RoadMonitor: An Intelligent Road Surface Condition Monitoring System

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Abstract Well maintained road network is an essential requirement for the safety and consistency of vehicles moving on that road and the wellbeing of people in those vehicles. On the other hand, guaranteeing an adequate maintenance by road managers can be achieved via having sufficient and accurate information concerning road infrastructure quality that can be as well utilized concurrently by the widespread means of users' mobile devices both locally and worldwide. This article proposes a road condition monitoring

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framework that detects the road anomalies such as speed bumps. In the proposed approach, the main indicator for road anomalies is the gyroscope around gravity rotation in addition to the accelerometer sensor as a cross-validation method to confirm the detection results that were gathered from the gyroscope.

Key words: Road monitoring; Smartphone; Wireless Sensor Network; Gyroscope; Accelerometer; Speed bumps; Path holes

1 Introduction

The road surface condition is one of the major indicators for road quality (safety or dangerous road). Road anomalies such as bumps, potholes, patching, cracking and small defects on the surface can be used for the characterizing of road surface quality. So, detecting speed bumps (road bumps), potholes and roughness levels is key to road condition monitoring [1]. Bad roads are a big problem for vehicles, drivers and pedestrians, this is because they are one of the main reasons of vehicles damage, are sometimes very dangerous to drivers and pedestrians [1, 2]. Accordingly, road surface condition monitoring systems are very important solutions to improve traffic safety, reduce accidents and protect vehicles from damage due to bad roads.

Both road managers and Drivers are interested in fixing road conditions quickly. However, these conditions have to be detected firstly. Municipalities and road managers can guarantee an adequate maintenance, via having sufficient and accurate information concerning road infrastructure quality. Also, drivers can drive safely. To gain this information, they need to use special equipments. For Municipalities and road manager, they use Ground Penetrating Radar (GPR) for surface analysis. But this equipment is very expensive and therefore limits its accessibility [3]. For drivers, they need to build some equipment in their vehicles to gain this information. Another alternative is to use sensing technologies to gain this information to solve the problem of road surface condition monitoring.

Nowadays, smartphone is widely used. Most of them are equipped with various kinds of sensors like camera, accelerometer, GPS, gyroscope, microphones etc. So, Smartphone based road condition monitoring is one of such useful application where built-in sensors are used to monitor road conditions [2].

This article introduces a road condition monitoring framework that detects the road anomalies such as speed bumps, which based on sensors built in Smartphones. In previous approaches, the main indicator for road anomalies is the accelerometer sensor, as it will be described in the following subsection. In the proposed approach, in addition to the accelerometer,we use the gyroscope around gravity rotation as a cross-validation method to confirm the detection results.

The rest of this article is organized as follows. Section 2 introduces some resent research work related to monitoring of road surface conditions. Section 3 presents the core concepts of smartphones supported sensors and the fundamentals of the support vector machines (SVMs) classification algorithm. Section 4 describes the different phases of the proposed framework, discusses the tested dataset and presented the obtained experimental results. Finally, Section 5 presents conclusions and future work.

2 Related work

Most of todays smartphones are enabling sensing capabilities through a number of powerful embedded sensors, such as accelerometer, gyroscope, GPS, ambient light sensor, and barometer. These sensors evolved a new application paradigm across a wide variety of domains such as healthcare monitoring, gaming and entertainment. One of these proposed applications is the building of a road monitoring framework that collects basic information about road surface quality.

Kasun et al. in [4] used an acceleration sensor boards for their current running project (BusNet), which basically was proposed for monitoring environmental pollution, to monitor the road surface condition in Sri Lanka. The acceleration sensor boards are capable of measuring the existence of a pothole through the change in the vertical acceleration, in addition it determines the car speed change using the horizontal acceleration. The main drawback in the BusNet road surface monitoring is the uncertainty of the pothole since a change in the horizontal components of the acceleration does not necessarily indicate a rough patch of road; it may indicate a traffic jam.

