Pervasive and Mobile Computing 40 (2017) 71–88

Contents lists available at ScienceDirect

Pervasive and Mobile Computing

journal homepage: www.elsevier.com/locate/pmc

Smart patrolling: An efficient road surface monitoring using smartphone sensors and crowdsourcing

Gurdit Singh [a,*], Divya Bansal [a], Sanjeev Sofat [a], Naveen Aggarwal [b]

[a] Department of CSE, PEC University of Technology, India
[b] Department of CSE, UIET, Panjab University, India

ARTICLE INFO

Article history:
Received 14 August 2016
Received in revised form 20 March 2017
Accepted 5 June 2017
Available online 10 June 2017

Keywords:
Intelligent transportation systems
Smartphone sensors
Dynamic Time Warping(DTW)
Smart-Patrolling
Potholes
Bumps

ABSTRACT

Road surface monitoring is an important problem in providing smooth road infrastructure to the commuters. The key to road condition monitoring is to detect road potholes and bumps, which affect the driving comfort and transport safety. This paper presents a smartphone based sensing and crowdsourcing technique to detect the road surface conditions. The in-built sensors of the smartphone like accelerometer and GPS[1] have been used to observe the road conditions. It has been observed that several techniques in the past have been proposed using these sensors. Such techniques either use fixed threshold values which are road or vehicle condition dependent or use machine learning based classified training which requires intensive and continuous training. The motivation of our work is to improve classification accuracy of detecting road surface conditions using DTW[2] technique which has not been researched on data based on motion sensors. The main features of DTW is its ability to automatically cope with time deformations and different speeds associated with time data, its simplicity is to be used in resource constrained devices such as smartphones and also the simplicity in its training procedure which is must as fast as compared to techniques such as SVM,[3] HMM[4] and ANN.[5] Our technique shows better accuracy and efficiency with detection rate of 88.66% and 88.89% for potholes and bumps respectively, when compared with the existing techniques with the use of the proposed technique, prioritization of the road repair and maintenance can be decided based on real-time data and facts.

1. Introduction

Potholes, bumps and road roughness are one of the most annoying hazards and anomalies experienced by the commuters and vehicles [1]. Vehicle itself gets damaged in terms of suspension, steering misalignment, tyre punctures [2] etc., which also lead to accidents [3,4]. A study by the U.S. department of transportation has shown that the road conditions are an essential factor for providing quality transportation experience [5]. One of the major goal of this research is to detect these

* Corresponding author.
E-mail addresses: gurditsinghpec@gmail.com (G. Singh), divya@pec.edu.in (D. Bansal), sanjeevsofat@pec.ac.in (S. Sofat), navvagg@gmail.com (N. Aggarwal).

1 Global Positioning System.
2 Dynamic Time Warping.
3 Support Vector Machines.
4 Hidden Markov Model.
5 Artificial Neural Network.

http://dx.doi.org/10.1016/j.pmcj.2017.06.002
1574-1192/

events, so as to reduce the number of serious damages. The traditional approach to road damage detection is to use manual reporting of the presence of potholes and bumps on the roads. Another approach is to use existing techniques like Ground Penetration Radar (GPR) [6] or some other commercial products [7] by installing specific hardware along the road side. The overall cost and maintenance of these equipments is very high which reduces the system feasibility.

Nowadays, high end vehicles are also equipped with various sensors such as accelerometer, GPS etc. which are capable of detecting the road conditions and driving behavior. But these features are only available in high end models of vehicles due to the cost involved. Some commercial products like [8,9] and [10] are also available in the market which can be mounted in the vehicles for tracking purposes such as tracking taxis by various taxi agencies. However, smartphones can also be used as an alternative solution to detect the road surface conditions, which are all almost pervasive and available with the commuters and possess many sensory inbuilt capabilities. Sensors such as accelerometer, magnetometer, gyroscope, GPS etc. equipped in the smartphones can be used simultaneously, to collect data from the roads. The accelerometer sensor of the smartphone produces significant patterns when the vehicle passes over a pothole or bump as compared to the smooth road surface. Smartphones can be used to collect sensory data from various sensors along with the GPS traces and processed at the central server for further analysis. This information when processed, is disseminated in the form of pothole map of the city which can be useful to commuters especially for sensitive groups such as senior citizens, patients, expecting women, home delivery service providers and many others while they are commuting on the road.

Moving along this direction, reports about the existence of potholes or bumps can also be filed either by manually or automatically. In manual reporting, the user interacts with an application [1,11] installed on smartphones (participatory sensing) whereas in automatic detection mechanism, an algorithm runs in the background of the smartphone where human input is almost zero (opportunistic sensing). There are many popular applications such as Waze [11], Street Bump [1], Google Maps [12] which provides navigation services with live traffic conditions when we set the source and destination. But such applications do not provide any information pertaining to road surface conditions.

In this paper, motion sensors of the smartphones have been used to detect the road anomalies such as pothole and bumps. During the conduct of this empirical study, data was collected from various roads of Chandigarh city (located in northern region of India) using smartphone sensors. Unique patterns of pothole and bumps have been observed from the sensor readings during the ground truth phase which are stored in the database and are referred to as reference template. These template references along with crowd-sourced data collected from accelerometer is fed to DTW to find the closeness or similarity. Based on this technique, a model had been proposed named as "Smart-Patrolling", which uses DTW and crowd-sourcing techniques together to detect the road anomalies in a real environment. The prototype of "Smart-Patrolling" has been implemented on Android-based mobile devices which validates the feasibility in the real environment. The entire experimental validation has been done on the roads of Chandigarh city in India.

Challenges: The main challenge is to detect an event with *variable speed, vehicle condition* and *road types*. It may be not possible to train the models with existing techniques (machine learning and threshold) to cover all the conditions.

Key Idea: The key idea is to minimize the tedious task of training and implementing the *DTW technique* which is independent of time and space. In this work we found that DTW as a technique for detecting events corresponding to road surface monitoring has a huge potential because of the reasons attributed below:

1. DTW is capable of comparing two given time independent sequences which may vary in speed.
2. DTW is able to automatically cope with time deformation and different speed associated with time dependent data.
3. DTW is suitable for implementation on resource constrained small scale embedded devices such as smartphones.
4. The training procedure in DTW is very simple and fast as compared to other techniques such as SVM, HMM and ANN and require relatively small number of template references.

The implementation of this technique is further elaborated in next sections.

1.1. The problem

This paper focuses on the problem of detecting road conditions like potholes and bumps on the roads using efficient and low cost techniques. Many researchers have proposed different techniques for the detection but as discussed earlier, most of them are based on threshold values and machine learning techniques. The threshold values are dependent on type, condition of the vehicle and sensitivity of the sensor and cannot accurately distinguish between different road anomalies thereby reducing the accuracy because same threshold values are used on different roads. On the other hand, machine learning based techniques require intensive and continuous training to detect the road conditions and hence do not work so efficiently for such applications. Collecting training data across different roads of different cities itself makes the approach inappropriate for real time deployment. Our study particularly focuses on Indian road conditions where presently the work of road maintenance and its prioritization is done based on manual investigation. Our proposed technique does not use any additional sensors other than smartphones of the commuters and the data is crowd-sourced from the smartphones of the commuters to determine the road conditions and thus our proposed technique is cost efficient and effective.

1.2. Key contributions

The main contribution of this paper are as follows:

1. *A technique called "Smart-Patrolling" has been proposed to detect and identify the road anomalies like potholes and bumps using sensory abilities of the smartphones. This information can be useful to commuters especially for senior citizens, patients, expecting women and home delivery based organizations. Our technique does not require any training.*
2. *Use of DTW technique to match patterns and find the similarity score between different patterns has been investigated. It not only helps in detecting the road anomalies using the accelerometer sensor data but also distinguishes the type of the anomaly. Instead of using fixed threshold based values, DTW method has been used to overcome the limitations of existing techniques (further explained in Appendix) with reduced complexity.*
3. *Extensive experiments have been conducted by collecting data from the sensors of the smartphones. The results show that "Smart-Patrolling" can identify the specific types of road anomaly with enhanced accuracy when compared to existing techniques.*
4. *Aid in generating city pothole maps of road conditions for commuters and civic authorities to reduce maintenance time.*

The rest of the paper is organized as follows: Previous work related to road surface condition detection has been discussed in Section 2. In Section 3, the methodology used to carry out the work of detection of road surface anomalies has been discussed. In Section 4, experimental design has been described. Data acquisition and pre-processing phases of raw values of sensors has been explained in Section 5. The conceptualized proposed model capable of road surface detection has been presented in Section 6. Results are presented and analyzed in Section 7. Impact of proposed model due to road type, heterogeneity of models of smartphones and placement of smartphones has also been discussed and compared with the existing techniques. Conclusion and future directions of our work have been presented in the last section.

