Real Time Pothole Detection using Android Smartphones with Accelerometers

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***Abstract*—The importance of the road infrastructure for the society could be compared with importance of blood vessels for humans. To ensure road surface quality it should be monitored continuously and repaired as necessary. The optimal distribution of resources for road repairs is possible providing the availability of comprehensive and objective real time data about the state of the roads. Participatory sensing is a promising approach for such data collection.**

The paper is describing a mobile sensing system for road irregularity detection using Android OS based smart-phones. Selected data processing algorithms are discussed and their evaluation presented with true positive rate as high as 90% using real world data. The optimal parameters for the algorithms are determined as well as recommendations for their application.

***Index Terms*—mobile sensing; participatory sensing; potholes; accelerometers; algorithms**

I. Introduction

Dangerous road surface conditions are major distractions for safe and comfortable transportation. Both drivers and road maintainers are interested in fixing them as soon as possible. However, these conditions have to be identified first.

One approach to road damage detection is to use human reports to central authorities. While it has the highest accuracy, assuming that people are fair, it also has the most human interaction and is not comprehensive. Statistical analysis can be used to estimate damage probabilities of road segments based on their usage intensity. Integration of vibration and vehicle counting sensors in the pavement are used for statistical data collection [1]. Surface analysis methods using Ground Penetrating Radar (GPR) have been developed [2] and commercial products do exist [3]. Unfortunately, this technology is using expensive equipment and therefore limits its accessibility. As an alternative, participatory sensing has the potential to increase the collected data resolution and scope.

The simplest method might be to collect photos of road damage and hazards taken by the participants and to upload them to a central server. However, this requires strong participation and interaction from the users as well as manual image analysis. We believe that an automated approach for detecting potholes with little or no human interaction is more promising. This would ensure more comprehensive survey data with less errors caused by human factors than generated by mere enthusiasm of the participants.

An automated survey approach could be carried out by either customized embedded sensing devices or smart-phones. While the former has more sensing capabilities and adaptation potential, the popularity of smart-phones makes the latter approach very appealing in terms of practical usability.

To create a successful road surface monitoring system accepted by wide user community, it is important to make it attractive for the users - to provide added value without a significant process overhead. Therefore we envision our system as a service, which is added as a layer to existing navigation systems, such as Waze [4], which use real-time traffic information, collected by participatory sensing approach. Although contemporary smart-phones have high processing power and considerable memory, the detection system is recommended to avoid resource-intensive detection methods and to preserve initial user interface responsiveness.

Automated embedded sensing systems, including smart-phones, have two general classes of sensors to be used for pothole detection: microphone and accelerometers. In this paper we focus on accelerometer data processing for pothole detection This solution extends our proof of concept design [5], and is implemented on Android OS [6].

Related work is discussed in Section II. System requirements and assumptions are listed in Section III. Four algorithms are described and analyzed in Section IV. The evaluation of our approach includes a set of test drives, analyzed in Section V. The final section presents our conclusion that our approach yields high true positive rate.

II. Related Work

There are several vehicular sensing systems for pothole detection. Some of these systems use accelerometers for data acquisition. This section contains a short review of pothole detection algorithms implemented in such accelerometer-based systems. In addition the feasibility for implementation of these systems on platforms with limited hardware and software resources, such as Android based smart-phone, is considered.

BusNet [7] system developed at University of Colombo is using Crossbow MICAz motes and several sensor boards including accelerometer and GPS as hardware platform. This system does not have the functionality for real time data processing. The data is collected and stored locally for transmission through wireless network to collection nodes located at the bus stations for later processing. The only algorithm related to pothole detection is based on sensing acceleration and is used to start the data collection to save the limited storage space.

Pothole Patrol system [8] developed at Massachusetts Institute of Technology is using a specific hardware/software platform – Linux powered Soekris 4801 embedded computers with external accelerometers (sampling rate 380Hz) and an external GPS. Their pothole detection algorithm is based on simple machine-learning approach using X and Z axis acceleration and the vehicle velocity data as input. The algorithm consists of five consecutive filters: *speed*, *high-pass*, *z-peak*, *xz-ratio* and *speed vs. z ratio*. Each filter is used as a rejecter of one or more event types not related to potholes such as door slams or railway crossings. Additional training process is executed for optimal tuning of the last three filters.

