SMARTPHONE APPLICATION TO ESTIMATE ROAD CONDITIONS USING ACCELEROMETER AND GYROSCOPE

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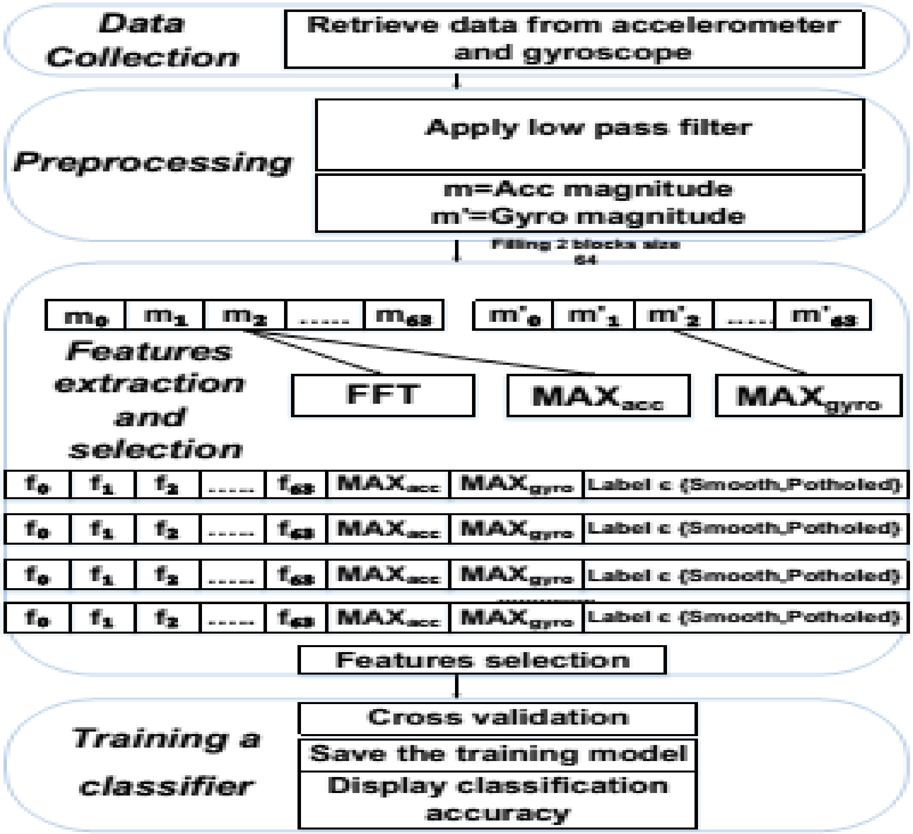
ABSTRACT

Monitoring the road condition has acquired a critical significance during recent years. There are different reasons behind broadening research on this field: to start with, it will guarantee safety and comfort to different road users; second, smooth streets will cause less damage to the car. Our motivationis to create a real-time Android Application Road Sense that automatically predicts the quality of the road based on tri-axial accelerometer and gyroscope, show the road location trace ona geographic map using GPS and save all recorded workout entries. C4.5 Decision tree classifier is applied on training data to classify road segments and to build our model. Our experimental results show consistent accuracy of 98.6%. Using this approach, we expect to visualize a road quality map of a selected region.Hence, we can provide constructive feedback to drivers and localauthorities. Besides, Road Manager can benefit from this systemto evaluate the state of their road network and make a check-upon road construction projects, whether they meet or not the required quality.

I. INTRODUCTION

Accordingto statistics provided by World HealthOrganization (WHO), road accidents have become oneof the top 10 leading causes of death in the world. Specifically,road accidents claimed nearly 1.25 million lives per year(2015). Studies in show that most road accidents are causedby poor condition of roads. Bad roads are a big problemfor vehicles and drivers, this is because the deterioration ofroads leads to more expensive maintenance, not only for theroad itself but also for vehicles. Accordingly, road surfacecondition monitoring systems are very important solutions toimprove traffic safety, reduce accidents and protect vehiclesfrom damage due to bad roads. Both road managers and driversare interested in having sufficient information concerning roadinfrastructure quality (safe or dangerous road).Consolidated approaches for monitoring road surface conditions involve the adoption of costly and sophisticated hardwareequipment’s such as ultrasonicor specific accelerometers with data acquisition systems. These approaches incura high installation and maintenance cost and require largemanual effort, which can induce error while deploying orcollecting the data. Another alternative is to use sensingtechnologies to gain this information to solve the problem ofroad surface condition monitoring. These days, smartphonesare widely utilized. The greater part of them are equippedwith various sorts of sensors like camera, accelerometer, GPS,gyroscope, microphones, etc. Thus, smartphone based roadcondition monitoring is one of such helpful applications tomonitor street conditions.

