

Similarly, a sinusoidal pattern can also be observed in the left lane change event shown in Fig. 4b, but in the opposite direction. There is, however, a subtle difference between the example shown in Fig. 4b and that shown in Fig. 4a. It should be noted that there are more than one rotation in the first phase of the lane change event shown in Fig. 4b. In the first phase, the steering wheel angle increases toward a local maximum at around $20^\circ$, indicating that the driver rotates the steering wheel counterclockwise. Next, the angle slightly decreases and then increases toward the next local maximum at around $28^\circ$, which means that the driver rotates the steering wheel slightly clockwise and then counterclockwise. Totally, there are three rotations in the first phase. This example demonstrates that it is possible to have more than one rotation in each phase. This generally applies to both the left lane change event and the right lane change event.

The sinusoidal pattern of the steering wheel angles during a lane change event is also reported in other studies which obtain the steering wheel angle signal directly from the OBD port of a vehicle (e.g., [3], [9], [10]). In fact, it is the common pattern used for lane change detection. The general technique employed by most studies is to come up with meaningful features, derived from the steering wheel angle signal and others, that can help identify this sinusoidal pattern. The number of features and the complexity of the features vary, as noted in Table 1. In contrast to the existing studies, in this paper, we aim at using only a single simple feature in detecting a lane change event.

As introduced earlier, in order to identify the sinusoidal pattern of the steering wheel angles during a lane change event, we dissect them into three phases. We can model these phases as the states that the vehicle goes through during a lane change event as shown in Fig. 5.
The first phase of the sinusoid translates to a state called “Depart.” In this state, the vehicle is departing from its current lane, and the steering wheel will be rotated toward the new lane that the vehicle is driving into. For a left lane change, this state will be referred to as $L_D$. Similarly, for a right lane change, this state will be referred to as $R_D$. The second phase of the sinusoid translates to a state called “Into.” In this state, the vehicle is getting into the new lane, and the steering wheel will be rotated back toward the departed lane, passing the zeroth degree reference angle. For a left lane change, this state will be referred to as $L_I$. Similarly, for a right lane change, this state will be referred to as $R_I$. Finally, the last phase of the sinusoid translates to a state called “Keep.” In this state, the vehicle is trying to keep its position in the new lane. The steering wheel will be rotated toward the new lane again in order to adjust the orientation. This state will be referred to as $L_K$ for a left lane change, and it will be referred to as $R_K$ for a right lane change.

In summary, during a left lane change, the vehicle would go through the three succeeding states, which are $L_D$, $L_I$, and $L_K$. Similarly, during a right lane change, the vehicle would go through the three succeeding states, which are $R_D$, $R_I$, and $R_K$.

C. PROBABILISTIC LANE CHANGE DETECTION

Generally, a drive can be viewed as a time series of left and right steering wheel rotations. In fact, even in a normal straight lane keeping situation, a driver unknowingly adjusts the steering wheel left and right continuously in order to keep the vehicle orientation. One way to detect a lane change event is to find a series of steering wheel rotations that correspond to the three phases of the sinusoidal pattern or equivalently the three states of the vehicle during the lane change. In this section, we discuss a technique which allows us to detect a lane change event effectively.

First, let us define a rotation more specifically. A right rotation is defined as a sequence of decreasing steering wheel angles from a local maximum to a succeeding local minimum. Similarly, a left rotation is defined as a sequence of increasing steering wheel angles from a local minimum to a succeeding local maximum. For example, in Fig. 4a, there is one rotation in each phase of the sinusoid. The starting point and the end point of each rotation are indicated by the red triangles. The rotation in the first phase is a right rotation because it is a sequence of decreasing steering wheel angles. In contrast, the rotation in the second phase is a left rotation because the angles in this sequence are increasing. Finally, the rotation in the last phase is a right rotation. In terms of states, the vehicle goes through three succeeding states which are $R_D$, $R_I$, and $R_K$, where there are exactly one rotation in each state.

