Road Surface Condition Monitoring via Multiple Sensor-Equipped Vehicles

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***Abstract*—Although governments have spent a great deal of effort to provide safer road networks, surface defects such as potholes, suck-in manholes, and defective street cuts are still commonly found on roads. The current methods of road surface monitoring depend on reports from drivers. However, these methods usually incur a long delay and thus it is difficult to obtain up-to-data information on road conditions. To overcome the drawbacks of the current methods, we propose an innovative and automated method that uses a mobile data collection kit mounted on vehicles. The kit includes an accelerometer, global positioning system (GPS) sensor and microcomputer. A local algorithm is embedded to increase the efficiency of data logging. Recorded data from multiple vehicles are transmitted to a back-end server, where a street defect detection algorithm is performed based on the large amount of collected data. We have tested our system in real road conditions. The identified road conditions are visualized on online maps.**

I. Introduction

According to the report [1], \$16.5 billion was annually spent on repairing the road network from 2009 to 2011 in the United States. However, the road surfaces are still not well-maintained, having defects such as potholes, suck-in manholes, and defective street cuts. These poorly maintained roads can damage vehicles and motorcycles, and furthermore they can cause life-threatening accidents. The current method of the road surface monitoring is still manual process, which depends on reports from people through hot-lines or websites. One drawback of the current method is that it is difficult to obtain up-to-date information on the conditions of the huge amount of public roads. For example, New York and California state have 114,546 and 171,874 mile public roads, respectively [2].

To automate the process of collecting the information, we developed a new road surface monitoring method, which uses a mobile data collection kit mounted on vehicles to collect data regarding road surface conditions [3]. The advantage of this method is that a large range of roads can be monitored simultaneously by simply mounting the kit onto normal vehicles. The collected data are transmitted to a back-end server, where the classification and trajectory clustering algorithms are used to identify road conditions based on the data.

II. Road Surface Monitoring System

The architecture of our proposed road surface monitoring system is illustrated in Fig. 1. It consists of two parts: a vehicle client (i.e., a mobile data collection kit that can be mounted onto vehicles) and a back-end server. In each vehicle client, an accelerometer, GPS sensor, micro computer, and local storage are included. Since a vehicle client may not always have Internet connection, the collected data are first cached on the local disk. Since the data are collected with a high frequency and the majority of the data are collected on smooth roads, we use a data logging algorithm that runs locally on each vehicle client to filter out unnecessary data that are collected on smooth roads. When Internet connection is available, the collected data are transmitted to the back-end server, where the data from multiple vehicle clients are combined to identify road surfaces conditions.

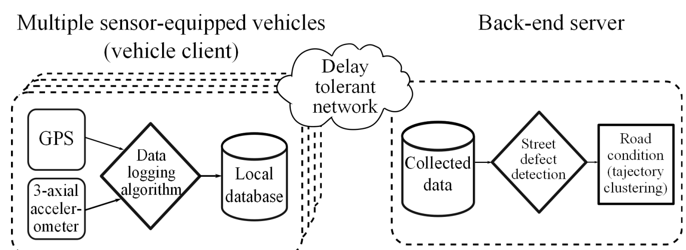

Fig. 1: Architecture of the proposed road surface monitoring system

A. Data logging Algorithm in Vehicle Clients

Logging all of the measured data into the local storage cannot be very efficient because only some of them contain useful information to detect road surface defects. As an example, the data recorded on smooth roads do not have significant excitation in measured signals and just take extra storage spaces. We design a *data logging algorithm* that runs in each vehicle client in order to increase the efficiency of the data logging. First, mean-shifting caused by normal vehicle movements, such as making turns, changing lanes, and going up or down hills, is corrected by taking out the exponential moving averages from the accelerometer signals. Then, the root mean square (RMS) values of the accelerometer signals are calculated in a fixed time window length, which is equivalent to 0.8 second. The data logging algorithm records the data only when the RMS values in both the y (left-right) and z (up-down) directions exceed their thresholds. The thresholds are pre-determined based on manually labeled ground truth such that data on non-smooth road segments can always be recorded

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(data on smooth road segment may be recorded too, but they will be classified as smooth by the street defect detection algorithm on the back-end server).

