Smartphone-based Risky Traffic Situation Detection and Classification

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***Abstract*—Although the number of traffic accidents occurring in Japan is decreasing, there still happen approximately 400,000 traffic accidents annually. Behind such accidents, there are frequent minor incidents (near-miss incidents) that may lead to such serious accidents. Analyzing such minor incidents is effective to reduce accidents, but the challenge is to design and deploy a method to collect and analyze such incident information. Drive recorders may be useful for such a purpose, but they cannot collect information from those vehicles without recorders. In this study, we propose the design and development of a platform that aggregates behavioral data from pedestrians and vehicle drivers using their smartphones, and automatically estimates risky traffic situations from the aggregated data. We present our preliminary result of detecting and classifying those events in a controlled environment and have achieved F-value 0.89 for four categories classification.**

***Index Terms*—smartphone, traffic safety support, a near-miss**

I. Introduction

It is said that behind traffic accidents, which are officially reported and recorded, a number of unrecorded minor incidents, which are significant signs for future serious accidents in the same or similar situations, have occurred. Actually, detection, collection and analysis of such minor incidents are not straightforward. For example, in Japan, there exists near-miss database [1] that collects videos from drive recorders installed in business vehicles, e.g., taxis. Those drive recorders are able to detect unusual stops (e.g., severe deceleration) of vehicles by built-in acceleration sensors and the video clips of several seconds before and after the events are stored in the local storage. Each video is then given to the manual classification by an administrator and is stored in the database if it is recognized as a case. However, it is reported that about 70% of such videos are false-positive data such as deceleration due to bumps, which are not actually the near-miss cases. Therefore, a considerable amount of human resources is required in data selection. Besides, drive recorders do not always capture all the scenes, as they record only the front views. Let us consider the fact that near-miss often occur due to pedestrians' unsafe behaviors (e.g., the sudden appearance of pedestrians from drivers blind spots). However, from the recorded scenes, the pedestrians' trajectories are not known and the deep understanding of the cause behind the near-miss is not possible. There are more complicated cases where multiple entities (vehicles, bikes and pedestrians) relate with each other to cause near-miss but the driver recorders may capture only a part of scenes.

There is also a requirement for communication infrastructure if we rely on crowdsourcing mechanisms to collect data. General participants do not like to consume their communication resources due to battery limitations, monetary cost and so on. Therefore, collecting video clips from crowds is not currently a promising solution. Also, most of the current consumer-level drive recorder does not have communication facilities. To collect a certain amount of data widely from crowds, a more lightweight way that naturally invites people to join the system is preferable.

We should also take into account that not only near-miss situations but many traffic situations that have potentially high risks. Examples of such situations are (i) pedestrians often forcibly cross streets even with heavy traffic, and (ii) some drivers with bad manners drive narrow community roads with high speeds to avoid traffic jams even children walk to their schools there. In order to realize a safe and secure traffic environment for pedestrians and vehicles, detecting and analyzing such traffic situations with potential risks is necessary.

In this paper, we introduce our preliminary study on designing a smartphone-based near-miss detection and a deep-neural model for situation classification. Based on continuous sensing via pedestrians' and drivers' smartphones, the proposed method enables us to understand the various traffic situations. The method collects location information and inertial sensor data of each smartphone via cellular networks. A particular behavior detected on one smartphone is used as a trigger for further analysis of the situation by the deep neural model with surrounding smartphones' behavior and the location map (street, intersection structure), and finally, the situation is classified into predefined classes. As discussed, these situations have not been grasped unless they led to accidents. Thus the proposed system enables us to quantitatively understand various traffic situations related to traffic safety and traffic manners. Our team, which consists of academic researchers and industrial partners (cellular company), is now trying to publicize this concept. In this work, we report the system design and our experiment result. Particularly, we have collected data in a dedicated field in Kobe with 20 volunteers and could achieve F-value 0.89 for classification into three near-miss categories.

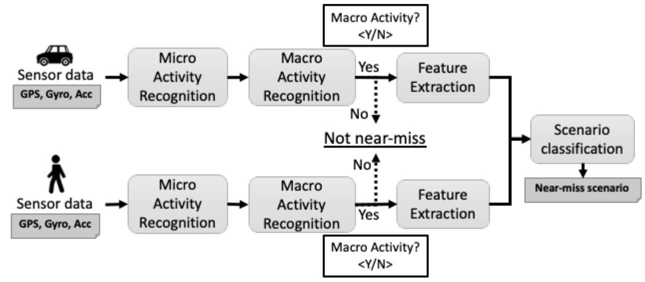


Fig. 1. System overview: Traffic situation analysis.