It is possible to have more than one rotation in each phase of the sinusoid and in each state of the vehicle. In Fig. 4b, for example, there are three rotations in the first phase. Particularly, the first phase starts with a left rotation, followed by a small right rotation, and then a left rotation. There is one right rotation in the second phase, and there is one left rotation in the last phase. In terms of states, the vehicle goes through three succeeding states which are $L_D$, $L_I$, and $L_K$, where there are three rotations in the $L_D$ state, and one rotation each in the $L_I$ state and in the $L_K$ state. In addition, it is important to note that the number of angles in each rotation is not fixed. Some rotations contain a larger number of angles than the others. This is in sharp contrast to the lane change detection methods that divide the steering wheel angles into fixed-length segments or constant time intervals. Since the duration of each lane change event varies, it is not appropriate to use fixed-length segments or constant time intervals.

In addition, let us define a rotation span, denoted by $\omega$, as the difference between the last angle and the first angle in the rotation. If a rotation $\Phi$ is a sequence of angles $\phi_1, \phi_2, \ldots, \phi_k$, then its rotation span can be written as

$$\omega_{\Phi} = \phi_k - \phi_1.$$  

Note that the sign of a rotation span also indicates its direction. A left rotation would have a positive rotation span; whereas, a right rotation would have a negative rotation span. Fig. 6 illustrates a box plot of rotation spans in various states of the vehicle. As introduced in Section III-B, $L_D$, $L_I$, and $L_K$ are the states of the vehicle during a left lane change. Similarly, $R_D$, $R_I$, and $R_K$ are the states of the vehicle during a right lane change. Finally, Neutral is defined here as the state of the vehicle during a normal lane keeping. It can be observed that the rotation spans during a lane change, especially those in the $L_I$ and in the $R_I$ states, are distinctively larger than those in the Neutral state. As anticipated, most of the rotation spans in the Neutral state concentrate around zero degree. However, there are a number of cases where large values of rotation spans are observed in the Neutral state. This happens due to road curves and obstacles avoidance, and it makes lane change detection much more challenging. We will use these rotation spans along with their corresponding states to build a probabilistic model for predicting a lane change event.

![A box plot of rotation spans in different states.](image-url)
In this probabilistic method, the states of the vehicle and their transitions will be modeled with a HMM. HMM is a powerful analytical tool for modeling and predicting time series data. Given a sequence of observations from the system, a HMM can predict the corresponding sequence of states that the system most likely undergoes. Particularly to our case, given a sequence of observed rotation spans, we can use a HMM to predict the corresponding sequence of states that the vehicle most likely goes through.

A complete HMM, denoted by \( \lambda = (N, M, A, B, \pi) \), can be characterized by the following set of specifications [23]:

1) \( N \), the number of states. Totally, there are 7 states in our model. A left lane change and a right lane change are modeled with three states each, and a normal lane keeping is modeled with a single state. A state transition diagram is shown in Fig. 7.

2) \( M \), the number of unique observation symbols. The observation symbols are the observed rotation spans. In order to make the number of unique observation symbols finite, the observed rotation spans are quantized into the integer values between \(-180^\circ\) and \(180^\circ\). For simplicity, a uniform quantizer with a step size of \( m \) is used. More precisely, if \( \omega \) is an observed rotation span, then its quantized value can be written as

\[
q(\omega) = \left\{ \begin{array}{ll} 180, & \omega > 180 \\ \frac{\omega}{m} + \frac{1}{2}, & -180 \leq \omega \leq 180. \\ -180, & \omega < -180 \end{array} \right.
\]  

This is equivalent to rounding the observed rotation span to the nearest \( m \) degree. The number of unique observation symbols, \( M \), is given by

\[
M = \frac{360}{m} + 1, \tag{4}
\]

and the possible symbols are

\[
q_k = mk - 180, \quad k \in \{0, 1, \ldots, M - 1\}. \tag{5}
\]

In this study, the value of \( m \) is chosen to be equal to 5. Thus, each rotation span will be rounded to the nearest five-degree angle, and there will be a total of \( M = 73 \) possible unique symbols (i.e., \(-180^\circ, -175^\circ, \ldots, 0^\circ, \ldots, 175^\circ, 180^\circ\)) in our model.