II. SYSTEM ARCHITECTURE



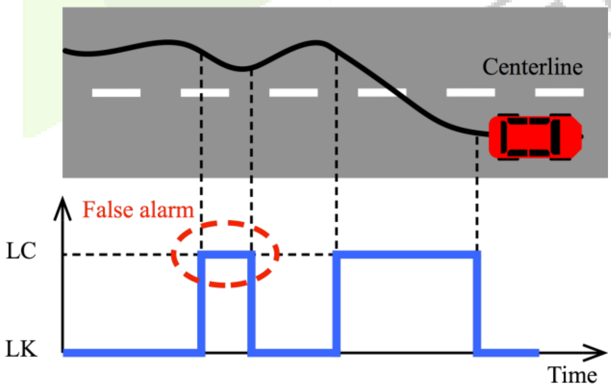


Fig. 1. Schematic illustration of false alarm caused by zigzag driving; previous methods have the problem of frequent false alarms. The graph at the bottom shows the detection result. LC denotes the state of lane changing, and LK denotes the state of lane keeping. We can see that LC was outputted during zigzag driving even though the vehicle did not change the lane.

sug- gested a detection method that uses only directly measurable information from the outside (e.g., lateral position, lateral velocity, and relative velocity) [7]. Mandalia and Salvucci suggested the use of the variance of the lateral position within a constant window size as a feature [8]. However, these methods have the problem of frequent false alarms caused by zigzag driving, as shown in Fig. 1. Here, a false alarm refers to a case in which the detection method determines a lane change when the vehicle does not change a lane, and this can result in the driver's distrust in the driving support system.

To decrease the number of false alarms that frequently occur when using previous methods, we propose a method to predict a vehicle's trajectory and use it for lane-change detection. Unlike previous methods that only use the past measurements until the current time, we focus on how human drivers predict a trajectory unconsciously. Our approach is to predict how other vehicles would move in certain scenarios and to extract information based on that prediction for use in lane-change detection. Most cases of zigzag driving are caused because of drivers aborting lane changes due to the presence of adjacent vehicles on the next lane. When a sufficient distance is not achieved with adjacent vehicles, drivers abort a lane change. The proposed method considers the possibility of a crash with other vehicles, by using the potential field method. The potential field method has been generally applied to the navigation of mobile robots [9]-[11]. This method can generate

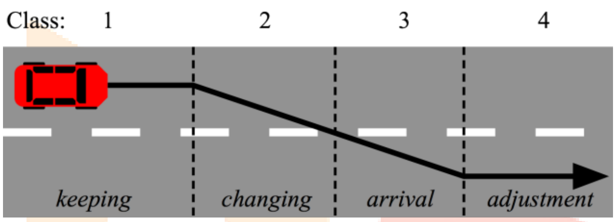


Fig. 3. Driving intentions.

II. OVERVIEW OF PROPOSED METHOD

For improving detection performance, we propose a new method that predicts the trajectory of a target vehicle and uses it for lane-change detection. Figure 2 (a) shows the overview of our method. First, we have installed the sensor system in the primary vehicle as shown in Fig. 2 (b). It consists of a position sensor (RT3003) and six laser scanners (ibeo LUX). The primary vehicle is able to acquire its position, the position of other vehicles, and the velocity of other vehicles by using these devices [15]. When these measurement values are inputted to the proposed method, it outputs whether the target vehicle would change the lane. We denote the output state of the proposed method by LC (lane changing) and LK (lane keeping). The proposed method consists of two parts: driving-intention estimation and vehicle-trajectory prediction. The proposed method defines three types of features: the distance from the centerline, the lateral velocity, and the potential feature. We use the distance from the centerline instead of the lateral position to take account of the curvature of the road. The lateral velocity is calculated from the first derivative of the distance. The potential feature can describe situations at which a vehicle changes the lane by using the relative amounts with adjacent vehicles [16]. These features are converted to the feature vector that serves as the input of the driving-intention estimation model. The proposed method uses the SVM as the estimation model. We define that drivers have four intentions when they perform a lane change: keeping, changing, arrival, and adjustment, as shown in Fig. 3. Each driving intention is defined as a class, and the proposed method treats the driving-intention estimation as a multiclass classification problem. The extracted feature vector is inputted to the estimation model, following which the driving intention at the current time is determined. The method of driving-intention estimation is explained in detail in Section III.