II. Related Works

In order to prevent or reduce traffic accidents, some efforts are being made to collect various traffic information. For instance, the International Road Traffic and Accident Database (IRTAD) [2] provides road crash data collected in more than 40 countries. Also, the National Highway Traffic Safety Administration (NHTSA) [3], the US Department of Transportation's Road Traffic Safety Administration, has published fatal accident statistics and accident cases. On the other hand, the Traffic Accident Analysis Center [4] analyzes the traffic accidents that occurred in Japan and their causes so that we can understand the background of the accidents. It is also recommended to collect data in not only accidents but also dangerous situations that no damages or injuries occurred. Tokyo University of Agriculture and Technology has been creating and analyzing a database of videos taken by drive recorders installed in taxis since 2005, and currently has classified over 140,000 videos into several categories [1]. SAFETY MAP project [5] collects acceleration data from vehicles when the vehicles stop suddenly, and derives a map based on the database by sharing locations where customers feel safe or dangerous.

Also, several methods are proposed to detect abnormal behaviors that may lead to serious situations for preventing accidents. Zhou et al. [6] proposed a method to detect abnormal behaviors in crowded scenes based on a trajectory model. Rasouli et al. [7] proposed a collision avoidance method that analyzes pedestrians' behavior observed by cameras when pedestrians walk at crosswalks. This method models interactions between drivers and pedestrians in several locations and different weather conditions, and identify factors that influence pedestrian decision-making at the point of crossing. Li et al. [8] proposed a joint detector of temporal and spatial anomalies in crowded scenes. Zhang et al. [9] collected sensor data such as speed, engine rotation, and steering from over 29,000 vehicles. They also made a driving model based on the data and estimated anomaly states which are not observed often. Aloul et al. [10] proposed a method that can detect collisions by acceleration sensors in a smartphone mounted by a car. It also has a functionality to notify the collisions to nearby police or hospital so that the response time required to notify emergency responders can reduce.

Although these researches collect data from only one-side, it is feasible to collect both vehicles and pedestrians to investigate situations. Our system can measure data in near-miss situations in detail by collecting sensor data from smartphones in both pedestrians' and drivers' sides so that we can quantify risks in traffic situations by analyzing the data in minor incidents.

III. Overview and design

A. System overview

The outline of the proposed system is shown in Fig. 1. Our system assumes smartphones of pedestrians and drivers and OBDII of vehicles, if available. The smartphones collect the positions and inertial sensor data (i.e., 3-axis acceleration and angular velocity) and send them to the cloud server by mobile networks. The smartphones also collect the data of OBDII via Bluetooth, if available and send it to the cloud server. Abnormal behaviors of pedestrians and vehicles are detected by analyzing time-series sensor data collected on the cloud server.

We use the detected abnormal behavior of a pedestrian and/or a vehicle as a trigger for further analysis to classify the risky traffic situation. In the analysis, we aggregate the sensor data collected in the proximity of the detected abnormal behavior in terms of space and time. The trained DNN estimates the traffic situation by using the information on the activities and positions of smartphones of pedestrians and drivers in the proximity. By using DNN, we aim to detect near misses that are difficult to find by humans.

B. Definitions of Micro/Macro Activities for Abnormal Behavior Detection

In order to input the behaviors and positions of pedestrians and vehicles to DNN, we need to represent these behaviors as features. For this purpose, we define short-term behaviors as *micro activities*. Then, we also define the time series of micro activities as *macro activities*. The candidates of the micro and macro activities are defined beforehand, which are represented as category numbers. By the combination of micro and macro activities, we aim to estimate the high-level context of the behaviors of pedestrians and vehicles. In this way, we reduce the volume of the input data for DNN and extract features that are useful for near-miss detection.

1) Micro Activity: The micro activities are estimated by the sensor data collected from pedestrians and vehicles. We use a two-second time window for micro activity recognition with a sliding step of 0.5 seconds.

TABLE I
PEDESTRIAN MACRO ACTIVITIES

Macro activity	Time-series of micro activities
keep waiting	all activities are *still*
start running suddenly	start with *still* and/or *walk* longer than 2 seconds followed by *run*
keep running	all activities are *run*
keep walking	all activities are *walk*

Pedestrian Micro Activity: The classes of the pedestrian micro activities are *still*, *walk*, and *run*.