2. Related work

In the literature, a plethora of work has been reported on road surface condition monitoring using mobile devices. Use of smartphones with in-built sensors has been proposed to monitor the road surface conditions. Related work both in research and commercial applications has been discussed in the forthcoming section.

2.1. Road condition detection

Pothole Patrol [13], is a study which presents techniques used to detect potholes on road surfaces using mobile sensors. The sensors were explicitly deployed on 7-vehicles running over thousands of kilometers in Boston City. Accelerometer data was extracted and used to detect the potholes and other road anomalies. According to the author, the vehicles were equipped with various sensors (accelerometer, GPS) where the data is coagulated on central server to find the road anomalies. Sensors were placed at different positions inside the vehicle to evaluate as to how does the placement affects the sensing quality. The potholes were detected using algorithms consisting of different types of filters. The results showed that the proposed algorithm misidentifies road features (having potholes) less than 0.2% of the time in controlled experiments.

Nericell [14], had proposed a system used to find the potholes and bumps on the road surfaces. A smartphone, cellular phone and external accelerometer was used to collect the data from the streets of Bangalore and Seattle. The accelerometer sensor was oriented in the direction of vehicle. The sensor was well-oriented using Euler's angle with the sequence of Z–Y–Z axis. Two speed profiles (low and high) were considered for detecting bumps where a particular algorithm was used for each condition. The proposed system uses threshold techniques to find the potholes and bumps.

Wolverine [15] is a system proposed by IIT Bombay, which presents a nonintrusive method to find bumps on the road surface using smartphone. The system uses accelerometer, GPS and magnetometer sensors for the detection purpose. This method is an extension of [14] where a threshold based fixed value was defined to find the road anomalies, whereas Wolverine uses SVM based machine learning method. The system was implemented and result showed that the system produces a false negative rate of 10%.

Mednis et al. [16] designed a system which detects the road conditions like potholes using the inbuilt sensors of the smartphone. They had used accelerometer sensor of the smartphone which extracts the values and detects the existence of potholes in real time. They had developed an application in Android OS and tested using four different techniques to detect road anomalies. The proposed system is based on threshold technique in which they were able to detect the road surface conditions at an accuracy of 90%.

Table 1 shows the comparison between different existing techniques used to detect the road anomalies like potholes and bumps. Authors have considered data from the z-axis of the accelerometer after re-orientation because the variation in the data due to pothole and bumps is primarily reflected along z-axis.

The overall comparison of existing technique has been done in Table 2. From Table 2, it can be inferred that the authors have used several methods to declare a road anomaly as pothole, bump or other road conditions. The Pothole Patrol and Nericell techniques are old and only rely upon the fixed threshold whereas the method used in Wolverine relies upon the machine learning technique (K-Means clustering and Support Vector Machine) which requires extensive and exhaustive training.

Table 1
Inferences drawn from related work.

Parameters	Wolverine [15]	Nericell [14]	Pothole Patrol [13]	Mednis [16]
Sensors	Accelerometer, Magnetometer, GPS	Accelerometer, Microphone, GSM, GPS	Accelerometer, GPS	Accelerometer, GPS
Methods for reorientation	Reorientation using magnetometer and GPS bearing	Reorientation using Euler Angle using formula (Z–Y–Z)	Mounted on the same place and in same orientation of each car	Not Defined
Value/Axes taken into consideration	Z-axis Stdev on 1 sec window of accelerometer	Z-axis raw values from accelerometer	X and Z-axis of accelerometer	Raw values of Z-axis of accelerometer

Table 2
Technical comparison of existing work.

Parameters	Wolverine [15]	Nericell [14]	Pothole Patrol [13]	Mednis [16]
Techniques Used	Machine Learning used to detect bumps and braking	Threshold is used to detect potholes, bumps, honking and braking	Machine Learning is used to detect potholes	Z-Thresh, Z-Diff, STDEV, G-Zero
Actual sampling rate of accelerometer	50	310	380	100
Location for Experimentation	IIT Bombay Campus	On the roads of Bangalore and Seattle	On the roads of Boston	Vairoga iela, Riga, Latvia
Sampling rate taken into consideration per second	50 values	Took 10 s window	256	100
Equipment used for Data Collection	Smartphone Sensors (Google Nexus S, HTC Wildfire S)	Windows Smartphone, WiTilt accelerometer, HTC Typhoon for cellular localization	Sensor deployed on embedded computers in cars	Samsung i5700 Samsung Galaxy S HTC Desire HTC HD2
Vehicles used	Suzuki Access 125, Auto-rickshaw	Toyota Qualis (4-Wheeler)	7-Taxis	BMW 323 Touring (4-Wheeler)
Distance Covered (KM)/ Travel Time (Hours)	Not Reported	622 KM/27.6 Hrs	4.4 KM	174 KM / Few weeks
Mount Points	Not defined (placed in certain arbitrary orientation)	Back and Middle Seats, dashboard and hand-rest of vehicle	Dashboard, Right side of windshield, Attached to Embedded PC	Front Dashboard
Detection Purpose	Bumps, braking	Bump, potholes, braking and honking	Potholes	Potholes
Threshold used	Not Reported	Speed $<$ 25 kmph = 0.8 g Speed $>$ 25 kmph = 1.45 g and 1.75 g	XZ-filter $t_x = 1.5$ Speed vs Z-ratio $t_x = 2.5$	Z-Thresh = 0.4 g Z-Diff = 0.2 g STDEV = 0.2 g G-Zero = 0.8 g
Output	FN - 10% (2-wheeler) FP - 8% (3-wheeler)	FN - 20%–30% FP - 5%–10%	FP $<$ 0.2%	90% of True Positives
Energy Consumption	Consumes 58% lesser energy than Nericell	Low power sensors trigger the high power sensors	Not Reported	Not Reported

2.2. Commercial systems

RAC Mobile Traffic App [17] is a popular UK based GPS navigation applications which lets the users to view road incidents, expected delays, and ongoing road works. It also has a route planner for planning shortest or quickest route with live traffic updates along the way.

Amongst one of the most popular GPS based application is **Google Maps** [12] which is a system that crowd-sources the traffic information. This service encourages user to passively contribute congestion related traffic information as they drive. Google Maps began offering traffic data in real-time using Google Traffic, with a color map overlay to display the speed of vehicles on particular roads using crowdsourcing (to obtain the GPS determined locations from a large number of smartphone users), from which live traffic maps are produced. Google later launched a public transport route planner called

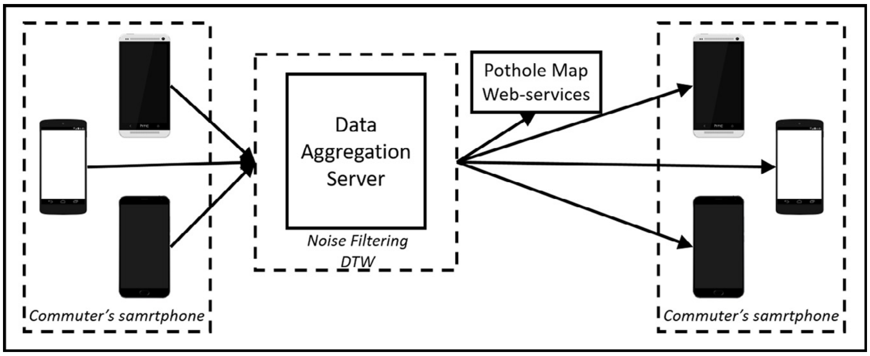


Fig. 1. Methodology.

Google Transit [18] which offers the provision to investigate feeds and provides a service to calculate route and transit time for public transportation systems which can be used by civic authorities.