Pothole Patrol (P^2); a mobile sensing application [5] that detects and reports the road surface conditions. The system depends on a number of accelerometers that are placed inside a taxi cabinet. Through manually labeling, and collecting a set of predefined patterns for road anomalies, the system detects 90% of potholes. The experiment required an integration of specific hardware components; for each taxi an embedded computer running Linux was used, a WiFi card intended for transmitting collected data, an external GPS (mounted on the roof of the car), and a 3-axis accelerometer. Authors in [6] extended this approach by using Vehicular Sensor Networks over wireless sensor networks (customized embedded device).

Girts et al. in [7] initiated a participatory sensing approach for road surface quality monitoring via using smartphones sensing hardware platforms. Their approach required an Android smartphone with GPS, 3-axis accelerometer and communication channel (Cellular or WiFi). The main feature of their framework is the periodically synchronization with database server to store sensors data. The final assessment of the introduced hypothesis needs more in-depth evaluation which had been considered well in [8] and in [9].

3 Preliminaries

3.1 Smartphones supported sensors

Modern mobile phones are smart, that is they come with a variety of built-in sensors such as accelerometer, gyroscope, compass, and GPS [10]. An accelerometer is an electromechanical device that is used to measure acceleration change in one, two, or three orthogonal axes (dimensions). The natural of the accelerometer based applications include detecting orientation, vibrational change, and velocity measurement.

The use of the accelerometer to simultaneously detect gravity change and motion accelerations may become a problem; that the sudden stop or sudden change in motion acceleration may detected as a change in gravity (an obstacle). Therefore there is a need for another device that can be used as a cross-validation for gravity change. This device is the Gyroscope (Gyro) sensor [11]. Whereas the accelerometer measures the linear acceleration, the gyroscope measures the angular orientation change (rad/s). Therefore it is known as the angular rate sensor or angular velocity sensor. The use of mobile embedded gyroscope sensor will provide the existence and severity of road bumps. Figure 1, and figure 2 represent captured road condition data gathered respectively from the accelerometer, and the gyroscope.

3.2 The Support Vector Machines (SVMs)

The Support Vector Machine (SVM) is one of the well-known Machine Learning algorithm [12–14] that used to search for the optimal separating hyperplane between classes. The final outcome class is a positive class from another negative class. Assigning a training dataset with n samples

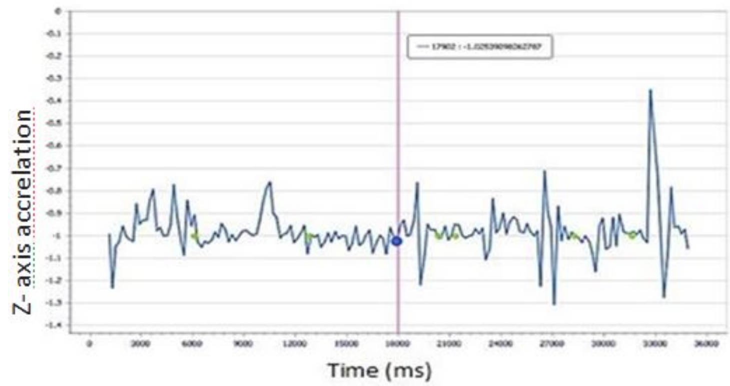

Fig. 1 Accelerometer readings over Z-axis

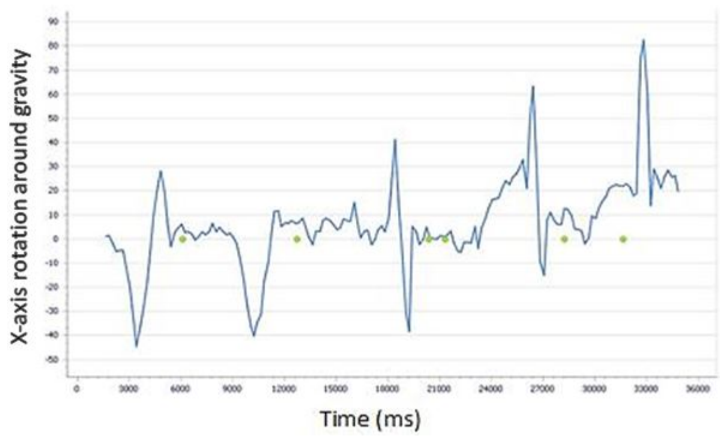

Fig. 2 Gyroscope gravity readings around X-axis

$(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$, where x_i is a feature vector in a v-dimensional feature space and with labels $y_i \in -1, 1$ belonging to either of two linearly separable classes C_1 and C_2. Equations (1) and (2) show the maximal margin to separate the two classes.

