Mode Classification for Mixed Traffic Flow Based on Smartphone Data

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Abstract: In Southeast Asian countries, fixed-point sensors for road traffic are under development, while the information and communication infrastructures have rapidly improved. Thus, smartphones with various sensors, such as GPSs and accelerometers, are commonly used. As a result, it is possible that traffic conditions could be monitored in real time using smartphone data rather than fixed-point traffic detectors. We have developed a method to classify transportation modes (i.e., passenger vehicles or motorcycles) using data collected from smartphones. The experimental results indicate that the standard deviation and spectrum of synthetic acceleration are measures that can accurately classify transportation modes.

Keywords: mixed traffic, motorcycles, smartphone, mode classification, support vector machine

1. INTRODUCTION

In most Southeast Asian cities, motorcycles are widely used in urban areas because they are more reasonable than passenger vehicles in terms of purchase price, maintenance costs, high flexibility in route choice, and congestion avoidance. Although the number of passenger vehicles is rapidly increasing because of recent economic growth in Asian countries, motorcycles are still dominant in some cities (Shiomi, 2014). As a result, motorcycles and passenger vehicles are mixed in urban traffic flows. In terms of the size, speed, and movement characteristics, this heterogeneous and mixed traffic situation causes various serious social problems, including inefficient and unsafe traffic. To improve this situation, it is essential to monitor traffic in real time and to implement active traffic management based on ITS technology. However, conventional traffic monitoring systems with loop coils and ultrasonic waves are ineffective in mixed traffic situations because such systems attempt to detect four-wheel vehicles only. Traffic detectors based on image processing techniques may be appropriate for monitoring mixed traffic; however, occlusions often occur because of the variety of vehicle sizes, which can cause errors in the detected traffic counts and speeds. Furthermore, such monitoring systems installed in road infrastructures require maintenance. Thus, it can be said that conventional monitoring systems are not sustainable for most developing countries.

In contrast, information and communication infrastructures have developed extensively, and mobile devices, such as smartphones, are popular in such countries. Many types of sensors are embedded in smartphones, and they can collect various data, such as location (GPS), acceleration, sound, and geomagnetism. There is great potential for detecting traffic situations, including speed and travel time, if such data can be even partially collected online from smartphone users through applications. However, it should be noted that such data would be
collected from anonymous users, which means that the information about the transportation modes of smartphone users would typically be absent. In Southeast Asian cities, this would become a serious obstacle for detecting traffic appropriately because the data sources would be mixed in a complicated manner because of the high proportion of motorcycles. In general, the movements of four-wheeled vehicles and motorcycles differ. Motorcycle behavior is characterized by the following (Lee, 2010): (i) traveling alongside another vehicle in the same lane; (ii) oblique following; (iii) filtering; (iv) moving to the head of a queue; and (v) swerving and weaving. Furthermore, the accelerations and highest speeds of motorcycles differ from those of passenger vehicles. Note that even in identical traffic conditions, the speeds and travel times estimated from data collected by motorcycles may differ from those obtained using data from passenger vehicles. Thus, to monitor traffic with high accuracy, it is essential to classify the transportation mode based on smartphone data.

In this investigation, based on a field experiment conducted in Makassar, Indonesia, we established an algorithm to classify transportation modes as passenger vehicles or motorcycles, using acceleration data collected from smartphones carried by passenger vehicle drivers or motorcycle riders. This study focused on how people carry their smartphones because the characteristics of acceleration data may differ depending on how smartphones are carried (e.g., attached to the motorcycle handle, in a pocket, hung by a neck strap), which may have significant influence on classification accuracy. In this paper, we first discuss evidence from the field experiment that suggests travel times measured by motorcycles and passenger vehicles differ. Then, the characteristics of data collected by smartphones are examined graphically. Finally, a classification algorithm that employs a support vector machine (SVM) is proposed, and the classification accuracy is presented.

The remainder of this paper is organized as follows. Section 2 summarizes state-of-the-art for transportation mode classification. In Section 3, the details of the field experiments are given, and the collected data are described. Section 4 presents the proposed classification algorithm and discusses its accuracy. Conclusions are given in Section 5, including suggestions for future work.