WAZE [11] is yet another very popular community based traffic and navigation application. It provides realtime traffic and road information for daily commuters. It learns from users' driving times to provide routing and realtime traffic updates. It provides several services such as reporting accidents, traffic jams, speed and police traps, etc. Like all other crowd sourcing based applications, Waze also requires a critical mass of users to have real utility. Waze simultaneously sends anonymous information, including users' speed and location, back to its database to improve the service as a whole.

From the literature review, it is evident that the authors had performed re-orientation of the smartphone first and then filtered the Z-axis of the accelerometer for further analysis to detect potholes and bumps. The authors have used fixed threshold based and SVM based machine learning techniques to detect the road anomalies, which either is impractical for wide deployment or requires extensive learning and study. In this paper, a novel "Smart-Patrolling" technique has been proposed to find the existence of potholes and bumps on the road surface.

3. Methodology

The "Smart-Patrolling" prototype have been shown in Fig. 1, where the data is crowd-sourced from different smartphones of the commuters. The data is collected and analyzed by the server where the noise filtering and DTW techniques are applied. The processed information is then disseminated to different users regarding the road condition status. Observing the limitations of existing work, present methodology introduces DTW, crowd-sourcing and filters to detect the road anomalies. Extensive experimentation has been carried out using six different smartphones placed inside the vehicle at different positions. The smartphones were aligned with the moving direction of the vehicle as shown in Fig. 2. Data collected using sensors of the smartphones was sent to the central server for further analysis. Before the analysis, the smartphones were virtually re-oriented to its original axis (as explained in Section 5.1). Filters were applied on the raw accelerometer data to eliminate various noises such as vibrations of car and gravity component which got added in the accelerometer readings. Patterns were derived empirically from the readings of accelerometer after passing them through different filters and stored in database called template reference. The template references for potholes & bumps and live data collected using smartphones are fed to DTW to find the closeness score between the template reference and collected data. This way road anomalies can be detected and marked corresponding to its GPS location. The output of DTW (pothole location) was then matched with observed locations to find the false positive and false negative rates of the proposed technique.

4. Experimental design

In order to investigate the road surface conditions like potholes and bumps, following experimental plan was designed and performed (parameters defined in Table 3).

The experiment was conducted on the various roads of Chandigarh city using a car and smartphones. An application was developed using Android SDK,[6] which interacts with the sensors of the smartphone to collect accelerometer and GPS data. The experiment was conducted for a period of one month covering around 220 KM per day.

The smartphones were placed inside the vehicle, having Y-axis of accelerometer in the moving direction of vehicle as shown in Fig. 2.

If the smartphone was placed as per the placement shown in Fig. 2, then the smartphone was considered to be well-oriented, otherwise it needed to be virtually re-oriented before performing analysis. This is explained in detail in Section 5.1.

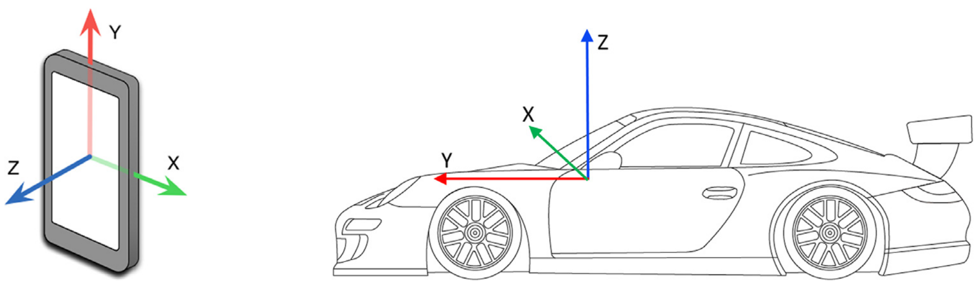
A brief explanation about the experimental design of the data collection is explained in Fig. 3.

6 Software Development Kit.

Table 3
Summary of data collection.

	Parameters Considered
Technique Used	DTW (Dynamic Time Warping)
Location for Experimentation	Chandigarh City, located at the northern region of India
Actual Sampling rate	10 Hz [a]
OS platform of smartphone	Android 5.1 SDK 22
Equipment used for Data Collection	Smartphones (2 x Nexus 5, Samsung S5, Samsung Note3, Moto E, Samsung S4 Mini)
Vehicle(s) used	Toyota Etios (4-wheeler)
Distance Covered (KM)/ Travel Time (Hours)	(195–220 KM/4 Hrs) x 8 days
Mount Points	Front Dashboard (Pilot, Co-Pilot), Backseat
Detection Purpose	Location of potholes, bumps on the roads

[a] 10 Hz actual sampling rate has been considered during analysis because the road anomaly was found to be accurately detected at the selected sampling rate. When sampled at higher rate the complexity of DTW ($O(n^2)$) increases. This is due to the fact that size of the window is directly proportional to the time taken for detection and comparison of road anomaly.



(a) Phone Axes. (b) Vehicle Axes.

Fig. 2. Smartphone and Vehicle Axes.

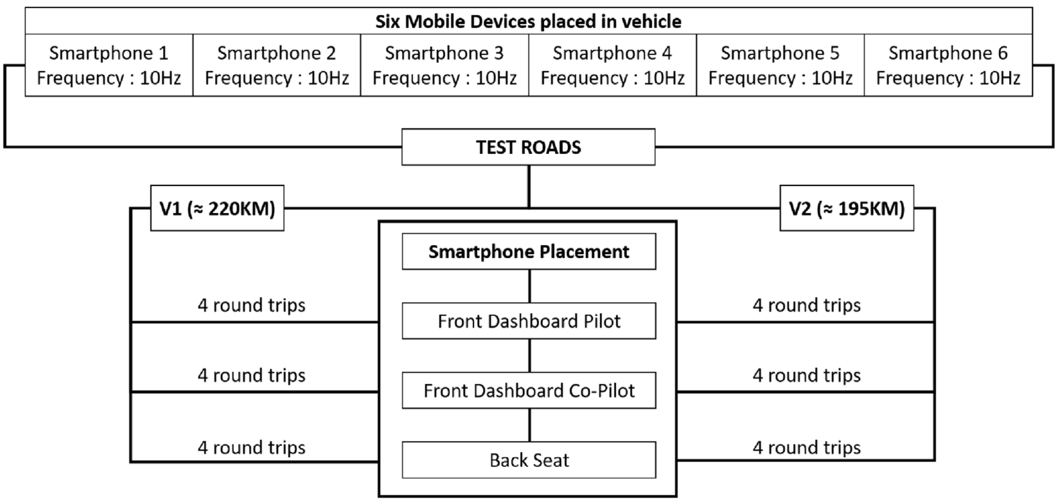


Fig. 3. Experimental Design for Data Collection.

The experimental setup for the data collection process has been shown in Fig. 3. Data from six smartphones was collected, the accelerometer was sampled at 10 Hz because during our analysis we found that the road anomalies could also be detected with reasonable accuracy even at low sampling rate thus saving the overall communication and processing cost. In our experiments for data collection the smartphones were placed inside the vehicle at different positions (front dashboard pilot,

(a) V1 Roads. (b) V2 Roads.

Fig. 4. Representation of V1 and V2 Roads of Chandigarh city.

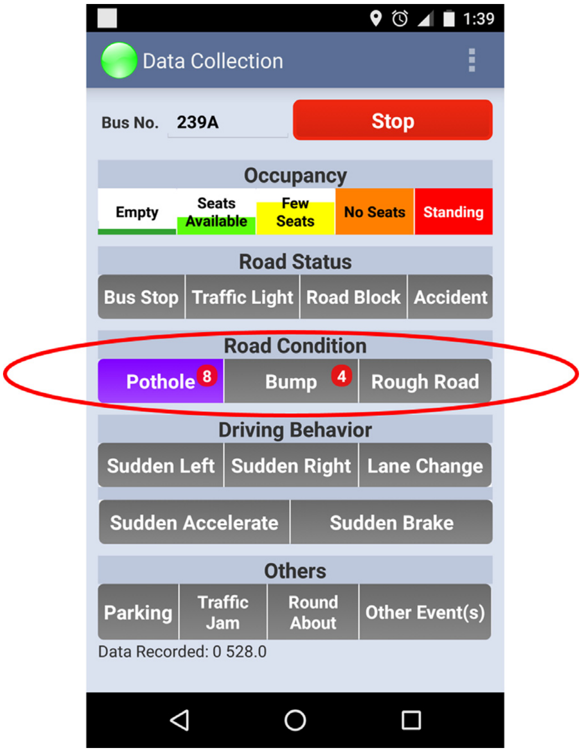


Fig. 5. An android application designed for data collection.

co-pilot, backseat and so on)[7] and the trips were made to cover V1 and V2 roads[8] to collect the road surface health data. On the application a user has to mark the anomalies like potholes & bumps and location was determined using corresponding GPS traces.