Vehicle Micro Activity: For vehicles, the micro activities are estimated for each of the three categories: forward/backward direction, left/right direction, and speed. We define the classes of the forward/backward direction as *sudden acceleration*, *stable*, *sudden deceleration*. The classes of the left/right direction are *sudden left turn*, *stable*, *sudden right turn*. As for the speed, we define the classes as *still*, *low speed*, and *high speed*. Compared to pedestrians, vehicle movement is relatively limited where the travel direction is clear. Therefore, the vehicle movement is detected separately between the front/rear direction and the left/right direction. The speed is also used to understand driving behaviors. Normal start, stop, left/right turn belong to *stable*.

2) Macro Activity: The macro activities are estimated from the time-series of the micro activities in the past few seconds. Since the duration of the macro activities is different between pedestrians and vehicles, we set different window sizes for pedestrians and vehicles.

Pedestrian Macro Activity: The pedestrian macro activities are defined as *keep waiting*, *start running suddenly*, *keep running*, and *keep walking*. The detection rules are shown in Table I. The macro activities are estimated by the time-series of the micro activities. We use a three-second time window with a sliding step of one second. Therefore, a single time window consists of six micro activities. We detect *keep waiting/running/walking* if all of the micro activities in the time window are *still/walk/run*. *start running suddenly* is detected when the time series of the micro activities start with *walk* and/or *still* longer than 2 seconds followed by *run*.

Vehicle Macro Activity: The pedestrian macro activities are defined as *sudden stop*, *sudden avoidance of obstacles*, *keep driving at low speed*, *keep driving at high speed*, and *keep waiting*. The detection rules of the macro activities are shown in Table I. The macro activities are estimated by the time-series of micro activities. We use a 4-second time window with the sliding step of 1 second. This means a single time window consists of 8 micro activities. *Sudden stop* is detected when *still* activities are detected after *sudden deceleration*. *Sudden avoidance of obstacles* is detected when a sudden left/right turn followed by a right/left turn occurs in the time window. The macro activities *keep driving at low speed*, *keep driving at high speed*, and *keep waiting* are detected when all of the micro activities in a single time window are *low speed*, *high speed*, and *still*, respectively.

TABLE II
VEHICLE MACRO ACTIVITIES

Macro activity	Time-series of micro activities
sudden stop	*still* are detected after *sudden deceleration*
sudden avoidance of obstacles	a *sudden left/right turn* followed by a *right/left turn*
keep driving at low speed	all activities are *low speed*
keep driving at high speed	all activities are *high speed*
keep waiting	all activities are *still*

TABLE III
TRAFFIC SITUATION SCENARIOS

No	Traffic situations
1	A vehicle avoids pedestrians on residential roads
2	A pedestrian cannot cross pedestrian crossings without traffic lights due to continuous traffic
3	A vehicle is about to contact with a pedestrian when turning left at the intersection
4	A vehicle passes near a pedestrian at a dangerous speed on residential roads
5	A pedestrian crosses a road coming from behind a parked vehicle
6	A pedestrian is not aware of an approaching vehicle and obstructing the residential road
7	A vehicle turning at an intersection is about to collide with a vehicle going straight
8	Pedestrians rush out into an intersection and a vehicle stops suddenly

C. Traffic Situation Analysis by DNN

When abnormal behaviors of pedestrians or vehicles are detected as macro activities, the sensor data of the pedestrians and vehicles in the proximity is analyzed to understand the traffic situation. Specifically, when a macro activity is detected from a road user, we collect the information on the macro activities of road users in the proximity. Then, all the information is aggregated as input to DNN for the traffic situation classification.

Table III shows our target traffic situations. The residential road is defined as *a road where the sidewalk and the roadway are not clearly separated*. We explain the flow of our traffic situation classification by taking the situation 1 as an example. In situation 1, we assume that pedestrians in front of the vehicle obstruct the narrow residential road and the vehicle cannot proceed without avoiding the pedestrian. Therefore, the vehicle has to move to the left or right to avoid the pedestrian, pass either side of the pedestrian, and then return to the original lane. Situation 1 requires detecting the presence of pedestrians on the residential roads and vehicles avoiding obstacles. This means we need to capture the spatial-temporal features of pedestrians and vehicles. In our method, the movement of the vehicle is decomposed into a time series of micro activities. Then, macro activities are estimated from the time series of micro activities. For situation 1, *sudden avoidance of obstacles* is detected, triggering further analysis