3) \( A \), the state transition probability matrix. The element \( a_{ij} \) in the matrix \( A \) represents the transition probability from state \( S_i \) to state \( S_j \). The value of \( a_{ij} \) can be obtained empirically from the collected data, by observing the rate of transitions that the vehicle makes from state \( S_i \) to state \( S_j \). For example, a transition probability from state \( Neutral \) to state \( Right \) can be obtained by determining, out of all the transitions from \( Neutral \), how frequently the vehicle transits from \( Neutral \) to \( Right \).

4) \( B \), the observation symbol probability matrix. The element \( b_{ik} \) in the matrix \( B \) is the probability of observing the symbol \( q_k \) given that the system is in state \( S_i \). This probability can also be obtained empirically from the collected data. For example, the probability of observing a 35-degree rotation span given that the vehicle is in state \( Right \) can be obtained by determining, out of all the rotation spans observed in this state, how frequently the 35-degree span appears.

5) \( \pi \), the initial state probability vector. The element \( \pi_i \) in the vector \( \pi \) represents the probability that the system is initially in state \( S_i \). This can also be obtained empirically from the collected data, by determining the overall frequency that the vehicle is in state \( S_i \).

Note that this HMM is designed to detect only the successful lane change events. Unsuccessful lane changes that occur during a drive will be treated as non-lane change events because the vehicle does not actually get into the new lane. The corresponding state during any non-lane change event in this HMM is \( Neutral \). In addition, other maneuvering types such as left turns, right turns, and U-turns, are not yet modeled in the current HMM. If these maneuvers occurred during a drive, they would be treated as non-lane change events. Nonetheless, the current model can be extended to detect these maneuvering types by including additional states that correspond to them.

In order to build and evaluate the model, the data in Dataset 1 are divided into two mutually exclusive sets, namely a training set and a test set. The training set is used for building the HMM. This allows us to obtain the transition probability matrix \( A \), the observation symbol probability matrix \( B \), and the initial probability distribution vector \( \pi \). The trained HMM is then used for predicting the states of the vehicle based on the rotation spans observed in the test set. The most probable state sequence is determined through the Viterbi algorithm [23]. A lane change event is declared if the algorithm predicts that there is a transition from the Into state to the Keep state, since this transition signifies that a complete lane change is about to occur. Accordingly, a left lane change event is declared if a transition from state \( L_L \) to state \( L_K \) is predicted. Similarly, a right lane change event is
declared if a transition from state $R_I$ to state $R_K$ is predicted. In addition, in order to ensure the generality of the model, the HMM trained on Dataset 1 will also be evaluated with Dataset 2, which was collected by a different driver and a different vehicle. The performance of this detection method is discussed in Section IV.

IV. PERFORMANCE EVALUATION

In this section, we evaluate the performance of the lane change detection method.

A. PERFORMANCE METRICS

Accuracy of the lane change detection method will be quantified in terms of precision and recall. Precision measures the ability of an algorithm to correctly classify the target event with low false-positive rate. It is defined as

$$\text{Precision} = \frac{TP}{TP + FP}$$

where $TP$ is the number of true-positive occurrences and $FP$ is the number of false-positive occurrences.

Recall measures the ability of an algorithm to correctly classify the target event with low false-negative rate. It is defined as

$$\text{Recall} = \frac{TP}{TP + FN}$$

where $TP$ is the number of true-positive occurrences and $FN$ is the number of false-negative occurrences. A good detection algorithm is expected to have both high precision and high recall.

B. PROBABILISTIC LANE CHANGE DETECTION

Evaluation of the probabilistic lane change detection method is carried out in two phases. The first phase involves building a HMM and evaluating its overall accuracy. Only Dataset 1 will be used in the first phase. In the second phase, the HMM trained on Dataset 1 will be evaluated with an independent dataset (i.e., Dataset 2). The main purpose of this phase is to ensure that the HMM generalizes well on a different driver and a different vehicle.