The layout of Chandigarh city is divided into V1 and V2 roads, which are shown in following Fig. 4.

5. Data acquisition and pre-processing

The user interface of android application that was designed and installed on the smartphone is shown in Fig. 5.

7 The data was collected using all smartphones simultaneously but the manual marking of the road anomaly was done only on one smartphone, that is, user taps the button only on one smartphone to collect ground truth data pertaining to location of potholes and bumps. Some of them were also verified by spot checking on the location of potholes and bumps to account for GPS errors.

8 The layout of Chandigarh city is rectangular in shape where the city is divided into sectors. The road which separates the two sectors are called V1-roads and the road which further divide the sector into blocks are called V2-roads.

The user collecting the data has to tap the button to collect ground truth data when the road anomalies like potholes and bumps are encountered. It may be noted that the manual marking done by tapping on the application is done only for collecting ground truth data.

5.1. Accelerometer orientation

The accelerometer sensor of the smartphone can detect the linear acceleration along 3-axes by measuring the inertial forces. The acceleration along x, y and z-axis of the accelerometer can be represented as a_x, a_y, a_z respectively. The smartphone must be placed in the direction of the vehicle as shown in Fig. 2, to determine the acceleration experienced by the vehicle when it is driven over a pothole or a bump. If the smartphone is not oriented in the direction of vehicle then it must be virtually re-oriented using Euler's Angle [19] . Euler angles are the means of representing the spatial orientation of any reference frame (coordinate system or basis) as a composition of three elemental rotations. The reference orientation can be taken as an initial orientation from which the frame virtually rotates to reach its actual orientation [19]. The rotation around the x-axis can be represented by an angle α (roll angle), one around the y-axis by β (pitch angle) and one around the z-axis by γ (yaw angle) [20]. Ideally the values of accelerometer while resting on the dashboard, are represented as:

$$a_x = 0\ \mathrm{m/s^2}, \quad a_y = 0\ \mathrm{m/s^2}, \quad a_z = 9.81\ \mathrm{m/s^2}.$$

Given this condition, we can find two of the three Euler angles as represented by equation below:

$$\alpha = \tan^{-1}\left(\frac{a_y}{a_z}\right) \tag{1}$$

$$\beta = \tan^{-1}\left(\frac{-a_x}{\sqrt{a_y^2 + a_z^2}}\right) \tag{2}$$

The reoriented accelerations along the three axes can be estimated as:

$$a'_x = \cos(\beta)a_x + \sin(\beta)\sin(\alpha)a_y + \cos(\alpha)\sin(\beta)a_z \tag{3}$$

$$a'_y = \cos(\alpha)a_y - \sin(\alpha)a_z \tag{4}$$

$$a'_z = -\sin(\beta)a_x + \cos(\beta)\sin(\alpha)a_y + \cos(\beta)\cos(\alpha)a_z. \tag{5}$$

The roll angle α, from Eq. (1) is defined in the range of $[-\pi; \pi]$, while the pitch angle β, from Eq. (2) is defined in the range of $[-\pi/2; \pi/2]$. The a'_x, a'_y, a'_z, from Eqs. (3)–(5) are the new re-oriented values[9] of the accelerometer which have been used for detecting road surface conditions.

6. System design

The objective of this work is to detect the road surface conditions like potholes and bumps using smartphones. When the vehicle runs over a pothole or a bump, significant changes in the readings of the accelerometer can be observed as compared to when it runs over a smooth road. The readings are observed by the smartphone and stored into a local file, which can either be sent to a central server in real time or be synced later with the server if it is off-line. The detection mechanism of the potholes and bumps using the smartphone is illustrated in Fig. 6.

As stated in earlier sections, the raw values from the accelerometer are fed to the filters, where the data is smoothened/normalized. The process of deriving "Template References"[10] for potholes and bumps which serve as signatures in the form of accelerometer patterns is explained in Section 6.3. These patterns in the Template References are then fed to DTW algorithm, which detects similar patterns from the data collected in real-time to detect potholes and bumps. The working and explanation of each filter is explained below:

6.1. Filters

The raw values from the accelerometer also comprises of a gravity component and vibrations from the vehicle which gets added to the accelerometer data. These components need to be removed from the accelerometer data so as to correctly deduce the affect of other external forces. In Fig. 6, each filter tries to smoothen / normalize the raw values of the accelerometer in a different manner. Filters like Speed, Virtual Re-Orientation, Filtering Z-axis, SMA and Band-Pass filter have been used and are described as follows:

9 The re-orientation of the accelerometer as done in case of Nericell is performed using two accelerometers. One is well-oriented and the other is not. Nericell re-orients the non-oriented accelerometer by taking the readings of well-oriented accelerometer using it as reference. In our proposed method there is no need of reference well-oriented accelerometer, instead we use Euler's angle to compute an angle w.r.t. the vehicle's direction and re-orient the smartphone's accelerometer to its original axes.

10 In DTW there is no need for training, it needs only the patterns in its database which are used to find similar patterns in the data under consideration.

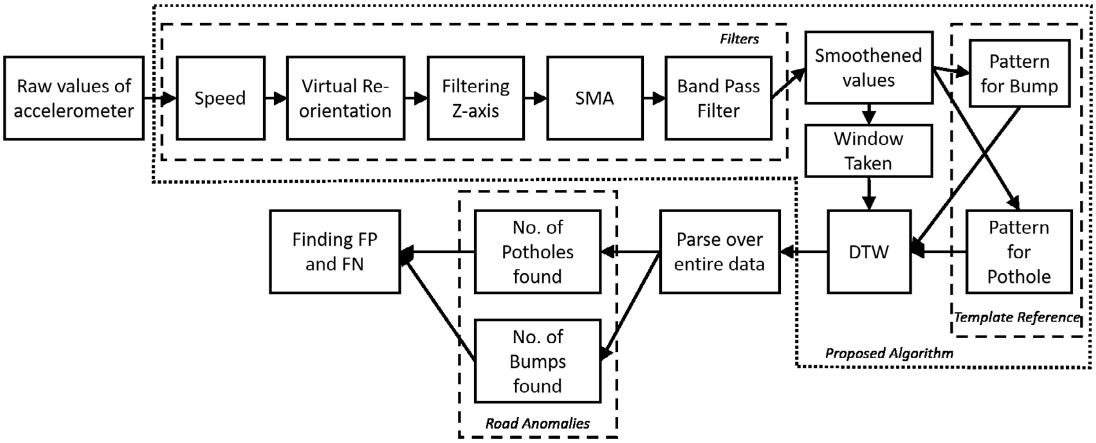


Fig. 6. Working model of Smart Patrolling.

6.1.1. Speed

In case, the vehicle is stationary, the accelerometer does not produce significant change in readings. These values need to be removed from the overall data before processing. If they are not removed, the overall execution time and storage will be more. Speed of the vehicle is calculated using GPS sensor of the smartphone. The points where the GPS speed is found to be less than 5 kmph (in stationary vehicular speed, GPS shows the speed values below 5kmph (as per our experimentation)) are discarded.

6.1.2. Virtual orientation

As discussed in Section 5.1, virtual reorientation has to be done to re-orient the accelerometer axes to its original axes using Euler's Angle.

6.1.3. Filtering Z-axis

After virtual re-orientation of the accelerometer sensor values along the Z-axis (re-oriented) are taken into consideration because the potholes and bumps influence only on Z-axis. Thus values along X and Y-axis are discarded using this filter.