$$maximize \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j . K(x_i, x_j) \tag{1}$$

$$Subject - to : \sum_{i=1}^{n} \alpha_i y_i, 0 \leq \alpha_i \leq C \tag{2}$$

where, α_i is the weight assigned to the training sample x_i. If $\alpha_i > 0$, x_i is called a support vector. C is a regulation parameter used to trade-off the training accuracy and the model complexity so that a superior generalization capability can be achieved. K is a kernel function, which is used to measure the similarity between two samples. There are a number of kernel functions that were previously applied (e.g. the Gaussian radial basis function (rbf), polynomial of a given degree, linear, and multi-layer perceptron MLP). These kernels are in general used, independently of the problem, for both discrete and continuous data.

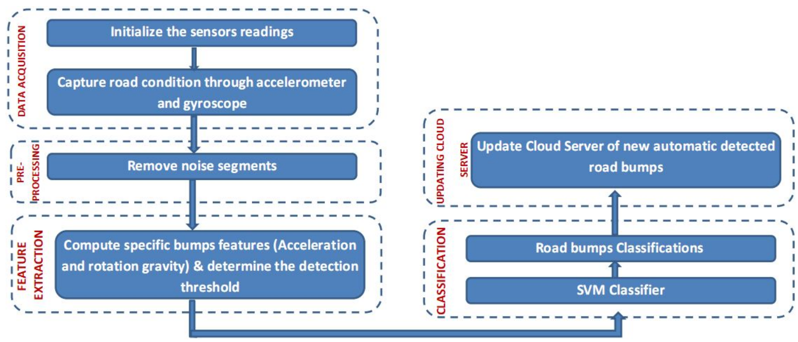

Fig. 3 The proposed road condition monitoring framework

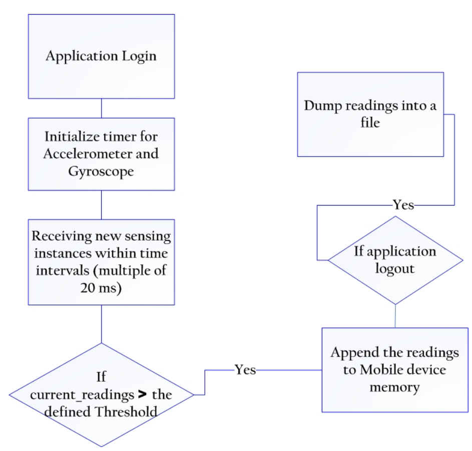

Fig. 4 Data Acquisition phase

4 Proposed Framework

This article proposes a road condition monitoring framework that detects the road anomalies such as speed bumps. the framework contains five phases as it is illustrated in figure 3. The following subsections will describe in more details these phases. While the main indicator for road anomalies is the accelerometer as described in previous related work section, our detection approach uses the gyroscope around gravity rotation combined with the accelerometer as a cross-validation method to confirm the detection results.

4.1 Data acquisition

Data acquisition phase is the most important one; since it is responsible for collecting road information. The data acquisition process has been done using Nokia Lumia 820 mobile device that was placed inside both a Volkswagen Jetta and Chevrolet Aveo vehicles. Readings of road surface conditions were gathered using both accelerometer and gyroscope sensors. The sensors gathered data along the vehicle path. The collected data was stored locally within the mobile device memory. Also, the GPS coordinates of the manually marked road bumps points are kept within the memory.
The application is not dedicated only for Lumia 820 device, it can be customized to work on other smart devices. Figure 4 that shows the data acquisition framework, starts by checking the existence of accelerometer and gyroscope sensors. Once they are exist, the application initializes a timer to start receiving sensors data. For saving mobile memory space, specific readings were preprocessed before being stored, like optimizing the time structure in the log files by putting the difference with a certain time stated at the beginning of the file. Another preprocessed optimization is done over sensors readings; for example, the readings of the gyroscope are appended to the device memory if the current sensed rotation rate (in radians/s) is greater than the previous one stored within the rate vector. Once the user stops the data acquisition, the application dumps the log files exist within the memory into to the inserted micro SD card.