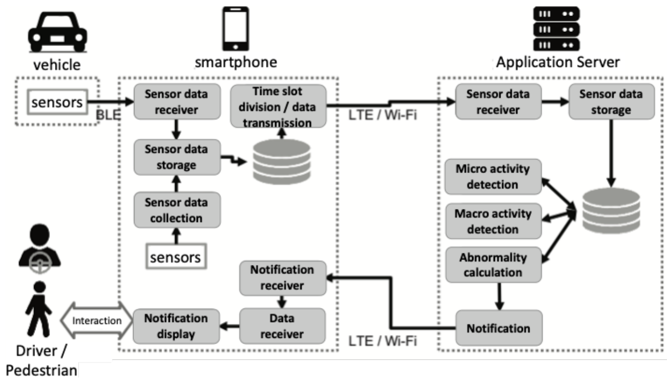


Fig. 2. Function-layout of the prototype.

using DNN. We aggregate the sensor data of the triggering vehicle and smartphones in the proximity as input to DNN for traffic situation classification.

IV. Prototype System

A. Function Layout

Fig. 2 illustrates the function-layout in the prototype. The prototype system consists of a smartphone application and a server application. Software parameters must be tuned according to the results of the evaluation experiment.

B. Smartphone Application

Data collection: The sensor data of pedestrians and vehicles are collected by a smartphone. In the prototype system, we collect acceleration, angular velocity, geomagnetism, azimuth, GPS location, and device environment. Those values are measured by Android smartphone. When collecting vehicle sensor data, it is assumed that not only by smartphones but also via OBD-II (vehicle-dedicated devices) that directly accesses the vehicle's diagnosis information. Note that, in this paper, we assume that all participants carry their own smartphone, dedicated device is not necessary to be installed on vehicles. In the prototype system, data is collected by freematics ONE device and transmitted to the smartphone via Bluetooth. The data collected by freematics ONE device includes collected time, travel distance, indoor temperature, coolant temperature, engine load, engine rotational speed, vehicle speed, throttle opening, intake pressure, intake air temperature, fuel pressure, fuel consumption (km / L), GPS estimated latitude, GPS estimation longitude, GPS estimation altitude, GPS estimation accuracy, and vehicle direction. Note that some of them are missing depending on the type of vehicle. The smartphone converts the acquired data to JSON format and sends it to the server.

Time Slot Division of Observation Data: Regarding any observation data, since the collection timings are not synchronized among sensors, all values cannot be measured at the same time. In the prototype, we define time slots, and we calculate the representative value by averaging the measured values in the slot.

C. Server Application

In the prototype, we adopt general-purpose server machine (ubuntu 16.04) and all softwares are installed on it. Replacing with cloud or edge clouds is for further study. As shown in Fig. 2, the server application consists of a sensor information storage function, a micro activity detection function, a macro activity detection function, and a near-miss score calculation function.

Database of the Sensor Data: Sensor information sent from a smartphone is received by nginx / 1.14.2 and delivered to Fluentd (td-agent 1.3.3). Sensor information received by Fluentd is sequentially stored in a MySQL (mysql Ver. 8.0.14) database.

Micro Activity Detection: The pedestrian's micro activities are defined as *stand still*, *walk*, and *run*. The time-series of sensor data are classified into one of three micro activities by k-means. The window width for the classification is 4 seconds, and the feature values for the classification are maximum value, minimum value, interval average, and interval variance of triaxial acceleration.

On the other hand, the vehicle's micro behaviors are defined independently as the front-rear direction (i.e., sudden acceleration, stable, sudden deceleration), left-right direction (i.e., sudden left turn, stable, sudden right turn), and speed (i.e., stop, low speed, high speed). As same as the pedestrian, the clustering algorithm is applied to the vehicle's behavior classification. The acceleration sensor is used for the front-rear direction, the gyro sensor is used for the left-right direction, and the acceleration integral and observed GPS speed are used for the speed.

Macro Activity Detection: Macro activity is defined based on the time-series patterns of micro activities. Every time sensor data is received, it is sequentially compared with predefined patterns. When the condition meets, the occurrence of the macro activity is recorded in the database. At the same time, the score of traffic situation abnormality is calculated.

Calculation of the traffic situation abnormality: In order to express the occurrence of macro activities in the surrounding space as a multi-dimensional array, the 50m square around the macro activities are divided into 5x5 grid cells. Each cell has an array of feature values that includes commonly-used statistic values of sensor data that collected from each traffic participant.