6.1.4. SMA (Simple Moving Average) [21]

SMA has been used to smoothen the values of accelerometer and also to remove the noise which gets added into accelerometer data due to vibrations of the vehicle. SMA is an arithmetic moving average which is calculated by taking the average of some data series.

6.1.5. Band pass filter

Sometimes it has been observed that the accelerometer sensor carries noise due to its hardware sensitivity. These values have to be normalized or eliminated, to find an event. The smoothening of data is done using low and high pass filters also known as BPF.[11] It is well known that low pass filters are used for passing low-frequency signals and reduce the amplitude of signals with frequencies higher than the threshold frequency whereas high pass filters are used to pass high-frequency signals and reduce the amplitude of signals with frequencies lower than the threshold frequency (detail of BPF is explained in Section 7.1). After filtering the Z-axis (oriented) of the accelerometer, Band-Pass filter is applied, whose mathematical equations are shown below:
Using `Low pass filter`: [22]

$$g_{xn} = \delta * g_{xn-1} + (1 - \delta) * a_x \tag{6}$$
$$g_{yn} = \delta * g_{yn-1} + (1 - \delta) * a_y \tag{7}$$
$$g_{zn} = \delta * g_{zn-1} + (1 - \delta) * a_z \tag{8}$$

where a_x, a_y, a_z are the original values of accelerometer and g_{xn} is the computed gravity component, which got added during the data collection in the accelerometer readings.

[11] Band Pass Filter.

Table 4
Parameters considered for experimentation.

Parameters	Values taken into consideration
Speed Filter	5 kmph
Delta (δ)	0.2
SMA (window size)	10 values
Mu (μ)	1.1
Pattern & Window size	5 values
Sliding/Shifting Window	Sliding Window

Using `High pass filter`: [22]

$$a'_x = a_x - g_{xn} \tag{9}$$

$$a'_y = a_y - g_{yn} \tag{10}$$

$$a'_z = a_z - g_{zn} \tag{11}$$

where a'_x, a'_y, a'_z are the new accelerometer values, where the gravity component gets eliminated.

6.2. Use of DTW (Dynamic Time Warping) for detecting road anomalies

DTW is a dynamic pattern matching technique which measures the similarity between any two patterns, that may differ in time and space. This technique is different from the traditional techniques in a way that in DTW each point of one pattern is matched with each and every point of the other pattern, and has an overall complexity of O(n^2). Historically the technique has been applied to temporal sequences of video, audio, graphics data and in-fact any such data which can be turned into linear sequence [23]. DTW computes similarities between two sequences of time series and returns a distance value. The lower this value better is the match and a distance is zero implies that the sequences are identical. The above two steps are compared for all of the sample/template data pairs. The pair that has the smallest "similarity measure" indicates a detected event (for readers not familiar with DTW, details of the technique is explained in Appendix for reference).

The output of DTW algorithm was parsed over entire data collected as illustrated in Fig. 6, to find the similarity patterns of potholes and bumps by comparing against the stored Template References. The location corresponding to the patterns matching with template references are then compared with manual marked GPS points of actual potholes and bumps and false positive and false negative rates are calculated.

6.3. Template reference

After applying various filters, the values from accelerometer were smoothened/normalized and saved into a file. It may be noted here that specific experiments were conducted where vehicle mounted with smartphones was driven over potholes and bumps. The accelerometer readings corresponding to these potholes and bumps were carefully extracted and saved into a database of patterns called Template References. The selection of Template Reference is one of the most important step in DTW based time series recognition applications. In this paper we have been used a simple technique for preparing reliable template to improve the event detection rate. The accuracy of implementation of DTW based event detection system greatly relies on the quality of prepared reference template [24]. The procedure follow in selecting reference template is to select one sample and then test its recognition rate against another sample test data. The pair that has smallest "similarity measure" close to zero indicates the detected event, if the recognition rate for many different samples is high then this reference is kept, otherwise it is discarded and another template has to be selected.

7. Evaluation

In this section, the evaluation of "Smart-Patrolling" is presented while traveling over V1 and V2 roads of Chandigarh city and also compared with other existing techniques.

7.1. Results and discussions

"Smart-Patrolling" technique has been developed to detect the road conditions like potholes and bumps, which is based on the analysis of accelerometer readings. In "Smart-Patrolling", DTW technique is used which is simple to implement and does not require intensive training as in the case of machine learning based techniques. The two streams of data points fed into the DTW were broken into same sized window i.e. five data points per window.

We have implemented five filters namely Speed, Virtual Re-orientation, Filtering Z-axis, SMA and Band-Pass filter, where some static values were used whose values are given in the following Table 4.

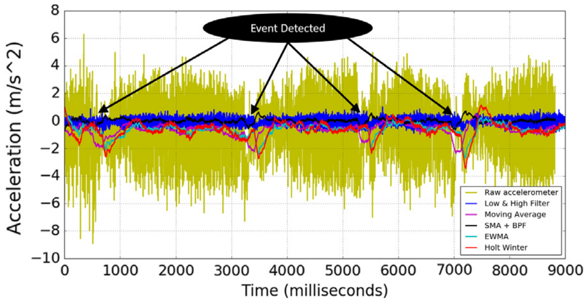
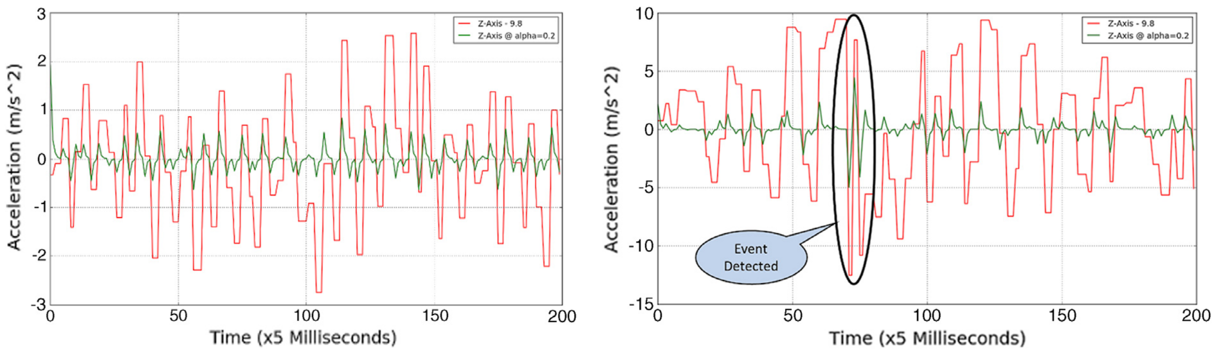


Fig. 7. Comparison of various existing filtering techniques.



(a) Non event window. (b) Event window.

Fig. 8. Comparison of raw vs reoriented values in case of non-event and event.

'δ' in the virtual reorientation process, called the smoothing factor, (constant value) was considered to be 0.2 (explained further in this section). SMA[12] of window size of 10 values is considered because during experimentation it was observed that when the window size is large, the signal looses its information. The size of reference template pattern and window size of the data collected, was considered to be same, that is window size of 5 values (smaller the window size, lower is the overall computation of the algorithm). These patterns are then fed to DTW technique for pattern matching whose upper limit is bound by the Eq. (12) where μ is constant, with the value as 1.1.

In the proposed model, low and high pass filters (often called BPF) were used to allow the low and high frequencies to pass through so that the noise and gravity component is eliminated from the actual values. Although there is a signal loss using this filter but it does not affect detection of an event from the collected data, it rather removes noise from the data. Various filters which were considered and applied on the accelerometer readings to compare the smoothness/normalized values are: Low and High Pass, Moving Average, SMA and BPF, EWMA and Holt Winter . The experimental result of selection of BPF over other existing filtering techniques is shown in Fig. 7.