4.2 Pre-processing phase

The Z-axis and X-axis readings for accelerometer and gyroscope, respectively usually contains irrelevant data (noises). These noises appear clearly when collecting data by the Chevrolet Aveo vehicle. Therefore a pre-processing phase should be applied in order to reduce signals noise and improve the road bumps detection. The article applies the second-order high-pass butterworth filter [15]. That maximally flat in the passband and the response rolls off in the stop band. A high-pass filter decreases all the frequencies below the defined cutoff frequency. While figure 5 and figurer 6 shows respectively, the original reading (contains noises) and the filtered readings for the Z-axis of the accelerometer, figure 7 and figure 8 shows the X-axis readings before and after applying the high-pass butterworth filter.

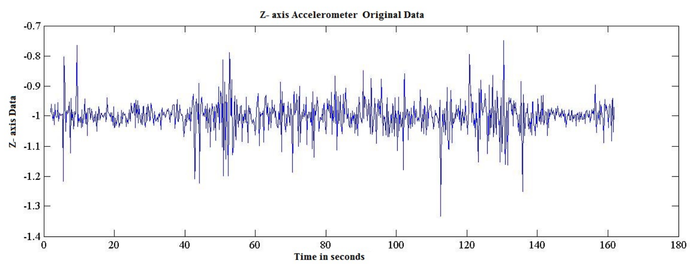

Fig. 5 Original unfiltered Z-axis readings for the Accelerometer

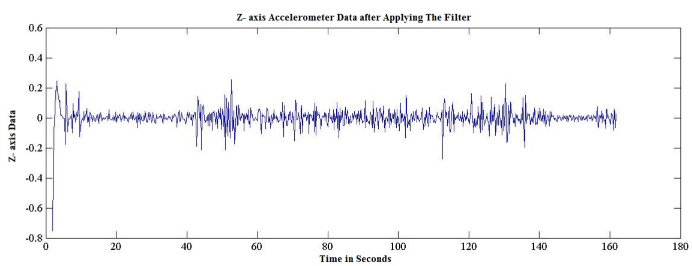

Fig. 6 Filtered Z-axis readings for the Accelerometer

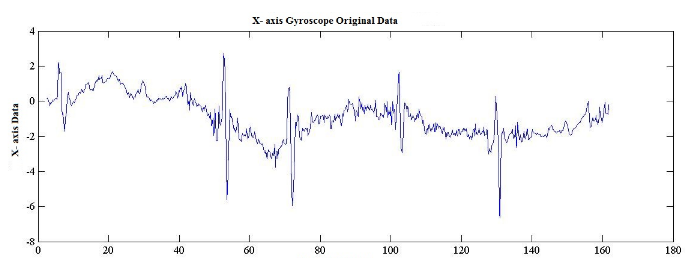

Fig. 7 Original unfiltered X-axis readings for the Gyroscope

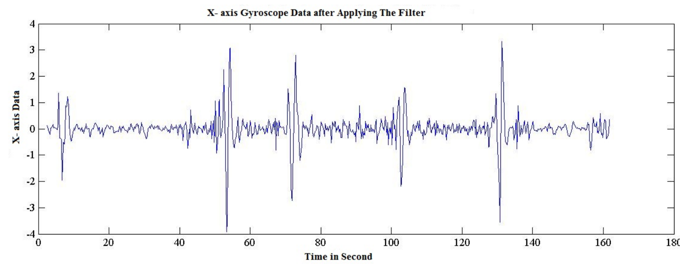

Fig. 8 Filtered X-axis readings for the the Gyroscope

4.3 Features extraction phase

In order to reduce input data representation, the input data will be transformed into feature vectors. Features extracted from the road condition data involve mean, standard deviation, the difference between minimum and maximum for both sensor readings.

