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On the Analysis of Road Surface Conditions Using Embedded Smartphone Sensors

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***Abstract*—Road conditions play a critical role in ensuring traffic safety and reducing traffic jams and congestions. Ensuring healthy conditions require constant monitoring to detect and predict potential road deterioration. This work proposes a low-cost solution that takes advantage of sensory capabilities of smartphones. By recording Gyro rotation sensor data, we show that abnormalities can be detected by calculating the second moment of sensor data. Our work is validated by drive tests that show results are consistent and repeatable. The work also proposed a dynamic time warping technique to measure similarity between drive results and to obtain accurate representation of multiple drives data.**

***Index Terms* — Road Condition, Gyro Rotation, DTW.**

I. Introduction

ADVANCES in smartphones and embedded sensors technology has transformed cell phones from simple voice communication devices into low-cost systems that have powerful processing, sensing and communication capabilities. Moreover, these advancements have turned handheld phones into valuable tools to support crowed-sourcing applications.

An important application that has been a focus of recent research is the use of embedded smartphone sensors to monitor urban road surface conditions and quality. Applications utilizing such devices enable governments and municipalities to gather crowed-sourced data about road surface conditions and abnormalities for the purposes of providing better maintenance and thus having higher quality and safer roads.

Recent research in this field focused on the utilization of embedded smartphone sensors to detect and classify road surface conditions and abnormalities. The work proposed in [1] utilizes the gyroscope and the accelerometer sensors of a smartphone in a five-phase framework for road conditions monitoring and classification of anomalies such as speed bumps.

Alessandroni *et al.* [2] studied the relation between vertical acceleration and the speed of a vehicle. In their work, the authors used data acquired by a triaxial accelerometer of a mobile device rigidly anchored to the vehicle's cabin. They used the GPS system to acquire the vehicle speed.

The work presented in [3] used a smartphone device to process the built-in sensory data of a vehicle for road condition monitoring and artifacts detection. The proposed system utilized the vehicle sensors such as speedometer, individual wheel speeds, individual suspension sensors and steering wheel angle captured through an OBD II interface with the CAN bus of the vehicle.

Ndoye *et al.* [4] proposed a signal processing approach for road surface condition monitoring. The proposed algorithm utilizes low-cost vehicle-mounted sensors such as accelerometers and GPS receivers to produce high quality roughness data.

Yi *et al.* [5] proposed a smartphone-based system mounted in vehicles running sensing programs to objectively assess bumping caused by road anomalies. The proposed system included the development of a signal processing heuristic that relied on the vertical acceleration component to identify road surface conditions such as potholes and bumps.

Moreover, smartphone embedded accelerometer and GPS sensors have been utilized for road surface classification in bike cycling route applications [6]. The researchers used an offline machine learning approach that teaches a smartphone-based online classifier for smooth, rough and bumpy surface detection and classification.

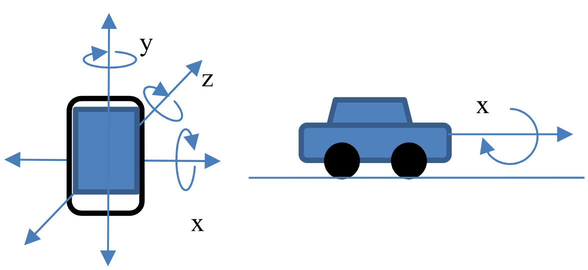
In addition to accelerometer sensors, some researchers used other sensors such as a microphone in a customized embedded device that was used for road surface monitoring [7] [8]. Furthermore, ultrasonic distance sensors were sometimes used in applications for monitoring bad road surface conditions [9].
The objective of this work is to develop a statistical approach based on smartphone embedded gyroscopic sensors data to monitor and detect road surface conditions and abnormalities. The rest of the paper is organized as follows. Section II, briefs the sensory information used in this work. The work procedure is presented in Section III. Section IV, shows preliminary results. Finally, Section V concludes the paper.

II. Sensory Information

Advances in mobile phone technology have transformed the mobile phone into a powerful processing unit. Fitting the phone with sensors enables seamless integration and the ability to develop applications that utilize sensor information and processing capability of the phone [10].

For this work, Apple Inc. iPhone 5s [11] is used to collect and process sensors information. The phone provides the following sensory abilities:

- GPS information
- Accelerometer
- Gyroscope
- Magnetometer



(a) (b)

Fig. 1 (a) Phone sensors reference, (b) Gyro Rotation in vehicle

The phone's processor is an A7 64-bit processor designed by Apple Inc. and accompanied with an M7 "motion co-processor" to process motion data from the accelerometers and gyroscopes [12]. The phone sensors reference is illustrated in Figure 1. The phone logs sensors data in the x, y, and z directions for the accelerometer and gyroscope sensors. In addition, the longitude and latitude GPS information and magnetometer readings are logged. It also provides and logs a time reference. The phone can sample readings at a rate of 100 Hz. In this work, all readings are sampled at a rate of 30 Hz.