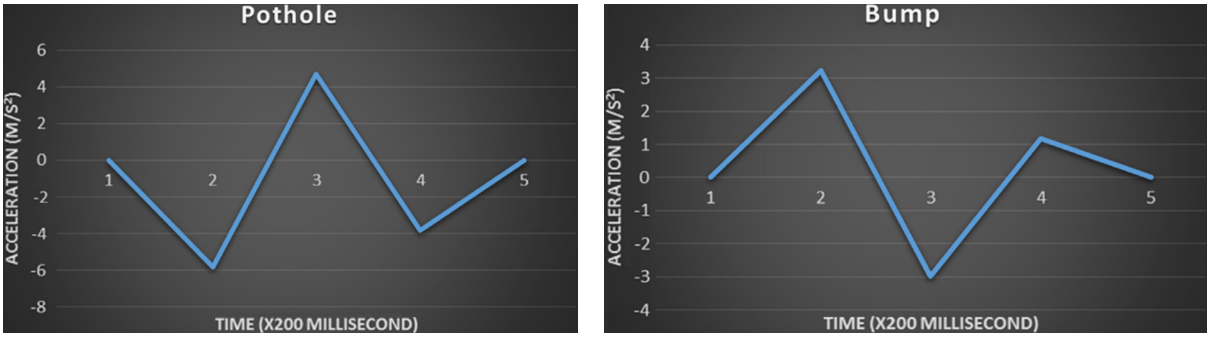
From the above Fig. 7, the comparison of different smoothing filters has been compared. Since, the outputs of EWMA and Holt Winter's are approximately same, but the output is not smooth enough to derive a pattern of potholes and bumps, so we used the combination of SMA & BPF and applied the filter on the raw values of the accelerometer. The output is shown in Fig. 7 as a black line. From the figure, it is evident that the black line (our proposed filtering technique), whose output is smoother than other filtering techniques, can be used further to derive the patterns of potholes and bumps.

The proposed filtering technique are further used and applied on data collected from the roads of Chandigarh city. The Fig. 8 shows the comparison of road anomaly and non-anomaly, when our proposed filtering technique is applied.

The comparisons of road anomaly and non-road anomaly after reorientation of the accelerometer is shown in Fig. 8. The Fig. 8(a) shows the output of non-event along Z-axis and Fig. 8(b) shows the output of an event after passing through all filters, with red and green lines respectively. The variation of the red line in the graph is because the original accelerometer values consist of gravity component as well as vibrations of the vehicle. When it is passed through the filters the values are smoothened as shown by green line. The green line clearly represents some event detected by the accelerometer.

Templates of the patterns of potholes and bumps have been derived from accelerometer data when marked manually using the data collection application and shown in Fig. 8(b). These templates had been stored into the database known as template reference (Section 6.3). Manually marked patterns of potholes and bumps are shown in Fig. 9.

12 Simple Moving Average.



(a) Template reference of pothole.

(b) Template reference of bump.

Fig. 9. Template references for pothole and bump.

Table 5
FNR Comparison of Pothole and Bumps of V1 & V2 - Roads.

Algo	Event	Actual	Found	FN	Detection Rate
DTW	Pothole	150	133	11.33%	88.66%
	Bump	90	80	11.11%	88.89%
Wolverine	Bump	90	42	53.33%	46.67%
Nericell	Bump	90	27	70.00%	30.00% [b]
Z-Thresh	Pothole	150	106	29.33%	70.67%
Z-Diff	Pothole	150	116	22.67%	77.33%
Z-Stdev	Pothole	150	0	100% [a]	0%

[a] The detection is 0% because the threshold value considered in *Z*-Stdev (proposed by Mednis et al.) is not able to detect pothole when applied on our dataset.
[b] The Nericell is also using threshold based technique to detect bumps on the roads. Since we have used the same threshold value (computed by author) and applied on our data set, we got 30% detection rate.

These patterns (template references) can be used to find the similar patterns from the data collected and the two accelerometer based data streams are compared using DTW technique. DTW takes two time varying data streams as inputs and computes the similarity. The output of DTW is the distance, which shows the similarity value. Lower the value, higher is the probability of the matching or vice-versa. In "Smart-Patrolling", we have proposed an upper bound for the distance as per equation below:

$$UB = MEAN(k) - \mu * STDEV(k) \tag{12}$$

where (k) is the number of windows selected for experimentation, μ is a constant whose value is set to 1.1 (calculated experimentally). If the output of DTW as distance, is lower than UB, the GPS value corresponding to window was noted. Those GPS values were then compared with ground truth values of GPS that were collected during experimentation to find the closeness and also to find the false positive and false negative rates.

7.2. Experimental results

The output of DTW was then compared with the manually marked GPS points of potholes and bumps to find the false positive and false negative rates.

Table 5 shows the comparison of our proposed technique with existing techniques. The data was crowd-sourced from different smartphones and collectively used to find the existence of potholes and bumps on the road. During experimentation it was found that there were 150 potholes and 90 bumps on the road. All the techniques were applied on the data which was collected on the roads of Chandigarh (described in Section 4). It is evident from Table 5 that the detection rate of our proposed model is higher than the existing techniques.

Further experiments were performed to find the detection rate of various smartphones individually. The detection rate corresponding to their false negative has been shown in Tables 6, 7 and 8:

It was observed that the sensitivity level of the sensors varies in different smartphones. Tables 6, 7 and 8, shows the detection rate of each smartphone. These smartphones were placed inside the vehicle at different positions (Front Dashboard (Pilot Seat/Co-Pilot Seat), Back Seat). When the vehicle experiences a pothole or bump the accelerometer sensor of smartphones records these variations. It is evident that the detection rate of Moto E smartphone is lower as compared to other smartphones because the smartphone was placed at the backseat of the vehicle which does not produce significant values to be considered as potholes or bumps.

Table 6
FPR & FNR Comparison of Pothole and Bumps of different smartphones (V1 - Roads).

Smartphone	Event	FN	Detection Rate
Moto E	Pothole	69.00%[a]	31.00%
	Bump	81.00% [a]	19.00%
Nexus 5	Pothole	10.11%	89.89%
	Bump	22.81%	77.19%
Nexus 5 (2)	Pothole	4.49%	95.51%
	Bump	3.51%	96.49%
Samsung Note 3	Pothole	1.12%	98.88%
	Bump	5.26%	94.74%
Samsung S4 Mini	Pothole	8.99%	91.01%
	Bump	17.54%	82.46%
Samsung S5	Pothole	5.62%	94.38%
	Bump	7.02%	92.98%

[a] The detection of Moto-E smartphone is lower because it was placed at the backseat of vehicle which absorbed some of the shocks. Thus, sharp signals could not be detected which could have been labeled as bumps or potholes.

Table 7
FPR & FNR Comparison of Pothole and Bumps of different smartphones (V2 - Roads).

Smartphone	Event	FN	Detection Rate
Moto E	Pothole	25.00%[a]	75.00%
	Bump	53.00% [a]	47.00%
Nexus 5	Pothole	11.94%	88.06%
	Bump	39.47%	60.53%
Nexus 5 (2)	Pothole	8.96%	91.04%
	Bump	21.05%	78.95%
Samsung Note 3	Pothole	1.49%	98.51%
	Bump	7.89%	92.11%
Samsung S4 Mini	Pothole	14.93%	85.07%
	Bump	36.84%	63.16%
Samsung S5	Pothole	0.00%	100.0%
	Bump	21.05%	78.95%

[a] The detection of Moto-E smartphone is lower because it was placed at the backseat of vehicle which absorbed some of the shocks. Thus, sharp signals could not be detected which could have been labeled as bumps or potholes.

DTW vs other techniques

DTW technique has an advantage over Machine Learning and Threshold based techniques. In machine learning [25] the dataset is divided into two categories, in ratio of 70% and 30% for training and testing respectively. In training, the values with their labels are fed, where the machine learns itself, and predicts the output based on testing values. Rigorous and continuous learning is needed for the machine learning technique to predict the output accurately. On the contrary, the threshold techniques are obsolete and cannot be used in real scenarios because the threshold value varies with different types of smartphones, roads, vehicles, condition of vehicles etc. DTW technique, can be an alternate to the existing techniques where it uses the pattern matching technique independent of time and speed. Additionally , the training procedure in DTW is very simple & fast as compared with SVM, HMM and ANN. The ability to DTW to cope with time deformations with different speeds associated with time dependent makes it quite suitable to be applied on our chosen application. Thus, we do not need to feed different template references for different road conditions or type of vehicles. Patterns of the events are stored in the database called template reference. These template references along with given pattern are fed to DTW, to find the closeness or similarity match. Another difference between DTW and Machine Learning is that the complexity of Machine Learning is O($n^2 * m$) where n is the number of samples and m is the number of features whereas the complexity of DTW is O(n^2) where n is the number of samples. The advantage of using DTW is that when the input of accelerometer signal has low or high amplitude but the signal pattern is same and is compared with an event pattern, it can still be detected/recognized it as an event.

