A Road Condition Classifier via Lock Embedded IMU on Dock-Less Shared Bikes *

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ABSTRACT

Shared bikes have been gaining popularity worldwide in recent years, and the number of riders has also been increasing rapidly. However, not all riders have the same riding abilities, and these differences can potentially pose a risk to beginners. In addition, while certain types of bikes such as mountain bikes can handle bumps and holes, the uncertain road conditions might make it uncomfortable and even dangerous for riders of shared bikes. To solve this problem, road conditions should be detected by some effective methods and uploaded to online maps so that riders can choose routes which are suitable for their riding preferences. Therefore, we designed a road classifier based on a lock-embedded inertial measurement unit (IMU) on shared bikes with enabled road surface detection while riding. For training and evaluating the system, 20 subjects were recruited to collect data on dock-less shared bikes with an embedded IMU. To accurately classify road conditions, first, data rotation and feature extraction were performed. Then, linear discriminant analysis (LDA) was used to establish a final model. Cross-validation was performed and showed the accuracy of the model of classifying asphalt road, pebble path, and bumpy path pavement was 95.3%, which showed promising potential in the information expansion of an online mapping which could significantly enhance rider experience.

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CCS CONCEPTS

- **Computing methodologies~Machine learning**

KEYWORDS

Shared Bike, Machine Learning, Application, Road Conditions

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1 Introduction

Bicycling, as a convenient and environmentally friendly transportation method, is a popular means of transportation worldwide. In recent years, the explosive growth of shared bikes has resulted in a rapid increase of bike riders. Therefore, finding a route with proper riding conditions could be a big issue. Especially for riders without advanced riding skills, riding on roads with bad conditions could not only be dangerous for riders but also be harmful for the bikes. In the struggle against roads with bad quality that are dangerous for bike riders, the first step is to determine what roads are suitable for riding. One potential solution could be individual riders reporting bad roads. However, manually checking for road conditions could be expensive, inefficient, and time consuming. Therefore, seeking for a new method to detect the road condition is crucial. Not only inexpensive and efficient approaches are required, but also should large scale of investigation with low cost be feasible to achieve the goal of uploading data for online maps.

There are several kinds of research related to this topic. One popular approach is to calculate an industry roughness factor (IRI) to determine the road surface texture. By mounting accelerometers on vehicles [4,14], these kinds of methods provide cheap solutions for detecting the road surface quality. However, automobiles are unlikely to detect most of the riding routes due to the limitations of size and of traffic rules. With the same principle, motor bikes are also used to determine the IRI [9], but there are either many legal restrictions on motor bikes in large cities or the motor bikes must travel in the standard car lanes meaning that they could not be used to measure the road conditions of bike lanes. Besides, several road condition detection devices are also adopted to explore the anomaly surface such as potholes, bumps, or other kinds of failure. For example, Pothole Patrol [5] uses a collection of sensor-equipped vehicles, with captured accelerometer data, to identify potholes and some other severe road surface anomalies via machine learning algorithm with the accuracy of over 90%. However, potholes are not the main problems for bike riders because compared with cars, bicycles are much smaller and more agile and are more capable of avoiding the anomalies. RoADS [13] uses a smart phone IMU to investigate the road surface. Using wavelet decomposition analysis to extract features from the time domain and the frequency domain, the model created by the support vector machine (SVM) is obtained, and the three different road surface anomalies are classified with an average accuracy around 90%. Nevertheless, on one pass, the expectancies of detecting all road anomalies are not high. Wolverine [2] is also a non-intrusive method which used mobile phone sensors to monitor braking events. Street Bump [3] uses the accelerometer in mobile phones as well, but creates an “anomaly index” to describe how serious the road pavement failures are, which mostly care about the maintains of city construction. Several other devices [1,8,10] and applications are implemented in automobiles to investigate the road damage as well. Biketastic [12] offers a platform for riders to record the road condition they have been ridden on and share with friends. Although the inquiry of the bad road conditions seems to be much easier using techniques mentioned above comparing to the traditional road condition investigation methods, they are also labor-dependent, which means that the expansion of the measurement to a large scale could be a challenge.