III. Procedure

To detect variations on road surface conditions due to potholes, cracks and markings, we utilize the gyro rotation information obtained from a sensing device. In this case a mobile phone with gyro sensors. To evaluate the ability of sensor data to predict potholes, a drive test is conducted. The path is shown in Fig. 2. The round trip for the path is approximately 3.7 km. The drive was repeated 5 times to ensure consistency and repeatability[1]. The path is selected since it has special marking for alerting drivers to pay attentions. The markings are placed in groups of strips and repeated every 75 meters.

A mobile phone placed on the dashboard is used to collect Gyro Rotation along the x axis. The phone also logs sampling time, speed, and GPS locations.

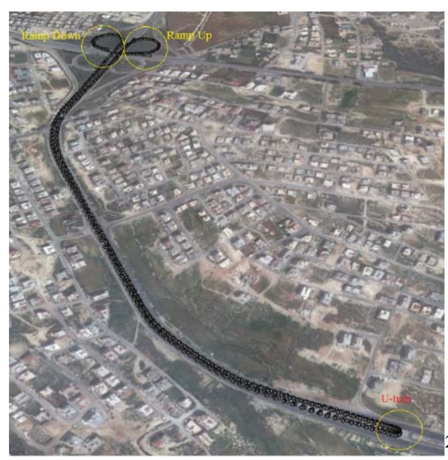


Fig. 2 A map showing travel path.

[1] During the field test, the vehicle must make a complete stop due to unforeseen circumstances.

IV. Results

Although, gyro rotation data contains information about road surface variations, it is hard to visualize or conclude information from this graph. Fig. 3 displays the collected gyro data during the drive test.

To obtain information about road surface we consider the variability of gyro rotation data. This variability is an indicator of the presence of irregularities in road surface such as roughness or potholes. The variability is measured using the variance, defined as

$$v = \frac{1}{N-1}\sum_{i=1}^{N}|X_i - \mu|^2,$$

where μ is the mean of X and is given by

$$\mu = \frac{1}{N}\sum_{i=1}^{N} X_i.$$

To analyze the data, we use moving variance which is calculated as

$$v(n) = \frac{1}{m}\sum_{i=n-m+1}^{n}|X_i - \mu(n)|^2,$$

where

$$\mu(n) = \frac{1}{m}\sum_{i=n-m+1}^{n} X_i,$$

and m is a window size that is used to calculate the moving variance.

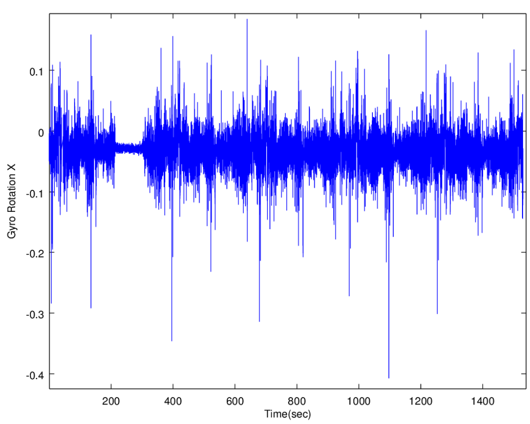


Fig. 3. Raw Gyro Rotation X vs. time

The moving variance plotted against the distance travelled is shown in Fig. 4. The drives data are overlaid to facilitate comparison. The figure clearly shows the variation of the road condition along the drive. The spikes in the graph indicate high variability of gyro rotation data which is caused by the road surface. The graph also shows that the data are consistent and repeatable.

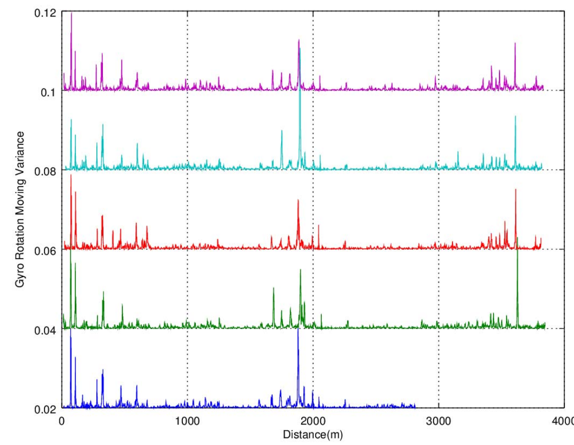
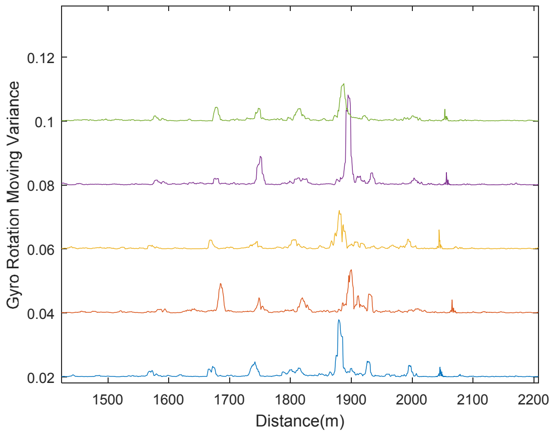