2. STATE-OF-THE-ART

Mobile data collection systems are among the most significant technologies developed in the last several decades. The rapid and wide spread of smartphones enables them to have great potential to replace conventional traffic data collection methods, such as cross-sectional observations represented by loop-coil or ultrasonic traffic detectors and person-trip surveys. The advantages of mobile data collection are the ease and low cost of collecting large amounts of data. Mobile data collection also has huge potential in developing countries where sensor infrastructures have not been established. If a transportation mode classification algorithm can be achieved, the spatial distributions of transportation modes in the road network, including the short-term and longitudinal variations, can be clarified, which has not been accomplished by conventional methods.

Previously, efforts to develop methods to identify transportation modes and activities based on unified sensing data, including gyro sensors, have been considered in the context of “life-log” (e.g., Cho et al. (2009), Long et al. (2009)). In these studies, walking, running, passenger travel, and vehicle operation were considered the activities to be identified. Furthermore, transportation mode identification problems have been addressed by several studies. Asakura et al. (2001) developed a method to identify walking, cars, buses, and trains, and Zheng et al. (2008) focused on walking, bicycles, cars, and buses. Kobayashi et al. (2009)
focused on walking, bicycles, cars, buses, trains, and stay. Essentially, it is rather easy to separate non-motorized transportation, such as walking and bicycles, and motorized transportation, such as cars, because of the vibrations caused by engines. Furthermore, it is not difficult to differentiate between trains and buses because trains move only along rails, which can be detected by GPS data, and buses stop at predetermined locations at certain time intervals. However, in Southeast Asian countries, motorcycles compose a high portion of the vehicles on the roads. Thus, the method by which motorcycles and other vehicles are classified is a challenging task. Ohashi et al. (2015) proposed an algorithm to differentiate between motorcycles and passenger vehicles based on GPS and acceleration data collected in India and Vietnam. They reported that their algorithm could classify passenger vehicles at 85% accuracy and motorcycles at 58% accuracy. However, in that study, the manner of carrying smartphones was not considered. Furthermore, the data were primarily collected in non-congested traffic where the travel speed was greater than 20 km/h, although traffic conditions are more crowded in CBD, and the mobile data collection system must be significant in congested traffic situations.

We explicitly consider the possible ways for a motorcycle operator to carry a smartphone as follows: (i) fixed to the handlebar of a motorcycle by an attachment tool (hereafter attachment), assuming that the smartphone is used as a navigation system; (ii) in the pocket (hereafter, pocket); and (iii) hung by a neck strap (hereafter neck strap). Furthermore, as a benchmark, data was collected from smartphones fixed to the bodies of motorcycle riders by adhesion tape (hereafter fixed), where it is expected that the vibrations caused by motorcycles would be mostly absorbed. For the passenger vehicle situation, the smartphone was considered to be fixed to the dashboard by an attachment tool, which assumes that the smartphone is used as a navigation system. In total, five patterns of smartphone data were collected. Based on the data, a classification algorithm to distinguish between motorcycles and passenger vehicles was developed.

3. FIELD EXPERIMENT

3.1 Data Collection System

To collect data from smartphones, we developed an original Android OS app that stores the following data in the internal data storage of the device: the 3-axis acceleration (m/s²) and yaw, pitch, and roll angles every 20 ms and the latitude, longitude, and travel speed every 1 s. The data were collected offline from each smartphone and used for further analysis.

3.2 Experimental Design

In this study, the classification algorithm to distinguish between passenger vehicles and motorcycles was developed by targeting traffic in which the proportion of motorcycles was high and congested traffic could be observed. Thus, experimental fields that satisfied the following criteria were selected: (i) various traffic conditions can be observed; (ii) waiting space is available for the test drivers and riders; and (iii) it is easy to find suitable circular routes. As a result, Jl. Urip Sumoharjo (hereafter Urip) and Jl. A. P. Pettarani (hereafter Pettarani) in Makassar, Indonesia were selected as test sites. The experiment was conducted on September 20, 2013, between 7 am and 10 am at Urip and between 3 pm and 6 pm at Pettarani.
For this experiment, we hired two passenger vehicle drivers and five motorcycle riders. They were asked to drive around the fixed circular courses shown in Figure 1 at certain time intervals while carrying smartphones in the manners discussed in the previous section. The numbers of observations are summarized in Table 1.