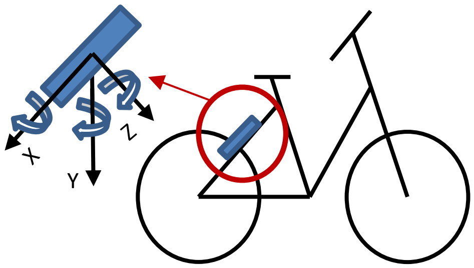
To address the above problem and challenges, in this paper, a ubiquitous road condition classification system on shared bikes via lock-embedded IMU is introduced. This system is designed to be implemented in shared bike smart locks and aims to facilitate the road pavement information collection process so that the system can take the advantage of the enormous amount of shared bike users to achieve large scale route condition investigation. The main contribution of this paper is to introduce a novel framework for ubiquitously classifying road condition. The main principle can be summarized as follows. Using a portable data acquisition system so that this system can be implemented in the shared bike smart locks. The system with accelerometer and gyroscope captures the dynamics of the route while riding. Therefore, data can be collected by the shared bike itself when it is ridden. Based on the collected IMU data, road roughness along a route can be inferred. Features are generated from the acceleration and angular velocity data from the accelerometer and gyroscope, respectively. Finally, based on the features, surface of the route is classified into the assigned type. In this way, road pavement can be classified, which makes it possible for uploading road conditions to online map to help riders optimize their riding routes. With the enormous number of shared bikes and shared bike users, large scale inspection of road conditions could be feasible.

2 Methods

2.1 Experimental Setup and Road Conditions

(a) Hellobike

(b) Mobike



(c) Axes of sensors

Figure 1: Testing bikes and prototype implementation

A survey [11] shows that in November of 2018, the numbers of monthly active users of Hellobike and Mobike were 6.9 million and 18.6 million respectively, which shows that Hellobike and Mobike were two of the most popular kinds of shared bikes. Because of this, a Hellobike and a Mobike Light were adopted for investigation. In order to maintain consistence between sensor placement, only one of each of the bikes were used. Both of the bike models have solid tires. The weight of Hellobike is 17.8 kg while Mobike is in a lighter weight of 16.9 kg. The tire diameters of Hellobike and Mobike are similar at 65 cm and 66 cm, respectively. There is also a difference between the axle-to-axle length of two bikes. For Mobike, the axle-to-axle length is 115 cm while the length of Hellobike is 110 cm. In summary, Mobike is lighter, longer, and has larger tires compared to Hellobike. The prototype is illustrated in Figure 1, a custom board with BHI260 (Bosch, Germany) was used for the experiment. The embedded system was mounted in the middle the smart lock flat area with several layers of foam tape. The x-axis, y-axis, and z-axis of accelerometer gauged the acceleration three orthogonal axes (Figure 1). The pitch, roll, and yaw of gyroscope measured the rotation of x-axis, y-axis, and z-axis respectively (Figure 1). The sampling rates of the accelerometer and gyroscope used in this case are adjustable, but in this experiment, 100Hz was used.

Three kinds of roads which were investigated are commonly used in city construction as asphalt, pebble path, and bumpy path, which are illustrated respectively in Figure 2. Asphalt is the most common texture of city's road with a relatively smooth surface. Pebble path is a path with small stones scattered on the ground. Bumpy path is a path composed of significant bumps.

(a) Asphalt **(b) Pebble path** **(c) Bumpy path**

Figure 2: Three testing conditions

For data collection, 20 subjects were recruited following several principles. First, the amount of male and female subjects should be identical. Second, each bike was ridden by 10 subjects with the same 1:1 gender ratio. Additionally, the height and weight of subjects were randomly chosen. The statistics for the height and weight of the subjects were 171 cm of the average height, 8 cm of the height standard deviation, 61.1 kg of average mass, and 8.8 kg of mass standard deviation.