Nericell [9] and TrafficSense [10] systems developed at Microsoft Research India are using Windows Mobile OS powered smart-phones as hardware/software platform with an array of external sensors such as accelerometers (sampling rate 310Hz), microphones and GPS. Their algorithms for pothole detection *z-sus* (for speeds $<$25km/h) and *z-peak* (for speeds $\geq$25km/h) are based on simple threshold-based heuristics. Additional algorithm *virtual reorientation* is used to compensate arbitrary orientation of the smart-phone during driving in the vehicle.

A system developed at National Taiwan University [11] is using motorcycle-based mobile phones HTC Diamond as a hardware platform with built-in accelerometers (sampling rate $\leq$25Hz) and external GPS. Their approach for pothole detection is based on supervised and unsupervised machine learning methods. Client side tasks include filtering, segmentation and feature extraction. Server side tasks use two learning models - support vector machine and a smooth road model. Road abnormality detection is performed using histograms of a sequence of triaxial and overall acceleration data segments with different windows sizes representing data from 0.5-2.0 seconds of driving time.

Researchers from University of Jyväskylä propose a pothole detection approach in the context of offline data mining [12]. Accelerometer data (sampling rate 38Hz) is pre-processed using band-pass filters with frequency range 0.5-6.0Hz, a sliding window with different functions such as Chebyshev, Hamming, Taylor and normalization in the range [0,1]. The next step is feature extraction such as mean, peak-to-peak ratio, root mean square, standard deviation, variance, power spectrum density and wavelet packet decomposition. Reducing of the number of the features is done using backward and forward selection, genetic algorithm and support vector machine using principal component analysis. Although the test results of the proposed approach show good performance, it is not suitable for full implementation on a device with limited hardware and software resources. Nevertheless, some of the described methods could be useful for real time data processing.

Simple threshold based algorithms such as *z-sus*, *z-peak* etc. undoubtedly are suitable for implementation on Android based smart-phones. However, the available hardware and software resources on this platform are capable of more complex algorithms with better pothole detection parameters. Our algorithms for pothole detection are distinct from the prior work in two different aspects:

1) proposed solution assumes more advanced and heuristic real time event detection using limited hardware and software resources;
2) concentration on potholes as one specific event type assumes better utilization of available sensor data.

III. Technical Requirements

The following technical requirements were chosen as a basis for pothole detection system:

1) The system should be able to detect events (potholes in our case) in real time. Collection of raw data for off-line post-processing is classified as an additional feature.
2) The system should use a generic Android OS based smart-phone with accelerometer sensors as the hardware/software platform. Portability to other platforms is classified as an additional feature.
3) The system should be able to run on different smart-phone models with different parameters. During the system implementation process the set of minimal smart-phone parameters should be determined and described.
4) The system running on a smart-phone should be able to perform its native communication tasks at an adequate quality level. Utilization of all resources for pothole detection is not acceptable.
5) System should be able to detect events while driving in different four-wheel vehicle types such as passenger cars, minivans and buses. Two-wheel vehicles such as motorcycles and scooters are not considered.
6) System should have a calibration or self-calibration functionality, as different vehicles are likely to yield different sensor data when encountering a pothole. This functionality should be based on signal patterns specific to the certain vehicle types.

IV. Our Approach

Preliminary data from the accelerometer sensors were collected using a modified LynxNet collar device [13] on an urban road with various potholes. The device is based on Tmote Mini sensor node with Texas Instruments micro-controller MSP430F1611 and Analog Devices 3-axis accelerometer ADXL335. MansOS based software was used for raw acceleration data acquisition (sampling rate 100Hz) and transmission through USB interface to a laptop computer [14]. Previously developed RoadMic pothole detection methodology was used

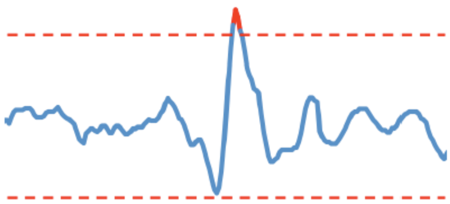

Fig. 1. Pothole detection algorithm Z-THRESH. Events are represented by measurements with values exceeding specified threshold levels.