Table 8
FPR & FNR Comparison of Pothole and Bumps of different smartphones (V1 & V2- Roads).

Smartphone	Event	FN	Detection Rate
Moto E	Pothole	47.00%	53.00%
	Bump	64.00%	36.00%
Nexus 5	Pothole	9.33%	90.67%
	Bump	26.14%	73.86%
Nexus 5 (2)	Pothole	6.00%	94.00%
	Bump	5.68%	94.32%
Samsung Note 3	Pothole	0.00%	100.0%
	Bump	3.41%	96.59%
Samsung S4 Mini	Pothole	7.33%	92.67%
	Bump	19.32%	80.68%
Samsung S5	Pothole	0.68%	99.33%
	Bump	9.09%	90.91%

Fig. 10. Visualization of Potholes of four consecutive weeks.

Comparisons on multiple smartphones

As shown in Tables 6, 7 and 8 above, the false negative rate of DTW technique is lower as compared to existing techniques. The main focus of this paper has been to detect the existence of a road anomaly by using smartphones and crowd-sourcing. Since the approach is participatory, majority of the times user did not mark the road anomalies properly or sometimes they missed to mark them, so to overcome this problem, crowd-sourcing technique was used where the data was collected from multiple smartphones such that when one user misses to mark the road anomaly at some location, the algorithm should be able to detect the same anomaly from another smartphone at the same location so as to keep a record of the existing road anomalies.

Road surface conditions like potholes and bumps are visualized on Google Maps where they are notified by a marker. The outputs of all smartphones are drawn on Google Map to find the concentration of points at a particular region. The concentration of points increases the probability of the existence of pothole or bump. The GPS points can be efficiently visualized by using Google Heatmaps [26]. For greater confidence we compare the results with the results of other days. If the results are similar for a long duration then it can be derived that the potholes or bumps have not been repaired immediately. Google heatmaps corresponding to the results are shown in Figs. 10 & 11 where each result is an output of V1 and V2 roads capturing potholes and bumps respectively.

Fig. 11. Visualization of Bumps of four consecutive weeks.

During the 4 weeks of experimentation, potholes were detected which are shown in Fig. 10, it can be observed that some of the road patches are seen to be highly dense. Over the weeks it has been observed that certain areas like Areas 1, 2 & 3 need maintenance but by week 4, all such potholes have been repaired[13] over the time during weeks under observation.

Crowd-sourced data of all smartphones during the 4 week of experimentation to find the existence of bumps is shown in Fig. 11. By visualization of the results, it was observed that there are some road patches where the heatmap is dense. These have been detected as bumps. Over the weeks it has been observed that certain areas like Areas 1, 2 & 3 need maintenance but by week 4, all such bumps have been repaired.[14] After analysis of the road surface over several weeks it was concluded that if heatmap shows regular concentration of bumps and potholes in a certain area, it can be declared that the road is patchy and needs maintenance. This information can be disseminated to civic authorities so that they can take necessary remedial actions.

7.3. *Impact of different smartphones*

In this paper the detection of the road surface had been done by taking the readings of in-built sensors of the smartphone. The sensitivity of the accelerometer sensor varies from phone to phone. High end smartphones have higher sensor sensitivity than the lower end models of phones. The detection rate of different smartphone on the roads is shown in Tables 6 and 7. It was observed that detection accuracy of potholes and bumps in Samsung Note 3 and Nexus 5 is higher as compared to other smartphones. This is because the accelerometer sensor of Samsung Note 3 and Nexus 5 has a higher sensitivity. As a result the detection rate of Samsung Note 3 and Nexus 5 has a higher accuracy of detecting the road conditions than other phones.

7.4. *Impact of orientation of smartphones*

Smartphones can also be placed arbitrarily inside the vehicle. During our experiments, smartphones were placed on different locations such as mounted on driver seat, passenger front seat and middle of the dashboard and on left rear passenger seat. The smartphones were aligned with the moving direction of the vehicle. Ideally the placement of smartphone should be plain that is the Y-axis of the accelerometer should be exactly aligned with the moving direction of the vehicle but in reality this does not happen. The dashboard may appear to be flat while placing the smartphone but in reality Y-axis does makes some angle with the direction of vehicle. To overcome this problem, virtual orientation technique has been used where the axes of accelerometer is virtually re-oriented to its original axes. Thus using this technique the original values of accelerometer can be drawn out. "Smart-Patrolling" prototype uses this virtual re-orientation technique independent of the placement of smartphone inside the vehicle.

[13] The areas that we highlighted on the maps were under our observation. We went for spot checking and verified that those roads have been repaired by fourth week.

[14] The areas that we highlighted on the maps were under our observation. We went for spot checking and verified that those roads have been repaired by fourth week.

7.5. Impact of road type

The road anomalies like potholes and bumps have been found on the roads of Chandigarh city. This research further investigates the impact of two different roads types of Chandigarh that is V1 and V2 when "Smart-Patrolling" prototype was implemented. The detection rate of potholes and bumps on V1 and V2 roads is shown in Tables 6 and 7. It was observed that the "Smart-Patrolling" achieves good accuracy both on V1 and V2 roads, but the accuracy of detecting potholes and bumps on V1 is slightly higher than the V2 roads. This is because road conditions on V1 roads were found to be in better condition than V2 roads. Thus V1 roads have patches at distinct places while V2 roads have continuous patches of varying intensities thereby reducing the overall detection rate. As a result, "Smart-Patrolling" achieved higher detection rate on V1 roads that on V2 roads.

8. Conclusion

In this research, a prototype of "Smart-Patrolling" has been proposed and validated on the roads of the city Chandigarh. The results from the proposed prototype have been compared with the existing techniques used for pothole and bump detection.

1. We also highlighted the difficulty in classifying different road anomaly events because of high variability in different road and vehicle conditions and use of heterogeneity of smartphones.
2. This research work demonstrates that combining multiple streams of accelerometer data of smartphones using crowdsourcing and analyzed using DTW technique, increased the accuracy of road surface anomaly detection. In our present application, when benchmarked against similar tests in our data, the accuracy of DTW is higher compared to all other existing techniques. Based on the literature, it is clear that task of detecting pattern from motion sensors of mobile devices is a challenging one. In this research, we found that DTW exhibits high accuracy and efficiency due to its ability to be able to compare two time dependent data series which may vary in speed. DTW can also automatically cope with time deformation and different speeds associated with time dependent data. We found that DTW engine is simple in its implementation and training procedure is also very simple and fast when compared with SVM, HMM and ANN.

The average detection rate of our proposed technique in case of potholes and bumps was found to be 88.66% and 88.89% respectively which is higher in comparison to all other existing techniques. Thus, our proposed prototype enhances accuracy of detection of potholes & bumps and is based on crowd-sourcing and is more efficient in comparison to the existing techniques and hence quite apt for resource constraint devices such as smartphones.

Future work

We plan to conduct further research into the use of enhanced versions of DTW to make it work even faster. We also propose to evaluate DTW on datasets collected from roads of different cities with variable road conditions.

Acknowledgments

The authors would like to thank ITRA, Media Lab Asia, Ministry of Electronics and Information Technology, Govt. of India (ITRA/15(61)/Mobile/CARTS/01) for financial support.