The vehicle-trajectory prediction adopts the result of driving-intention estimation to identify the strategies that drivers may execute while driving. Generally, drivers execute different strategies with different driving intentions. When drivers have intentions such as keeping and adjustment, they aim at the front of the current lane and pay more attention to vehicles in the same lane than vehicles in the other lanes. They may attempt to remain at the center of the lane. On the other hand, when drivers have intentions such as changing and arrival, they aim at the front of the next lane and must consider adjacent vehicles on not only the current lane but also the next lane. Therefore, in addition to the strategy, drivers must consider surrounding vehicles while driving. The

proposed method uses the potential field method for trajectory planning and avoiding contact with surrounding vehicles. The goal, sidelines, and surrounding vehicles that generate potential energy are determined by following the driving intention. After planning, a collision check is conducted by updating the positions of other vehicles under the assumption that they move with constant velocity. If a collision with a surrounding vehicle occurs, the trajectory is re-planned. Then, the strategy is changed from changing to keeping, even though the estimated driving intention is changing. Such re-planning can be explained in a practical scenario as the abortion of a lane change due to the presence of adjacent vehicles. This re- planning in the driving-intention estimation can be expected to decrease false alarms caused by zigzag driving. The method of trajectory prediction is discussed specifically in Section IV.

III. DRIVING-INTENTION ESTIMATION

A. Feature extraction

For driving-intention estimation, we define the feature vec- tor as consisting of the distance from the centerline, the lateral velocity, and the potential feature. The feature vector x_t at time t can be

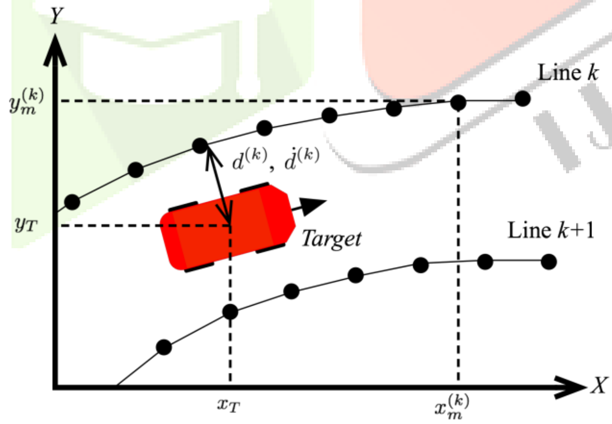


Fig. 4. Definition of features: $d^{(k)}$ and $\dot{d}^{(k)}$ are calculated by following the lane-changing side. For example, when the target vehicle changes the lane to the left lane, the centerline is chosen as the k^{th} line in this figure.

The possibility of changing lanes through a comparison of situations between the current lane and the next lane.

Because noises might be added to measurements taken in the real world, noise filtering should be conducted before the feature extraction. The proposed method conducts noise filtering by using a Kalman filter and a moving average filter. The detailed methods and results are given in our previous works [15], [16].

B. Driving-intention estimation

The proposed method uses the SVM to classify the feature vector into the driving intention classes. The driving intentions may lie in a high-dimensional feature space, and the SVM kernel can address this problem through a conversion of features from a low-dimensional space into a high-dimensional space [17]. The SVM determines the hyperplane parameters w and b that are used to classify the data:

Fig. 7. Potential field generated by following driving intentions: (a) a case in which the driving intention is keeping, (b) a case in which the driving intention is changing and arrival, and (c) a case in which the driving intention is adjustment. The red vehicle represents the target, the blue one generates repulsive potential energy, and the yellow one does not generate repulsive potential energy. The red line denotes a sideline that generates repulsive potential energy.

IV. VEHICLE-TRAJECTORY PREDICTION

A. Trajectory planning

The proposed method uses the potential field method to generate a trajectory of the target to a goal while avoiding adjacent vehicles. The potential field method used for trajec- tory prediction has no relationship with the potential feature. In trajectory prediction, the potential field method is just used to generate a path. This method generates attractive potential energy from the goal and repulsive potential energy from obstacles. In this research, we define three potential energies, and the total potential energy at the position (x, y) is derived as generate repulsive potential energy, and they make the target vehicle keep a lane. The preceding and following vehicles generate repulsive energy. This potential energy makes the target keep a gap between front and back. However, the driver is not concerned with the vehicles on the next lane during lane keeping. Therefore, the lead and rear vehicles do not exert any forces on the target.