2.2 Experimental Protocol

As long as there is a high level of symmetry in the road condition, the next trials started at the place where the last trial stopped so that if there was a small slope, both slope up and down information could be collected. Therefore, the influence of slope or some other factors which might not expected to be investigated could be reduced.

To collect experimental data, 20 subjects rode the prototype bikes along the predetermined route with 8 trials of each road condition. Subjects were required to ride with a speed that they normally ride with a shared bike to get data close to real application. Within a trial, subjects were instructed to keep the riding speed as constant as possible. In addition, pedaling was to be with the same strength on each side and smoothly. Throughout the trial, the subjects were always to be sitting on the bicycle seat while pedaling. Stand pedaling was strictly prohibited.

2.3 Road Classification Algorithm

Since the smart locks of different bikes were mounted with different angles, to establish a universal model which enables data from both bike types to be correctly classified using all of the bike type data, there is an important task that data from different bikes need to be transferred to the same coordinate system. Ideally, bike should be kept in a static stand position vertical to the ground to calibrate the rotation. However, using bike stand might not keep the bike in the ideal position. On the contrary, bike stands with different conditions might keep the bike to different standing position. Therefore, a dynamic calibration method was considered. Assuming that the subject is riding straight on flat ground with a smooth surface for a long distance, the weight of bike and subject distributes symmetrically on both sides. With the same force on each side of riding, averaging data individually from each axis, the result should be the same as the static vertical stand one. Based on the assumption, a trial of asphalt road was used to rotate the data. Comparing the acceleration data with gravity, data from two bikes could be rotated to the same direction.

After data rotation, data need to be cut into sections to generate features. For this, a sliding window approach [7] was adopted. To get more information from the texture for machine learning, longer window length was preferred. However, transition windows that included data points from different road conditions were inevitable. As a result, the number of transition windows was expected to be much less than the amount of all windows, which makes the errors from transition windows insignificant for most of the applications and thus a small window length was required. Too short of the window length might lead to a resolution which was not high enough for analyzing. To balance the two different demands, the window length was selected to be 1.28 second together with a 0.24 second shift (Figure 3). This window length was adopted also for taking advantage of the decreased computational complexity of fast Fourier transform (FFT). A number of features from both time and frequency domain were extracted for every window.

In more detail, the feature set for each axis and magnitude of the accelerometer and the gyroscope for each window included: mean, median, standard deviation, maximum value, minimum value, skewness, kurtosis, slope sign change [6], mean of frequency and median of frequency. The frequency features were computed using the results of an FFT on the window.

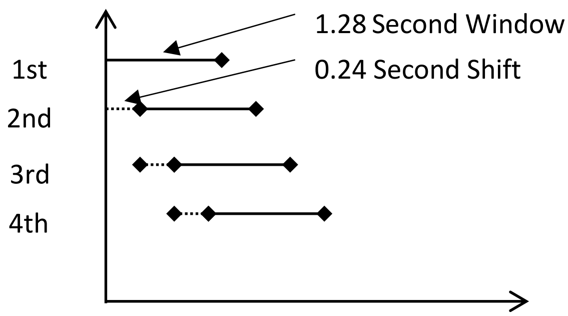


Figure 3: Sliding window method

2.4 Data Analysis

For analyzing the data, various machine learning methods are available to fit this case including linear discriminant analysis (LDA) and Random Forest (RF). To find a suitable approach, a preliminary test was performed with the database in which LDA and RF were inquired with analysis of variance (ANOVA). For each of the two methods, a 20-sample data set consisted of 20 accuracy values created by 20 different training-testing set with 19 subjects training and the left one testing, followed by a one-way ANOVA to test if there was difference between LDA and RF.