In the first phase, 100 experiment trials are conducted. In each experiment trial, 75% of the data in Dataset 1 are randomly selected and assigned to a training set, and the other 25% are assigned to a test set. The data in the training set are used for building the HMM, and the trained HMM is then evaluated with the data in the test set. On average, there are approximately 105 lane change events in the test set in each experiment trial. Out of these, around 36 of them are the left lane change events, and 69 of them are the right lane change events. Note that the data are randomly selected to create different pairs of training set and test set in every trial. This is done to ensure that the results are not selectively biased toward any specific pair of training set and test set. Finally, the number of true-positive, false-positive, and false-negative occurrences in these 100 experiment trials are combined to compute the overall average precision and recall.

Performance of the probabilistic lane change detection method is shown in Table 2. The first column describes the speed ranges at which the lane change events occur. Since the speed limit is 80 km/h, for simplicity we divide the speed into two different ranges, with a cutoff at 40 km/h. These ranges roughly represent a congested traffic condition and a less congested one. Precision and recall for the left lane change detection are shown in the second and the third column, respectively. Similarly, precision and recall for the right lane change detection are shown in the fourth and the fifth column, respectively. Finally, the overall precision and recall, considering both types of lane changes, are listed in the last two columns.

Generally, it can be observed that the proposed method performs very well. It is able to achieve a high level of accuracy. When the vehicle speed is above 40 km/h, the precision rates are around 95% and above. However, at the speed below 40 km/h, the precision rates decrease. A possible reason is that, in a low speed traffic (e.g., in congestion), the driver sometimes has to rotate the steering wheel to avoid obstacles such as the motorcycles that get into the lane (i.e., there are a lot of motorcycles on the road in Bangkok). This action of rotating the steering wheel back and forth to avoid obstacles may appear resemble to a lane change. This results in a higher number of false-negative occurrences, which in turn decreases the precision of the detection method.

In terms of recall, the proposed method performs very well when the speed is below 40 km/h. The overall recall rate in this speed range is around 95.3%. However, in the higher speed range, the recall rates decrease. This suggests that the detection method is unable to detect some of the lane change events when the speed is high. A possible reason is that, when the vehicle speed is high (i.e., light traffic), there is more space to complete the lane change. Consequently, the driver does not have to rotate the steering wheel much to change the lane. This makes the rotation in the Into state harder to detect, resulting in a higher number of false-negative occurrences and the degradation in recall.

The distribution of false-negative, false-positive, and true-positive occurrences in one of the experiment trials is shown in Fig. 8. This figure clearly reveals where the errors typically occur. It can be observed that the false-positive errors tend to occur when the vehicle speed is low, causing a degradation in precision. On the other hand, the false-negative errors tend to

| Speed Range (km/h) | Left Change | Right Change | Overall |
|-------------------|-------------|--------------|---------|
|                   | Prec. (%)   | Rec. (%)     | Prec. (%) | Rec. (%) |
| < 40              | 82.82       | 92.00        | 88.92    | 97.01    | 86.81    | 95.30    |
| > 40              | 96.23       | 86.18        | 94.95    | 91.12    | 95.39    | 89.36    |
| All               | 87.90       | 89.49        | 91.24    | 94.56    | 90.09    | 92.80    |

TABLE 2. Accuracy of the probabilistic lane change detection method on Dataset 1.
A comparison between the accuracy of our lane change detection method and that of the existing methods is shown in Table 3. This is the same information as that provided in Table 1; however, we reproduce it here for ease of comparison. The first column lists the references for each lane change detection method. The second column specifies whether the detection method uses a steering wheel angle signal. The number of features required in each detection method is given in the third column. Finally, the last two columns list the overall accuracy of each detection method in terms of precision and recall. The overall accuracy considers left lane change and right lane change altogether. The performance of our detection method is shown in the last row of the table. In terms of precision, our detection method is able to achieve around 90.09%. This is better than most of the existing studies. In terms of recall, our method is able to achieve around 92.8%. This is comparable to, and in many cases better than, those of the existing studies. In contrast to the existing studies, however, our method is able to achieve this high level of accuracy by relying only on a single feature (i.e., the rotation span). In practice, there might be applications where safety is of the highest concern (e.g., lane change assistant). In such a case, an extreme level of accuracy is required, and complex algorithms that use a large number of features may be necessary. However, for applications where safety is less critical (e.g., driving behavior analysis), the level of accuracy attained by our detection method, which requires only one feature, should be sufficient.