Fig. 4. Moving variance of 5 different trials

To better examine the results in Fig. 4, we look closely at the path traveled using google maps. Fig. 5 (a), shows the part of the path that has strips to alert drivers to slow down due to an upcoming U-turn. To validate the results, the measurements should be able to detect these strips. Fig. 5 (b) shows the gyro rotation moving variance corresponding to these locations. The figure clearly shows 4 spikes corresponding to 4 locations of street strips. The average distance between the spikes is 72 m which agrees with the actual distance.

(a)



(b)

Fig. 5. (a) Google map showing street marking placed approximately 75 meters apart. (b) A zoom into Gyro data that show the 4 peaks caused by street markings.

Although, the measured signals appear to have similar overall appearance, a more accurate measure of similarity is needed. Since the exact path traveled and velocity in each round might be slightly different, using measures like Euclidian distance will not yield accurate measures. In this work, we propose using Dynamic Time Warping (DTW).

In time series, DTW is a technique used to find alignment between two time sequences which vary in speed. The sequences are warped in nonlinear fashion to match each other i.e. stretched or contracted. DTW is widely used in speech recognition for measuring similarity between two temporal sequences that vary in time.

Given two time sequences X and Y of length n, and m, respectively, i.e.

$$X = x_1, x_2, \dots x_n$$
$$Y = y_1, y_2, \dots y_m$$

DTW aligns these sequences by generating an n×m matrix (D) of the distances between elements of the sequences, thus $D_{ij} = (x_i - y_j)^2$. Each warping path $W = \{w_1, w_2, \dots w_N\}$ corresponding to a mapping between X and Y. The objective of DTW is to find the path that minimizes the total cumulative distance i.e. $\sqrt{\sum_{n=1}^{N} w_n}$.

Using dynamic programming, the path can be efficiently calculated by computing a cumulative matrix, with elements given by

$$\gamma(i,j) = d(x_i, y_j) + \min\{\gamma(i-1, j-1), \gamma(i-1, j), \gamma(i, j-1)\},$$

Upon calculating γ, the optimal warping path can be found by tracking backward i.e. choosing the previous element with the lowest cumulative distance. The last element in the cumulative matrix i.e. $\gamma(n, m)$ gives the minimum distance between the sequences.

Using DTW to measure similarity between sequences, Table I shows the distance measure between trials. The table shows high similarity and more importantly comparable similarity between the trials.

Table1: DTW between different trials.

DTW between Trials

	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5
Trial 1	0	1.05	1.01	1.04	1.01
Trial 2		0	0.92	0.98	0.85
Trial 3			0	0.95	0.85
Trial 4				0	0.9
Trial 5					0

To obtain a better representation based on the 5 trials, 2 trials were averaged after they have been aligned using DTW. The two results were further averaged to obtain the graph in Fig. 6. The graph shows more clearly the spikes that result from road abnormalities based on all trials.

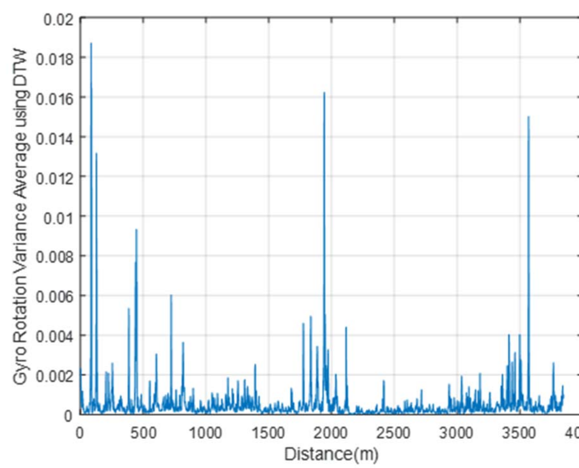


Fig. 6. A representation based on DTW

V. Conclusion

This work presented a new technique for characterizing the road conditions. The technique utilizes available sensory data of a mobile phone. By utilizing Gyro rotation data, variance information provides a good indicator of road condition and presence of any irregularities. The results are consistent and repeatable.

The technique can be used by volunteer drivers by sharing their collected data through a common repository. Through dynamic time warping multiple data source can be aligned to provide a more accurate representation of road conditions.

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