For evaluating the model, first, a leave-one-out cross-validation (LOOCV) was used to test the theoretical maximum accuracy. The result of the LOOCV was the average value of 20 different individual models' accuracies. The twenty models were established with 20 different training-testing sets the same as in the preliminary study mentioned above. The individual models were tested with different training-testing sets so that all of the models were different. The final result of LOOCV was the average performance of the 20 models. Second, the model was trained by first 10 subjects and tested by last 10 subjects to produce a more realistic result. In both training subject set and testing subject set, there were 5 subjects riding on Hellobike and 5 riding on Mobike, with the same 1:1 gender ratio of each set. In addition, the processing time of each method was calculated to shed lights on the feasibility of potential applications.

3 Results

ANOVA results showed, there was no significant difference between the classification accuracy of LDA and RF ($p = 0.68$). However, there was a significant difference in the processing time of these two methods. RF took significant longer time for training and testing the model (2.21s in average) than LDA (0.76 s in average) ($p < 0.01$). Considering practical scenarios, a huge training database might be established to get high accuracy in real-life application so that only LDA was adopted due to the short computational time

For LOOCV method, the combined recognition accuracies of three conditions are 95.29% with the accuracies of asphalt, pebble path and bumpy path are 98.4%, 92.9% and 94.2% respectively (Figure 4). The total accuracy of 10-subject-trian 10-subject-test validation is 93.79%, with the accuracies of asphalt, pebble path and bumpy path are 99.2%, 89.8% and 87.0% respectively (Figure 5).

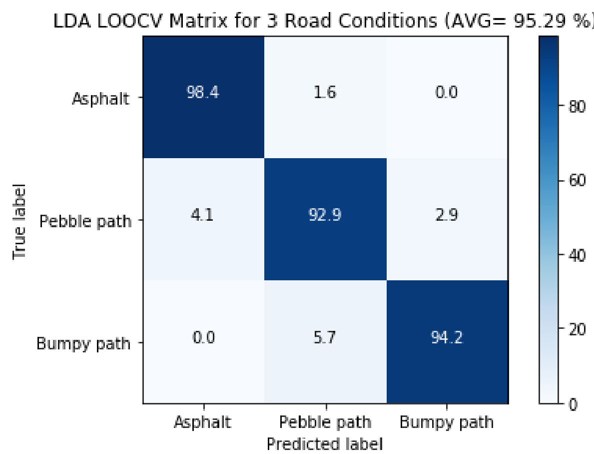


Figure 4: Confusion matrix of predicted and true road conditions

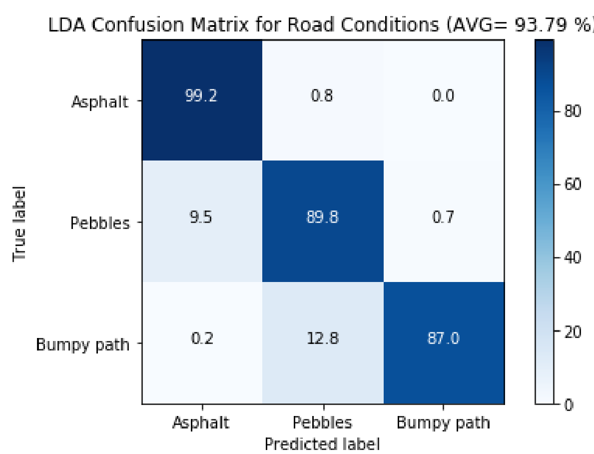


Figure 5: Confusion matrix of the model trained on the first half of subjects and tested on the other half

4 Conclusion and Future Work

In this paper, we have presented system which is able to capture road surface information based on accelerometer and gyroscope data and classify three determined road conditions. A sliding window technique is used to cut data for generating features and LDA to determine three kinds of road conditions which are asphalt, pebble path, and bumpy path. The LOOCV result is 95.25% while the 10-subject-trian 10-subject-test validation accuracy is 93.79% which showed promising potential in optimizing online map and guiding suitable routes for riders.

For future work, we plan to collect data from more road conditions so that the road can be classified more precisely. Second, events and failures on road surface will be detected for reporting the potential risks to riders. Finally, we plan to do a feature selection to reduce the computational time while keeping a comparable accuracy.

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