### 3.3 Traffic Conditions

Figure 2 illustrates the travel times observed by the GPS data collected from the smartphones within the sections of travel time measurement indicated in Figure 1. In Urip, the travel time was distributed between 20 s and 100 s, corresponding to speeds between 6.8 km/h and 34.2 km/h. In Pettarani, the travel time was distributed between 20 s and 120 s, corresponding to speeds between 8.1 km/h and 48.6 km/h. Note that the observations included congested and non-congested traffic conditions. Furthermore, the travel times of motorcycles and passenger vehicles were nearly identical when the travel time was low, while during the peak periods (10,000 s and later for Urip; between 3,000 s and 5,000 s, as well as greater than 9,000 s, for Pettarani), the travel times of the passenger vehicles were longer than those of motorcycles. This discrepancy indicates the behavioral differences of passenger vehicles and motorcycles, as well as the importance of classifying them when monitoring traffic conditions.
4. CLASSIFICATION ALGORITHM

Two steps were required to classify the transportation mode using the data collected from the smartphones: (i) determine the indices that characterize the differences between the transportation modes, and (ii) develop the classification algorithm.

4.1 Classification Indices

Differences between the acceleration data sensed by the smartphones of motorcycle and passenger vehicle operators are caused by the following: (i) differences between the engines; and (ii) differences between the movement behaviors, i.e., a motorcycle can move laterally more effectively than a passenger vehicle. To roughly capture the acceleration differences between the two modes, Figure 3 shows the variations with time of the speeds and synthetic accelerations for passenger vehicles and for motorcycles with each of the smartphone carrying...
manner. As can be seen, the uniqueness of the attachment case can be observed, in which case the synthetic acceleration fluctuates greatly. It is considered that, in this case, the engine vibrations were directly detected by the smartphones. By comparing the results for the passenger vehicles and motorcycles (without considering the attachment case), it appears that the synthetic acceleration of a passenger vehicle has a lower amplitude and shorter variations than those of motorcycles. However, the differences are not clear. Furthermore, clear differences cannot be observed in Figure 3 for motorcycles (without considering the attachment case).

(a) Passenger vehicles

(b) Motorcycles (attachment case)
(c) Motorcycles (pocket case)

(d) Motorcycles (neck strap case)
For further analysis, we focused on the power spectral density of the synthetic acceleration to detect differences in the cyclic characteristics. Figure 4 shows examples of the power spectral densities to which a smoothing filter based on a three-dimensional AR model was applied to the synthetic acceleration data every 30 s. Note that the times indicated above the figures correspond to the times in Figure 3. As can be seen, for passenger vehicles and motorcycles in the attachment case, the extrema are located in the low frequency region, and no distinct differences are observable for motorcycles between the pocket, neck strap, and fixed cases.

Thus, the following two indices were defined: (i) the low frequency proportion of the synthetic acceleration power spectrum density and (ii) the standard deviation of the acceleration. For the former, the low frequency criterion was defined empirically as $1/12$ or less. Figure 5 shows scatter plots of the low frequency proportion and of the standard deviation of the acceleration. Note that one plot shows the mean of each value; that is, if a vehicle took 300 s to drive the cyclic course, each value would be defined as the mean of 10 ($= 300 \text{ s} / 30 \text{ s}$) data points. As can be seen, the motorcycles attachment case data are distributed in the region in which the standard deviation of the acceleration is high, and the passenger vehicle data are distributed in the region in which the standard deviation is low and the low frequency proportion is relatively high.

4.2 Classification Algorithm and Validation Results

Among the various classification algorithms, SVMs are commonly applied to the classification of motorcycles and passenger vehicles. An SVM is a supervised learning model and the associated learning algorithms. An SVM optimizes the separation hyperplane to maximize the margins for a given finite set of learning patterns. By applying a kernel function, an SVM can be extended to non-linear classification problems.