B. *Street defect classifier at back-end server*

We use a supervised machine learning technique to classify the collected data fragments into three different categories at a back-end server. The first category is defined as an impulse class, where sudden vibrations are observed. Potholes, sunk-in manholes, and hummocks mostly produce narrow and tall spikes in acceleration responses, belonging to the impulse class. The second is a rough class. Unlike impulse responses, a long period of vibrations is shown due to the roughness of road surfaces. Continuous defective street cuts and bumpy roads account for this class. The last one becomes a smooth class. In this class, no signification vibration is presented in acceleration responses. We use a multilayer feed-forward neural network to classify the collected data fragments into the three classes. For training the model, 421 data fragments with the manually labeled output classes are used. The manually labeled data fragments are collected from already-known road defects. The manually labeled 421 data fragments are divided into the training, validation, and test sets, which are 70%, 15%, and 15% of the data fragments, respectively. The accuracy of the classification is 83.2%, 79.7%, and 91.9% for the impulse, rough, and smooth classes, respectively.

C. *Trajectory clustering: merging data from multiple vehicles*

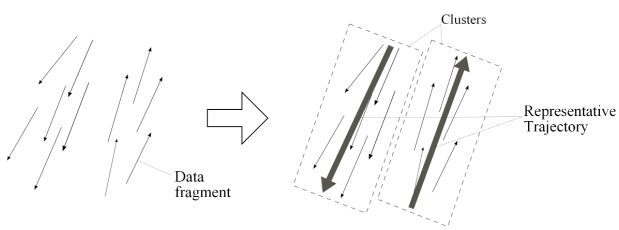
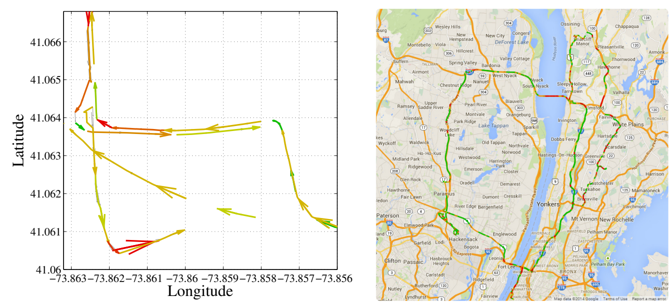


Fig. 2: Trajectory clustering

The results of the classifier from multiple vehicles at the same location are not always perfectly identical. The slight differences in the identified classes can happen when vehicles travel in different lanes and/or different directions. Moreover, it can also occur when some may try to avoid road defects although traveling over the same road location. The errors of the GPS sensor also can cause differences in the recorded locations. To solve above-mentioned problems, we design a trajectory clustering algorithm based on the algorithm in [4] and apply it to group the data fragments (i.e., trajectories) collected by multiple vehicle clients with respect to the location and direction. As a result, the performance of the road surface monitoring system is improved by identifying road conditions based on a large amount of data.

A distance function is defined in order to calculate the locational and directional differences between two trajectories. The distance function consists of three components: the *perpendicular distance*, *parallel distance*, and *angular distance*. Weights are adaptively determined for each of the three components based on the collected data. Then we use the hierarchical clustering algorithm to group the trajectories based on the customized distance function. The complete linkage clustering is used for the linkage criterion, which can prevent a chaining phenomenon. A representative trajectory is calculated for each cluster as shown in Fig. 2. It represents the overall movement of the trajectories belonging to the same cluster. Moreover, the road condition level for each representative trajectory is calculated by a voting method based on the trajectories in the cluster. We then use 10 color scales from the green (smooth road surface) to red (poor road surface) color to represent the identified road condition level for each representative trajectory. The results of the trajectory clustering are shown in Fig. 3.



(a) Representative trajectories (b) Identified road conditions

Fig. 3: Road surface conditions with trajectory clustering

III. Conclusion

We propose a road surface monitoring system that uses multiple sensor-equipped vehicles to automatically identify road surface conditions, and tested it on real roads. The proposed system increases the efficiency of the data logging process. Furthermore, the accuracy of the road defect detection is improved by clustering the classification results based on the locations and driving directions.

References

[1] Smart Growth America and Taxpayers for Common Sense, "Repair Priorities 2014: Transportation spending strategies to save taxpayer dollars and improve roads," Nov. 5, 2014 2014. [Online]. Available: http://www.smartgrowthamerica.org/documents/repair-priorities-2014.pdf

[2] American Society of Civil Engineers, "2013 Report card for America's infrastructure," Nov. 5, 2014 2013. [Online]. Available: http://www.infrastructurereportcard.org

[3] J. Eriksson, L. Girod, B. Hull, R. Newton, S. Madden, and H. Balakrishnan, "The pothole patrol: using a mobile sensor network for road surface monitoring," in *Proceedings of the 6th international conference on Mobile systems, applications, and services*. ACM, 2008, pp. 29–39.

[4] J.-G. Lee, J. Han, and K.-Y. Whang, "Trajectory clustering: a partition-and-group framework," in *Proceedings of the 2007 ACM SIGMOD international conference on Management of data*. ACM, 2007, pp. 593–604.