In addition, among the methods that employ HMMs for lane change detection, our method can achieve the highest level of accuracy. A comparison on the accuracy of our method and the existing HMM-based lane change detection methods is given in Table 4. Our model performs slightly better than that of [9] while requiring a lot fewer features to train it. In fact, the HMMs in [9] require 11 features; whereas, ours only needs the rotation span. This suggests that the rotation span is a significant feature, which is able to capture the important characteristics of the lane change maneuver. In comparison to [10], our model performs significantly better. One of the main reasons is that we are able to model the states of the vehicle during a lane change more thoroughly. The number of states modeled in our HMM is seven; whereas, only three states are modeled in [10]. In addition, the observation symbols used in our HMM is also more comprehensive.

Finally, in order to ensure that our model generalizes well, we evaluate the HMM trained on Dataset 1 with the data in Dataset 2, which were collected by a different driver and a different vehicle. The accuracy of the probabilistic lane change detection method is shown in Table 5. It can be observed that our detection method still performs very well on Dataset 2. This confirms that our model generalizes well and does not overfit. A similar performance trend as that observed in Table 2 is also observed here. The precision rates degrade when the speed is low whereas the recall rates degrade when the speed is high. The distribution of false-negative, false-positive, and true-positive occurrences in the experiment on
Dataset 2 is shown in Fig. 9. A similar characteristic as that observed in Fig. 8 can also be noted here. The false-positive errors tend to occur when the speed is low, and the false-negative errors tend to occur when the speed is high. Note that there is no false-positive error for the right lane change. As a result, the precision rates for the right lane change are 100% as shown in Table 5. Moreover, at the speed below 40 km/h, there is no false-negative error for the left lane change. As a result, the recall rate for the left lane change at this speed range is 100% as shown in Table 5.

Nonetheless, it should not be mistaken that a HMM trained on one type of vehicles will be applicable to all types of vehicles. Dataset 1 was collected with a Mazda 2, which has a steering ratio of around 15:1. Dataset 2 was collected with a Toyota Yaris, which has a steering ratio of around 13:1. Since there is not a huge difference between their steering ratios, a HMM trained on the data collected from one vehicle is still applicable to the other. However, larger vehicles such as trucks and busses typically have higher steering ratios than those of the passenger cars. In order to detect a lane change accurately on each vehicle type, a HMM needs to be trained separately for each type.

C. DISCUSSION

In this section, we discuss a few issues regarding the practicality of the proposed method.

1) PRACTICALITY OF USING A SMARTPHONE

The main goal of this study is to find an effective lane change detection method that requires only a single feature derived from the steering wheel angles. In the experiment, for convenience, we use sensors on a smartphone for measuring the steering wheel angles. However, in real practice, any smart device that is capable of measuring the steering wheel angles can also be used. For example, instead of a smartphone, a wearable sensor can also be affixed on the steering wheel to measure the steering wheel angles. Depending on the computing resource on the wearable device, the measured angles may be processed for lane change detection by the wearable device itself, or it can be relayed to the driver’s smartphone for processing.