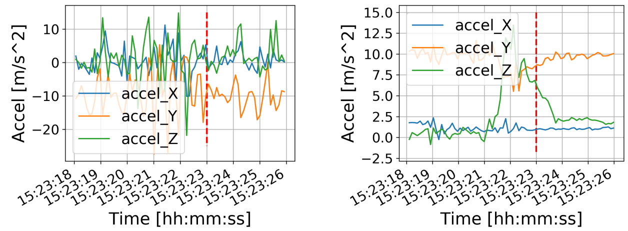
The multidimensional array generated by the above process is given to DNN as input. DNN uses the softmax function to calculate the likelihood of the observation data and the predefined risky traffic situation scenario to estimate the traffic situation. We adopt Cuda 9.0 and cuDNN 7.3.0 for DNN.

Near-miss notification: When a risky traffic situation is detected by the system, it notifies corresponding pedestrians and drivers. When the risky traffic situation is detected in advance, the relevant person is cautioned by notification of the system.

When the risky traffic situation is detected after the event occurs, it would be used to confirm if the event was a correctly

(a) Pedestrians rush out into the road and the vehicle stops suddenly. (b) Driver's view

Fig. 3. Data Collection Environment: Traffic Situation 8.



(a) The acceleration of the pedestrian. (b) The acceleration of the vehicle.

Fig. 4. The acceleration of the pedestrian and the vehicle in situation 8.

risky traffic situation. We have evaluated this system in the following section.

V. Experiments

A. Experiment Setting

We used a car driving course in the cooperation of Kobe Harbor Education and Training Association. The pedestrians had smartphones in their right pockets with the top of the device facing down and the screen facing out of the body. The smartphone of the vehicle was fixed between the driver and the passenger seat. The axes of vehicle sensor data are modified based on the direction of gravity. The positive directions of the X-axis, the Y-axis, and the Z-axis are modified to the vehicle's right direction, forward direction, ceiling direction, respectively.

As a preliminary experiment, we focus on traffic situation 8 in this experiment. For this purpose, we collected three types of test scenarios: 1) *start running suddenly*, 2) *keep driving at high speed*, 3) *pedestrians rush out into the road and the vehicle stops suddenly*. We note that the first two scenarios are macro activities independently performed by either pedestrians or a vehicle while the other consists of the simultaneous macro activities of the pedestrians and the vehicle in the proximity. Figure 3 shows the data collection environment. The ground truth of the occurrence of the risky traffic situations is manually labeled by annotators based on the video. The occurrence time is defined as the time when the macro activities of both the pedestrian and the vehicle are observed. We use the data collected by the above process for the evaluation of our system.

B. Experiment Scenarios

Our method recognizes the macro activities of pedestrians and vehicles and detects risky traffic situations by combining the sensor data in the proximity. Therefore, we need to evaluate whether our method can associate the macro activities of pedestrians and vehicles with those in the proximity. For this purpose, as we mentioned in Sec. V-A, we collected three types of test scenarios: 1) *start running suddenly*, 2) *keep driving at high speed*, 3) *pedestrians rush out into the road and the vehicle stops suddenly*. In addition, we collected the data of normal behaviors which are normal walking of pedestrians and normal driving of vehicles. We trained and evaluated the DNN model that classifies the data into four classes: pedestrian macro activity, vehicle macro activity, the risky traffic situation 8, and pedestrian/vehicle normal behavior. In the following sections, we explain the details of the experiment.

1) Macro Activity: start running suddenly: We collected the sensor data from 155 trials of *start running suddenly*. At first, pedestrians confirmed that there were no vehicles around them and they started walking normally from the sidewalk to the pedestrian crossing. Then, they started running suddenly when reaching the pedestrian crossing. After crossing the road, they walked normally. After a while, they stopped walking to finish the trial. During the trials, there was no vehicle around them.

2) Macro Activity: keep driving at high speed: The driver confirmed that there were no pedestrians around him and he kept driving at the speed over 30km/h. We continuously recorded the sensor data and divided it into 137 trials of *keeps driving at high speed*. During the trials, there were no pedestrians around him.

3) Traffic situation 8: We collected the 286 trials of sensor data in the traffic situation 8. In this situation, several pedestrians start walking from a sidewalk toward the roadway. When the pedestrians approach the roadway, they *start running suddenly* to the roadway and try to cross it, as shown in Fig.3. However, the pedestrians notice that a vehicle is approaching them, and they stop near the center-line of the roadway. On the other hand, the vehicle also notices that the pedestrians are rushing out, and it *stops suddenly*. After that, the pedestrians confirm that the vehicle stops and cross the roadway. The vehicle also confirms that the pedestrians have crossed, it drives again. During this trial, pedestrians and a vehicle performed their macro activities.