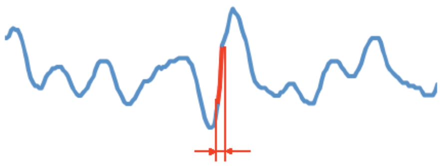

Fig. 2. Pothole detection algorithm Z-DIFF. Events are represented by consecutive measurements with difference value above specific threshold level.

to collect reference data. The test tracks were the same as for the RoadMic project [15].

After the acquisition of the first test data set, a search for potential event related features was performed. The emphasis was placed on features that did not require resource-intensive signal processing techniques and therefore were suitable for implementation for detection using devices with limited hardware and software resources.

The first and the simplest event detection algorithm Z-THRESH (Fig. 1) were tested on the acquired data set. It is similar to *z-peak* algorithm used in Pothole Patrol, Nericell and TrafficSense systems, and is thresholding the acceleration amplitude at Z-axis. The features that classify the measurements are the values exceeding specific thresholds that identify the type of the potholes, e.g. a large pothole or a cluster of potholes. The algorithm assumes that the information about Z-axis position of accelerometer is known. Additional virtual reorientation of the accelerometer is possible, as described in Nericell [9]. However, we used a simpler approach - a controlled placement of the accelerometer, eliminating the extra processing required for the virtual reorientation.

Next, a slightly more advanced algorithm was Z-DIFF (Fig. 2) tested on the acquired data set. Contrary to Z-THRESH a search for two consecutive measurements with difference between the values above specific threshold level was performed. Thus the algorithm detected fast changes in vertical acceleration data. The algorithm requires the determination of the Z-axis position similarly to the previous approach.

After the analysis of the related work, the authors decided to implement some of the techniques that were used for post processing. One promising technique for implementation on a resource-constrained device was using a standard deviation of vertical axis acceleration. It was implemented in algorithm STDEV(Z) (Fig. 3). However, the window sizes and specific threshold levels had to be determined for the tuning of the algorithm and especially for pothole event detection.

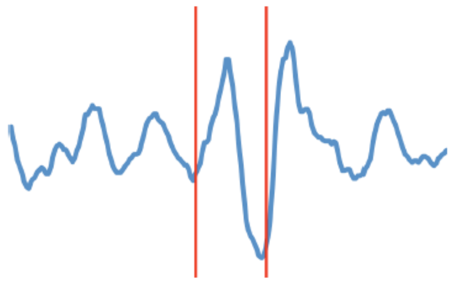

Fig. 3. Pothole detection algorithm STDEV(Z). Events are represented by measurements with standard deviation value above specific threshold level.

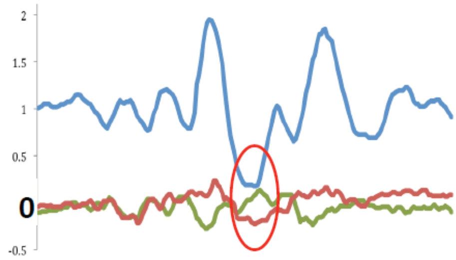

Fig. 4. Pothole detection algorithm G-ZERO. Events are represented by tuple of measurements with all three axis values below specific threshold level.

While using visual data analysis tools and searching for specific data patterns authors found that there exist certain events characterized by specific measurement tuple. All three-axis data in this tuple was with values near to the 0g. Empirical analysis of these data sets led to two preliminary conclusions:

1) such data tuples could be acquired when the vehicle was in a temporary free fall, for example, entering or exiting a pothole;
2) such data tuples could be analyzed without information about exact Z-axis position of the accelerometer.

We named this algorithm G-ZERO (Fig. 4) after the main feature of the detected event. The following section proceeds with the evaluation of these pothole detection techniques.

V. Evaluation

To evaluate the described algorithms the authors performed the following set of the activities:

1) marking of the ground truth for the selected test track using *Walking GPS* approach [16]
2) test drive session on selected test track with 4 different smart-phones as data acquisition devices
3) processing of collected data using selected event detection algorithms;
4) statistical analysis of algorithm performance in context of previously marked ground truth and the existing RoadMic methodology.