On the other hand, when the driving intention is changing or arrival, as shown in Fig. 7 (b), the goal is set to the center of the next lane ahead. The goal generates the attractive potential energy indicated along the Y axis, in contrast to a case of lane keeping. The centerline between the current lane and the next lane does not generate repulsive potential energy. For example, when the target conducts a lane change to the right lane, the left sideline of the current lane generates repulsive potential energy. In contrast, the right sideline of the current lane does not participate, while the right sideline of the next lane generates repulsive potential energy. Lastly, the lead and rear vehicles generate repulsive potential energy. When a driver changes a lane, he may check the gap and relative velocity with vehicles on the next lane.

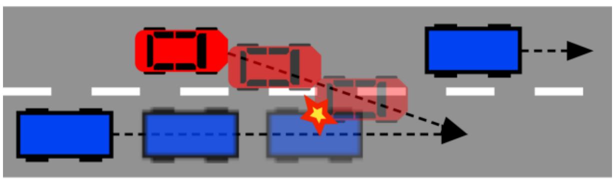


Fig. 8. Collision check: the proposed method considers the possibility of a crash between the target and adjacent vehicles. The red vehicle is the target; blue ones are adjacent vehicles. Transparent color denotes the predicted position. If a collision occurs during a lane change, the predicted trajectory is re-planned.

collision occurs during a lane change, the predicted trajectory is initialized and re-planned. The potential field is re-generated based on the strategy, keeping, even if the estimated driving intention was changing. This strategy can be explained as the abortion of a lane change by a driver when he/she feels unsafe because of the insufficient gap or velocity. This strategy is expected to eliminate false alarms caused by zigzag driving.

The proposed method extracts the features based on the predicted trajectory for use in lane-change detection. The extracted features are applied as the future measurement, and the driving intention is re-estimated using the features. Finally, the proposed method outputs LK or LC. When the re-estimated driving intention is keeping or adjustment, LK is outputted. Otherwise, when the re-estimated driving intention is changing or arrival, LC is outputted.

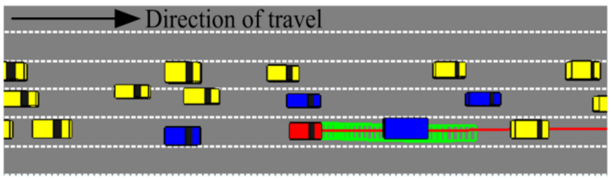
V. EXPERIMENTAL RESULTS

We trained and tested the proposed method using a real traffic dataset published by the Federal Highway Administration of the United States [19]. The dataset was collected on eastbound I-80 in the San Francisco Bay Area. The measurement area was approximately 500 m in length and consisted of six freeway lanes. The dataset consisted of measurements taken per 0.1 s for 15 min, for a total of three times. Data from 5,678 vehicles were collected. Among them, we used

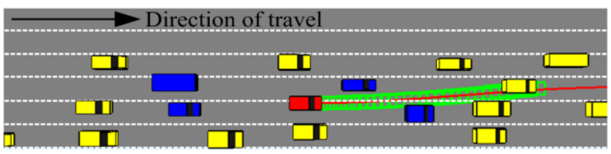
300 lane-change data for the training and 523 lane-change data for the test.

A. Evaluation of the vehicle-trajectory prediction

We confirmed that the trajectory of the target was properly predicted. The parameters should be evaluated to consider how they balance with one another in order to avoid collisions with other vehicles. Parameter imbalance can be a cause of colli- sions with other vehicles, in addition to causing an unstable trajectory in the lateral direction. Therefore, parameter values largely determine the accuracy of a trajectory prediction. The parameters were manually tuned in order to obtain the mini- mum error of trajectory prediction during lane changes. As a result, the parameters have been set to the following values: $\omega_{gx} = 0.5$, $\omega_{gy} = 1.0$, $\omega_s = 2.0$, $\sigma_s = 1.1$, $\omega_a = 12.2$, $\sigma_{ax} = 5.0$, and $\sigma_{ay} =$ 17.4. The prediction time has been determined by the detection performance and the computation. A short prediction time is not sufficient for the collision check. In contrast, long prediction time requires additional computation and does not ensure improved detection performance. We



(a)



(b)

Fig. 9. Results of trajectory prediction (a) when the target keeps the lane and (b) when the target changes the lane. The green rectangle represents the predicted position at each time step, and the red line shows the ground truth. The red vehicle is the target, the blue ones are adjacent vehicles, and the yellow ones are other vehicles that are not considered.