Appendix A

DTW (Dynamic Time Warping)

DTW measures the similarity between two sequences that may differ in time or space. It can be applied for all types of data that are represented linearly according to time such as audio, video and graphics. It is a well-known technique which can be used in various applications such as speech recognition applications, e.g. [27] and gesture recognition [28]. The working of DTW is explained in Fig. 12:

Suppose we have two time series, a sequence A of length n and a sequence of length b, where

$$A = a_1, a_2, a_3, \ldots, a_i, \ldots, a_n$$
$$B = b_1, b_2, b_3, \ldots, b_j, \ldots, b_n.$$

To align these two sequences using DTW, we first construct an n-by-n matrix where the (ith, jth) element of the matrix corresponds to the squared distance, $d(a_i , b_j) = (a_i - b_j)^2$, which is the alignment between points a_i and b_j. To find the best

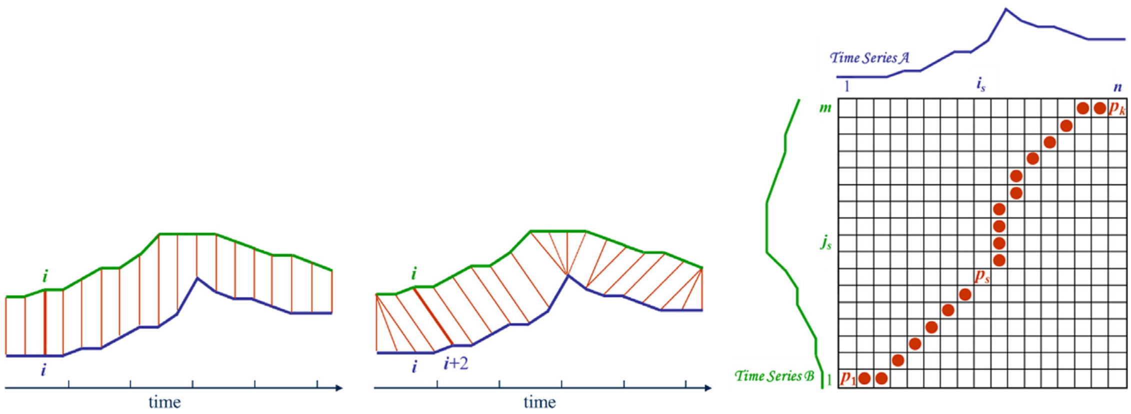


Fig. 12. Working Model of DTW.

match between these two sequences, we retrieve a path through the matrix that minimizes the total cumulative distance between them as illustrated in Fig. 1. In particular, the optimal path is the path that minimizes the warping cost

$$DTW(A, B) = \min\left\{\sqrt{\sum_{k=1}^{K} w_k}\right\}$$

where w_k is the matrix element $(i, j)_k$ that also belongs to kth element of a warping path W, a contiguous set of matrix elements that represent a mapping between A and B. This warping path can be found using dynamic programming to evaluate the following recurrence.

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

where $d(i, j)$ is the distance found in the current cell, and $\gamma(i, j)$ is the cumulative distance of $d(i, j)$ and the minimum cumulative distances from the three adjacent cells. According to the [29], there are some myths associated with it which severely affect the use of technique.

Myth 1: The ability of DTW to handle sequences of different lengths is a great advantage, and therefore the simple lower bound that requires different-length sequences to be re-interpolated to equal length is of limited utility.
Myth 2: Constraining the warping paths is a necessary evil that we inherited from the speech processing community to make DTW tractable, and that we should find ways to speed up DTW with no (or larger) constraints.
Myth 3: There is a need (and room) for improvements in the speed of DTW for data mining applications.

Many researchers use the DTW for pattern recognition with variable length and time and also tries to speed up the algorithm. Since these has been proven by the [30], that the inputs to DTW the patterns should be of equal length and defining the bounds to DTW will speed up the algorithm.

References

[1] S. Bump, Street Bump, 2016. URL http://www.streetbump.org/.
[2] S. Burgart, Gap Trap: A pothole detection and reporting system utilizing mobile devices, 2014.
[3] Pothole claims life of software engineer - The Hindu, 2016. URL http://www.thehindu.com/news/cities/bangalore/pothole-claims-life-of-software-engineer/article7666580.ece.
[4] Bangalore pothole kills 7-year-old riding with mother : Karnataka, News - India Today, 2016. URL http://indiatoday.intoday.in/story/bangalore-pothole-kills-7-year-old-riding-with-mother/1/460691.html.
[5] F.H. Administration, 2010 Conditions and Performance - Policy — Federal Highway Administration, 2016. URL https://www.fhwa.dot.gov/policy/2010cpr/.
[6] H.M. Jol, Ground penetrating radar theory and applications, 2008.
[7] R. Scanner, Roadscanners — Beyond The Surface, 2016. URL http://roadscanners.com/.
[8] T.D. Tracking, Teen Driver Safety System — Teen Driver Tracking Lytx, 2016. URL http://www.drivecam.com/our-markets/family/overview.
[9] W.M. Learning, Machine Learning, 2016. URL https://en.wikipedia.org/wiki/Machine_learning.
[10] Progressive, Snapshot—Progressive, 2016. URL https://www.progressive.com/auto/snapshot/.
[11] Waze, Free Community-based Mapping, Traffic & Navigation App, 2016. URL https://www.waze.com/.
[12] Google, Google Maps, 2016. URL https://www.google.co.in/maps/.
[13] J. Eriksson, L. Girod, B. Hull, R. Newton, S. Madden, 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, 2008 pp. 29–39.
[14] P. Mohan, V.N. Padmanabhan, R. Ramjee, Nericell: rich monitoring of road and traffic conditions using mobile smartphones, in: Proceedings of the 6th ACM Conference on Embedded Network Sensor Systems, 2008, pp. 323–336.

[15] R. Bhoraskar, N. Vankadhara, B. Raman, P. Kulkarni, Wolverine: Traffic and road condition estimation using smartphone sensors, in: Communication Systems and Networks (COMSNETS), 2012 Fourth International Conference on, 2012, pp. 1–6.
[16] A. Mednis, G. Strazdins, R. Zviedris, G. Kanonirs, L. Selavo, Real time pothole detection using android smartphones with accelerometers, in: Distributed Computing in Sensor Systems and Workshops (DCOSS), 2011 International Conference on, 2011, pp. 1–6.
[17] RAC, RAC Mobile Traffic Apps - RAC, 2016. URL http://www.rac.co.uk/news-advice/car-knowledge/trafficapp.
[18] G. Transit, Transit - Google Maps, 2016. URL https://maps.google.com/landing/transit/index.html.
[19] E. Angle, Euler Angle, 2016. https://en.wikipedia.org/wiki/Euler_angles.
[20] V. Astarita, M.V. Caruso, G. Danieli, D.C. Festa, V.P. Giofrè'', T. Iuele, R. Vaiana, A mobile application for road surface quality control: Uniqualroad, Proc.-Soc. Behav. Sci. 54 (2012) 1135–1144.
[21] Wikipedia, Moving Averages, 2016. URL https://en.wikipedia.org/wiki/Moving_average.
[22] A. Developers, Motion Sensors — Android Developers, 2016. URL http://developer.android.com/guide/topics/sensors/sensors_motion.html.
[23] DTW, Dynamic Time Warping, 2016. URL https://en.wikipedia.org/wiki/Dynamic_time_warping.
[24] K.M. Hsiao, G. West, S. Venkatesh, M. Kumar, Temporal data fusion in multisensor systems using dynamic time warping, in: SENSORFUSION 2005: Workshop on Information Fusion and Dissemination in Wireless Sensor Networks, IEEE, 2005, pp. 1–9.
[25] S. Machines, Seeing Machines — Safety in Motion, 2016. URL https://www.seeingmachines.com/.
[26] G. Heatmaps, Heatmap Layer - Google Maps JavaScript API; Google Developers, 2016. URL https://developers.google.com/maps/documentation/javascript/heatmaplayer.
[27] G. Kang, S. Guo, Variable sliding window DTW Speech Identification Algorithm, in: Hybrid Intelligent Systems, 2009. HIS '09. Ninth International Conference on, vol. 1, 2009, pp. 304–307. http://dx.doi.org/10.1109/HIS.2009.66.
[28] J. Liu, L. Zhong, J. Wickramasuriya, V. Vasudevan, uwave: Accelerometer-based personalized gesture recognition and its applications, Pervasive Mob. Comput. 5 (6) (2009) 657–675.
[29] C.A. Ratanamahatana, E. Keogh, Everything you know about dynamic time warping is wrong, in: Third Workshop on Mining Temporal and Sequential Data, 2004.
[30] P. Senin, Dynamic Time Warping Algorithm Review, Information and Computer Science Department University of Hawaii At Manoa Honolulu, USA, 2008, pp. 1–23.