The selected test track is 4.4km (2.73miles) long. It includes major multi-lane streets as well as minor single lane

TABLE I
GROUND TRUTH PARAMETERS

Class	24.03.2011	19.03.2010
Large potholes	3	3
Small potholes	18	18
Pothole clusters	30	30
Gaps	40	25
Drain pits	17	29
Total	**108**	**105**

TABLE II
ACCELEROMETER DIFFERENCES BETWEEN ANDROID SMART-PHONES, AVERAGED OVER 10 MINUTE DRIVE

Device	Sampling rate (Hz)	Z-axis StdDev (g)
Samsung i5700	26	0.3076
Samsung Galaxy S	98	0.1171
HTC Desire	52	0.1215
HTC HD2	47	0.1242

streets in the city of Riga, Latvia, and is characterized by a range of degree in road surface smoothness. Marking of the ground truth was performed using EGNOS-compatible GPS receiver Magellan eXplorist XL and RoadMic road irregularity classification with 5 classes - large potholes, small potholes, pothole clusters, gaps and drain pits. The actual ground truth parameters (24th of March, 2011) and historical ground truth parameters (19th of March, 2010) are shown in Table I. It is notable that the common road irregularity count and distribution between several irregularity classes show only minor differences between the years, although the local climate has snowy winters that are responsible for significant road damage every year. The decreased count of the drain pits is due to the more recent and improved multi-lane street ground truth marking methodology where only drain pits located in the lane used for the test track are classified as ground truth objects.

The test drive session included 10 consecutive laps on the selected test track and was performed in the same day as the ground truth was established (24th of March, 2011). Such approach ensured minimal road surface changes between the data acquisition activities. The technical equipment used during the test drive session included a passenger car BMW 323 Touring and four different smart-phones, described in more detail in Table II. The experience from earlier proof of concept test drive sessions as well as from the actual session results suggested that three of the four used smart-phones should be classified as typical items, but one (Samsung i5700) as untypical item due to the differences in acquired accelerometer parameters. The statistical analysis is based on acceleration data acquired by one of the "typical" smart-phones: HTC Desire.

Processing of the collected data is associated with tuning of appropriate threshold levels for all selected algorithms as well as appropriate sliding window size for STDEV(Z) algorithm. The authors performed this task using methodology similar

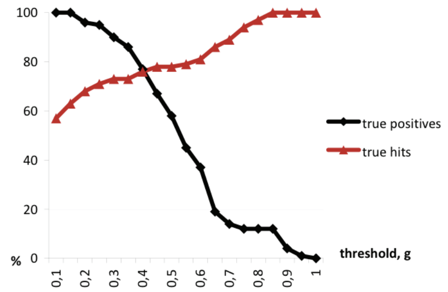

Fig. 5. Z-THRESH algorithm pothole detection performance using different threshold levels.

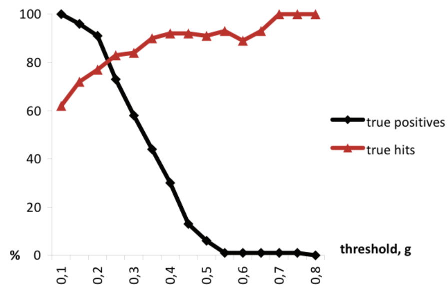

Fig. 6. Z-DIFF algorithm pothole detection performance using different threshold levels.

to the previous pothole detection related activities where the events detected in ≤15m radius from any ground truth item are classified as *true hits*. A ground truth item is classified as *true positive* if during 10 test drive laps at least 4 events in different laps are detected within ≤15m radius. Note, that all of the detected events that are not true hits are *false positives* - events that do not have any proximite ground truth points. For visual clarity, *false positive* graph is hidden from the figures.

During the tuning process the Z-THRESH algorithm was tested with threshold values between 0.1-1.0g. For further analysis 0.4g was selected as the optimal value (Fig. 5) characterized by 78% *true positives* and 76% of all detected events were classified as *true hits*.

Threshold values between 0.1g and 0.8g were used for tuning the Z-DIFF algorithm. Further analysis was performed using 0.2g as the optimal threshold value (Fig. 6). Using this value 92% of all ground truth items were *true positives*, and 77% of all detected events were in close distance with certain ground truth object (*true hits*).