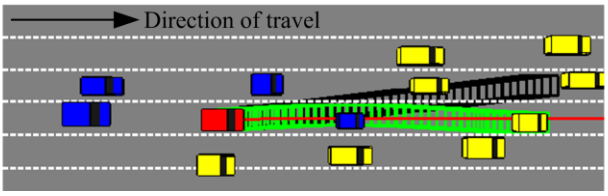


Fig. 10. Collision check and re-planning: the black rectangle represents the initially predicted trajectory. Re-planning was conducted because of the collision, and the green rectangle shows the re-planned trajectory. The red line shows the ground truth.

considered the balance and have determined that = 2.0 s. The prediction was conducted with a time step of 0.1 s. Moreover, the proposed method should satisfy the computation limit derived from the sensor system. Our sensor system has an update rate of 32 Hz; therefore, lane-change detection, including trajectory prediction, must be updated earlier than the sensors. We confirmed that the update rate of the proposed method is 56 Hz on average, the maximum rate is 77 Hz, and the minimum rate is 36 Hz using the complete testing dataset. This means that the proposed method is able to satisfy the system requirement. Figure 9 shows the results in one case from the test dataset. The red vehicle is the target, the green rectangle represents the predicted position at each time step, and the red line shows the ground truth. Figure 9 (a) shows the result at a point when the target kept the current lane; Fig. 9 (b) shows the result at a point when the target conducted a lane change. We can see that the predicted trajectory was quite consistent with the ground truth. In Fig. 9 (b), the target followed the lead vehicle smoothly, and a collision did not occur because the lead vehicle was faster than the target.

Figure 10 shows a case of collision check and re-planning. The black rectangle represents the canceled trajectory because collision was predicted. In this case, the driving intention was estimated as changing; however, the relative velocity with respect to the lead vehicle was not sufficient. As a result, the driver stopped to change the lane. Such situations have been the main cause of false alarms, and from the results, we qualitatively confirm that the proposed method properly

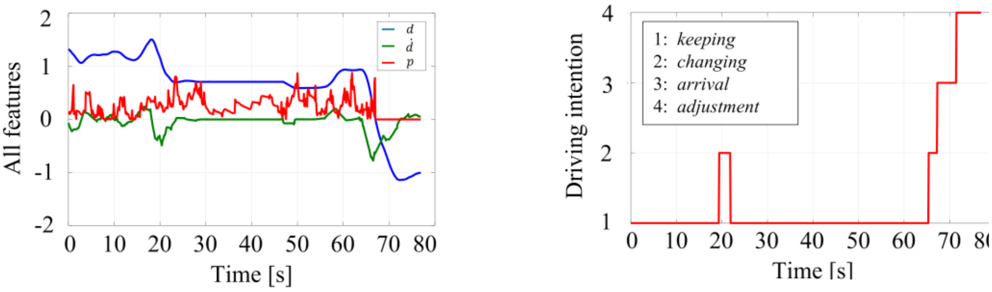


Fig. 11. Evaluation result of lane-changing case: (a) record of all features that are normalized, (b) driving intention estimated by the method without trajectory prediction, and (c) the driving intention estimated by the proposed method.

eliminated a false alarm in spite of the zigzag driving. The proposed method re-planned the trajectory as keeping the current lane even though the driving intention was initially estimated as changing. Through this collision check and re- planning, the proposed method is able to reduce false alarms.

TABLE I

RESULT OF LANE CHANGE DETECTION

Without trajectory prediction				Proposed	
		Detection result		Detection result	
		LC	LK	LC	LK
Ground Truth	LC	523	0	523	0
	LK	36	487	17	506

TABLE II

PERFORMANCE COMPARISON WITH PREVIOUS METHODS

Method	Precision	Recall	F1	τd
Mandalia[8]	80.0 %	81.1 %	80.5 %	1.33 s
Schlechtrieme	93.6 %	99.3 %	96.4 %	1.65 s
Proposed	96.3 %	100 %	98.1 %	1.74 s

The two methods have an aspect in common that adjacent vehicles are not considered on the next lane. Consequently, false alarms frequently occur in comparison with the proposed method. From above results, we can confirm that the proposed method dramatically improves performance in terms of both accuracy and early detection.

VI. CONCLUSION

In this research, we proposed a new lane-change detec- tion method based on vehicle-trajectory prediction. Previous methods have the problem of frequent false alarms caused by zigzag driving that can result in user distrust in the driving support system. Through comparison with previous methods, we confirmed that the proposed method with vehicle-trajectory prediction can reduce false alarms. In addition, the method can detect a lane change, on average, 1.74 s before the target vehicle crosses the centerline with 98.1% accuracy. We demonstrated that the proposed method outperforms previous methods in terms of the accuracy and early detection. The reason for improvement is expected to be due to the fact that the proposed method considers adjacent vehicles on the next lane, while previous methods do not.

As future work, we have continuously evaluated other variables that might affect driving intentions and are expected to improve the performance (e.g., traffic density, types of vehicles).

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