In this study, a Gaussian radial basis function was used as the kernel function, where the variance was set as a hyperparameter. A soft margin parameter was set empirically to 1. Then,
Figure 4 Power spectrum densities

(a) Passenger vehicles

(b) Motorcycles (attachment case)

(c) Motorcycles (pocket case)

(d) Motorcycles (neck strap case)

(e) Motorcycles (fixed case)
three-fold cross-validation, in which all data were randomly separated into three groups, was applied to determine the classification accuracy. Two of the three groups were used as training data, and the other was used as test data. Thus, the classification accuracy could be checked three times.

Table 2 summarizes the validation results. As can be seen, the total classification accuracy is greater than 83% for three of the cases. For motorcycles, the accuracy is approximately 90% and is higher for the attachment, pocket, and neck strap cases. However, it is rather low for the fixed case. For passenger vehicles, the accuracies are distributed between 60% and 78%. According to Figure 5, the distribution areas for the fixed case and for passenger vehicles overlap, which may reduce the accuracy. However, the fixed configuration is an unrealistic means of carrying a smartphone because the smartphones are attached to the body of the rider by adhesion tape. Thus, the fixed case data were excluded from the classification. Table 3 summarizes the results. As can be seen, the accuracies of all of the cases are improved. For passenger vehicles, the accuracy rates are between 66% and 85%. For motorcycles, they are approximately 90%. Thus, it can be said that, based on the chosen indices (i.e., low frequency proportion and standard deviation of acceleration), the SVM could classify passenger vehicles and motorcycles robustly with an accuracy greater than 90%.

5. CONCLUSIONS

We developed a method to differentiate between passenger vehicles and motorcycles using acceleration data collected from smartphones carried by the vehicle operators. In this study, we focused on the ways in which smartphones are carried because the carrying method may significantly influence the classification accuracy. The main findings of this study are as follows.
### Table 2 Classification results

<table>
<thead>
<tr>
<th></th>
<th>1st validation $\ (\sigma = 21.7)$</th>
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<tbody>
<tr>
<td></td>
<td>Passenger car</td>
<td>Motorcycle</td>
<td>Attachment</td>
<td>Pocket</td>
<td>Neck strap</td>
<td>Fixed</td>
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<td></td>
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<td>8</td>
<td>10</td>
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<td>13</td>
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<td>Accuracy rate</td>
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<td>61.1%</td>
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<td>80.0%</td>
<td>88.9%</td>
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<tr>
<td></td>
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</tr>
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<td>15</td>
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<tr>
<td>Accuracy rate</td>
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<td>100.0%</td>
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### Table 3 Classification results without fixed cases

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<td>Attachment</td>
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<td>Fixed</td>
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<td>Predictions</td>
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<td>3</td>
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<td>1</td>
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<td>13</td>
<td>3</td>
<td>9</td>
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<tr>
<td>Accuracy rate</td>
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<td>100.0%</td>
<td>75.0%</td>
<td>100.0%</td>
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<td>3rd validation $\ (\sigma = 21.8)$</td>
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<td>Predictions</td>
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<td>2</td>
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</tr>
<tr>
<td></td>
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<td>10</td>
<td>12</td>
<td>11</td>
<td>-</td>
</tr>
<tr>
<td>Accuracy rate</td>
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<td>100.0%</td>
<td>85.7%</td>
<td>91.7%</td>
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Through the field experiments, it was revealed that travel time differs for passenger vehicles and motorcycles in crowded traffic, which validates the need for a classification method to distinguish between passenger vehicles and motorcycles.

The differences between passenger vehicles and motorcycles can be characterized by the low frequency proportion of the synthetic acceleration power spectrum density (as sensed by smartphones).

The proposed classification algorithm can detect transportation modes with high accuracy without considering the manners in which smartphones are carried.

In this study, the full acceleration data obtained at 0.02 s intervals was used; however, this amount of data is excessive for an online processing environment. Thus, in the future, a robust algorithm should be developed that can perform the same characterization with sparse data. Furthermore, all of the data in this study were initially divided according to the length of the drive or ride. To implement the proposed algorithm in a real environment, it is also necessary to detect the duration that a smartphone carrier is moving in a vehicle.

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