The feature extraction process shows that there is a relationship between the road bump detection thresholds for the Z-axis of the accelerometer and X-axis readings of the gyroscope. That when the accelerometer Z-axis readings falls within this range (0.02 <= Z <= 0.085) and the gyroscope X-axis readings exist within the range (1.11 <= X <= 1.9) this indicates the presence of a road bump.

The features extraction phase exposed the problem of depending only on the gyroscope to detect road bumps that the accuracy of the results are questionable (Figure 9). On the other hand when we combine the accelerometer with the gyroscope readings (cross-validation) the framework accuracy increases (Figure 10); that all false positive readings by the accelerometer were removed.

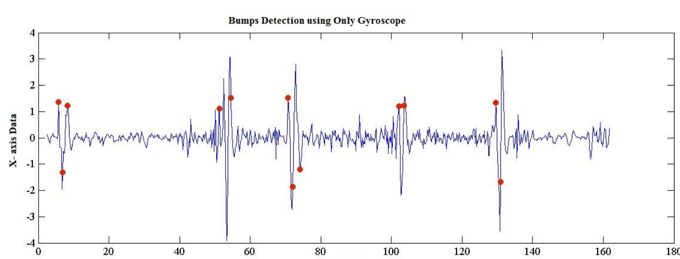

Fig. 9 Detected road bumps using Gyroscope only

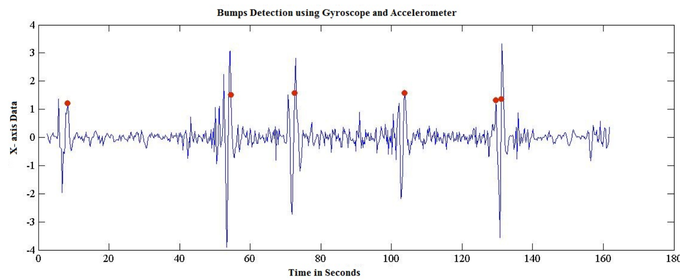

Fig. 10 The combination of Gyroscope and Accelerometer readings shows the real numbers of road bumps

4.4 Classification phase

Finally, for classification phase, the proposed approach applied SVM classification algorithm with two different kernel functions for classification of road severity (smooth or speed bump) . For SVM, The inputs are training dataset feature vectors and their corresponding classes, whereas the outputs are two classes either a smooth or rough. Table 1 shows different kernel functions applied for classification and their detection accuracy (Radial Base Function (RBF) with sigma =1 and Polynomial with order=3 kernel functions and N-fold cross-validation with N=3). The SVM with a polynomial kernel function, that represents the similarity of vectors (training samples), gives an acceptable classification accuracy for road bumps over the RBF, and MLP kernel functions.

Table 1 SVM Kernel functions and Road Bumps detection accuracy

SVM Kernel Function	Detection Accuracy
RBF	75.76%
MLP	66.67%
Polynomial	87.88

4.5 Updating cloud server

Sending coordinates of all detected speed bumps on a cloud server will enables users to save their log files online rather than on their mobile device. The logs include the GPS location of the detected speed bumps (longitude/latitude coordinates) and the severity of them. The intention behind saving road conditions is to build a road condition map. This map will be used in future to feed another application or a GPS navigation system to automatically alert road users of approaching bumps in their path. This early warning service will help road users to take quick responses.

5 Conclusions and Future Work

Usually smartphones offer opportunities to measure some sensory data. For getting benefits of these opportunities, this this paper represents a framework of five phases of a smartphone based application for monitoring road surface conditions in terms of speed bumps. Although, all the previously proposed solutions for road surface monitoring were based on the accelerometer sensing as the main indicator for road anomalies, it may give false positive indication; especially when there is a sudden stop or sudden change in motion acceleration. The proposed framework gives a cross-validation methodology for the existence and the severity of road bumps using additional sensor which is the gyroscope sensor. A pre-processing phase was applied on collected data to reduce irrelevant noisy segments. A feature extraction and classification phases were functional to classify new readings to their corresponding classes (smooth, or speed bump). As a future work we aim to improve the speed bumps detection algorithm through trying other machine learning classifiers with other pre-processing filters.

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