2) POSITION OF A SMARTPHONE

In this study, a smartphone is affixed to the steering wheel at the zeroth degree angle. In real practice, it is not guaranteed that a user will place the device perfectly at the zeroth degree angle. However, the absolute position of the device on the steering wheel does not affect the detection method. Note that the only feature used in this detection method is the rotation span, which is a relative quantity. In other words, it measures the difference between the last angle and the first angle of the rotation. Therefore, the rotation span of a given rotation remains the same, regardless of where the device is affixed to the steering wheel. For example, if a user places the device at the 30th degree angle on the steering wheel instead of at the zeroth degree angle, all the measurements will be shifted by 30 degrees. However, the rotation span of any given rotation is unaffected because both the first angle and the last angle of the rotation are shifted by the same amount, leaving their difference unaltered.

3) PRACTICAL APPLICATIONS AND USER ENCOURAGEMENTS

We have shown in this study that lane change events can be detected highly accurately by using sensors on a smartphone. The follow-up questions that naturally arise are: 1) what are the practical applications and 2) how to encourage drivers to use smartphones or other smart devices for lane change detection. Among many examples, some of the practical applications are insurance and traffic law enforcement. Along with other indicators, the number of lane changes that a driver makes can be used in assessing his/her driving behavior. For example, an aggressive driver tends to change lanes and overtakes a lot more frequently than a safe driver. An insurance company can use this information to assess the risk associated with each individual driver. This allows it to penalize a risky driver with a high premium and to reward a safe driver with a discount. Another potential application is traffic law enforcement. Combining with the location retrieved from a built-in GPS receiver, a lane change detected by a smartphone can be used to check whether the driver switches lanes or overtakes on parts of the road where it is illegal to do so. For these types of applications, the level of accuracy attained by our method, which uses only a single simple feature, is already adequate.

How to encourage drivers to use their smartphones for detecting lane changes as well as monitoring their driving behaviors is indeed challenging. Encouragements may come in forms of benefits such as discounts or rewards. For example, in the insurance application, an insurance company may offer a risk-based pricing model where a driver is charged based on his/her driving behavior. Essentially, safe drivers will be rewarded by paying at a lower price. By using the
driver’s smartphone, both the insurance company and the driver do not have to invest in a new device. This is beneficial to both the company and the customer. On the other end of the spectrum, a government may enforce all drivers to use their smartphones for driving behavior monitoring. The collected data can then be used to evaluate each individual driver at the time of his/her driving license renewal.

V. CONCLUSION
Lane change detection is crucial for many traffic applications such as automatic incident detection, driving behavior analysis, and driver risk assessment. Using mobile devices as in-vehicle sensors helps make these applications more realizable in practice. With a smartphone, an ordinary vehicle can be turned into a smart vehicle quite easily. In fact, many smartphone-based lane change detection methods exist. These smartphone-based methods commonly detect a lane change event from acceleration, speed, and steering (heading) of the vehicle. In sharp contrast, this paper explores a new alternative where a lane change event is detected from the steering wheel, the maneuvering source itself.

Particularly, a new probabilistic lane change detection method is introduced. It is shown that the proposed method can detect the lane change events with high accuracy. While requiring only a single feature, it is able to achieve around 90.09% for precision and 92.8% for recall. This is comparable to, and in many cases better than, the existing studies which require a larger number of features.

In addition, we discover that rotation span is a significant feature for describing the characteristics of the lane change maneuver. It captures the important traits of lane change well. This is clearly observed through the performance of the proposed method, which only relies on this single simple feature. Although our model is merely trained with this feature, it is able to achieve higher performance than many of the existing ones that require a larger number of features.

Finally, the applicability of our lane change detection method is not only limited to smartphones. In fact, it is applicable to any types of mobile and wearable devices, as long as they are able to measure the steering wheel angle accurately [24]. Note that, in this study, the built-in sensors (i.e., accelerometer and gyroscope) on a smartphone are only used for measuring the steering wheel angle. Practically, any mobile and wearable devices with similar built-in sensors (e.g., smartwatches and fitness trackers) can also be used for steering wheel angle measurement as well. These wearable devices are smaller than smartphones, and thus they can be attached to the steering wheel more conveniently. Our lane change detection method is applicable to these devices, regardless of their form factors. Ultimately, in addition to smartphones, users have a wide variety of choices on the devices that they can use comfortably.

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