Fig.3 shows acceleration data collected by pedestrians and vehicles in situation 8. In Fig.4(a), *accel_x*, *accel_y* and *accel_z* show acceleration data along the axis shown in the sectionV-A. The dashed red line in Fig.4 shows that a risky traffic situation occurs at around 15:23:23 since a pedestrian begins to rush out at 15:23:21 in this trial. There are significant changes in the acceleration on all axis in Fig.4(a). Their standard deviations of the acceleration on all axes also turn to be high. *accel_y* that is acceleration on the axis along the user's body is specifically affected by the movement of rushing out.

On the other hand, the vehicle responded to the pedestrian's rushing out *stops suddenly* at around 15:23:22. At

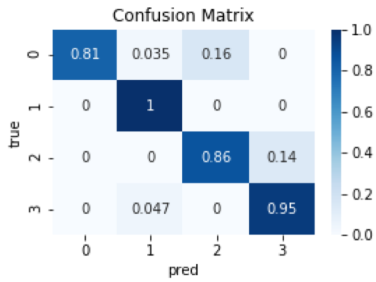


Fig. 5. Confusion Matrix (0 : traffic situation 8, 1 : vehicle's *keep driving with high speed*, 2 : pedestrian's *start running suddenly*, 3 : normal behavior).

that time, *accel_y* and *accel_z* are significantly changed, as shown in Fig.4(b). When the vehicle decelerates, about -1.0 G acceleration is observed in *accel_y* that is the acceleration in the direction of travel. When the vehicle *stops suddenly*, it completely stops after the deceleration. The situation of traffic situation 8 is detected by the time-series of micro/macro activities estimated by above features and the location data.

4) Normal Behavior: We also collected the 231 trials of sensor data for normal behavior. Pedestrians walk normally and a vehicle drives normally respectively in this situation.

C. Evaluation

We evaluated our method based on 809 trial data collected in four classes: situation 8, macro activity *start running suddenly* for pedestrians, macro activity *keep driving at high speed* for vehicles and normal behavior. We used 80% of the data for training and the rest for evaluation.

Figure 5 shows a confusion matrix for the result of the evaluation, and its F-value is 0.89. The labels 0 through 3 in Fig.5 are categorized into situation 8, macro activity *sudden stop* for vehicles, macro activity *start running suddenly* for pedestrians and normal behavior respectively. We can estimate *sudden stop* for vehicles and *start running suddenly* for pedestrians accurately. On the other hand, some cases of situation 8 are misclassified as *start running suddenly* for pedestrians and *keep driving at high speed* for vehicles. The DNN model classifies sensor data into which traffic situations occur based on the sensor data for 5 seconds from the occurrence time of the situations. Therefore, depending on time accuracy between smartphones, our method sometimes fails to associate macro activities for pedestrians and vehicles within 5 seconds or could not estimate macro activities from the sensor data. Although it takes time to get accurate positions from GPS, we started to collect location data at the beginning of each trials and GPS did not derive accurate positions. Thus, in the experiments, some macro activities for vehicles were not detected, and some trial of situation 8 are misclassified to other classes. However, our method still estimated the situation 8 with the 89.3% accuracy.

As shown in Fig.5, we see that our method could estimate *start running suddenly* for pedestrians and *keep driving with high speed* for vehicles with high accuracy. This may be because there is only a pedestrian or vehicle in these two scenarios. Therefore, DNN classification may have been strongly influenced by the type of actors. From the above results, we showed that our system could estimate macro activities for both pedestrians and vehicles and also a combination of the macro activities.

VI. Conclusion and Future Work

We have designed a smartphone-based near-miss detection and a deep-neural model for situation classification. Based on the continuous sensing via pedestrians' and drivers' smartphones, the proposed method enables to understand the various traffic situations. A particular behavior detected on one smartphone is used as a trigger for further analysis of the situation by the deep-neural model with surrounding road users' behavior and the location map (street, intersection structure), and finally the situation is classified into predefined classes. Through experiments, we have collected data in a dedicated field in Kobe with 20 volunteers and shown that the proposed method achieves F-value 0.89 for classification into three near-miss categories. As future works, we are planning to consider other scenarios so that the system can handle more complex situations. We are implementing the proposed model on smartphones so that the method can detect a sign of risky traffic situations in advance.

Acknowledgment

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