During the tuning of the algorithm STDEV(Z) a search for appropriate sliding window size was performed using a range of 4-80 samples. A tuple with maximal *true positive* (81%) and *true hit* values (76%) corresponded to window with 20 samples and threshold value 0.2g (Fig. 7).

Searching for the optimal threshold value between 0.1-1.2g performed tuning of the G-ZERO algorithm. The value 0.8g was selected as the best fit (Fig. 8) characterized by 73% *true positives*, while 76% of all detected events were classified as

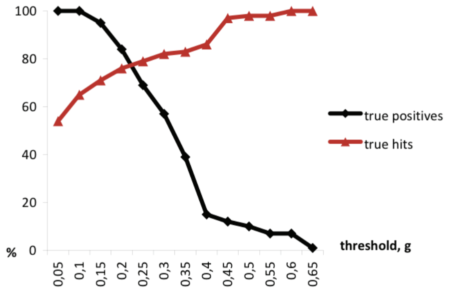

Fig. 7. STDEV(Z) algorithm pothole detection performance using different threshold levels and rolling window size 20.

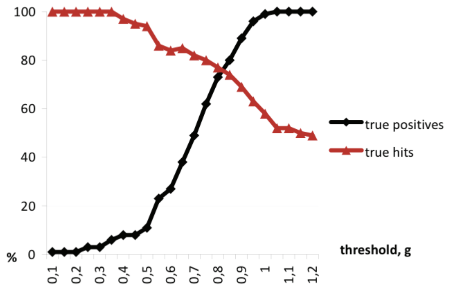

Fig. 8. G-ZERO algorithm pothole detection performance using different threshold levels.

true hit.

The performance results of the algorithms using previously determined optimal parameters are shown in Table III. As expected, the proof of concept test drive sessions detected irregularities on the main road for 100% of big potholes and 83-90% of pothole clusters. It is notable that 2 ground truth pothole clusters (7%) were not detected by any of used algorithms. Authors examined the positions of these objects and found that both of them are located at street junctions where the speed of a vehicle making a turn is too slow to make notable fluctuations in acceleration.

Depending on the algorithm 78-89% of ground truth for the small potholes were detected. It is notable that 9 of them (50%) were detected by all 4 algorithms for each of the 10 test drive sessions. This aspect suggests that smart-phone accelerometer sensitivity is sufficient for this application and approach.

The gaps were detected in the range of 68-90% of the previously marked ground truth objects. Only 3 items (8%) escaped from all 4 detection algorithms. These objects were located on the main multi-lane street where the total road smoothness is better than average and the transitions between several road segments have only minor impact on the suspension of the vehicles.

The fifth and final ground truth object class – drain pits were detected by a different algorithm with a rather wide range of 47-100%. This aspect is notable in the context of future work as a possibility to make assumption about the class of detected road irregularity. Depending of the goal for the event detection several irregularity classes could be included or excluded from the event type set.

TABLE III
TRUE POSITIVE RATE OF THE FOUR USED ALGORITHMS

Class	Z-THRESH	Z-DIFF	STDEV(Z)	G-ZERO
Large potholes	3 (100%)	3 (100%)	3 (100%)	3 (100%)
Small potholes	15 (83%)	16 (89%)	16 (89%)	14 (78%)
Pothole clusters	25 (83%)	27 (90%)	27 (90%)	27 (90%)
Gaps	31 (78%)	36 (90%)	30 (75%)	27 (68%)
Drain pits	10 (59%)	17 (100%)	11 (65%)	8 (47%)
Total	**84 (78%)**	**99 (92%)**	**87 (81%)**	**79 (73%)**

VI. Conclusion and Future Work

This paper describes accelerometer data based pothole detection algorithms for deployment on devices with limited hardware/software resources and their evaluation on real world data acquired using different Android OS based smart-phones. The evaluation tests resulted in optimal setup for each selected algorithm and the performance analysis in context of different road irregularity classes show true positive rates as high as 90%.

The future work includes experiments with combinations of algorithms and development of self-calibration functionality.

VII. Acknowledgment

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