Approaching Rutted Road-Segment Alert Using Smartphone

Asmaa AbdulQawy
Computers and Control Dept.
Tanta University
Tanta, Egypt
Email: asmaa_68573_pg@f-eng.tanta.edu.eg

Reem Elkhouly
Computers and Control Dept.
Tanta University
Tanta, Egypt
Email: reem_elkhouly@f-eng.tanta.edu.eg

Elsayed Sallam
Computers and Control Dept.
Tanta University
Tanta, Egypt
Email: sallam@f-eng.tanta.edu.eg

***Abstract*—Driving on unfamiliar poorly paved roads is risky even if the vehicle speed is kept under limits. A driver may lose control if his vehicle suddenly comes into road anomalies, especially at night. In developing countries, road anomalies are not only common, but also new ones usually exist without precautions. We present an alerting system that detects and localizes road ruts in order to release a prior-rut notification to the driver using no additional devices but his smartphone. Our system uses crowd-sourcing techniques to collect labeled data from smartphones built-in sensors that describe road ruts. We use this data to feed a machine learning engine to build models that can detect new ruts. Our system localizes identified ruts on the map via GPS coordinates and alerts drivers when they approach a rutted road. Our experiments show that the accuracy of the system can be raised from 59% up to 99% if the learning technique is carefully selected and the sensors data set size is increased to 100000 samples.**

I. Introduction

Location-based services (LBS) have expanded in the past few years, opening up avenues to facilitate our daily life with applications including social networking, navigation and travel, context-aware prediction, healthcare, and mobile marketing and advertising on the move. These services may either use the triangulation of signals from cell phone towers in various locations, aggregating the position of WiFi internet access points, or Global Positioning System (GPS) by using satellite relays. Over the past years GPS has worked brilliantly to help in Location Based Services (LBS) that rely on modern mobile devices such as smartphones, especially in outdoor localization. An outstanding factor that enhances the usage of smartphones in LBS is the availability of numerous built-in sensors (e.g. Accelerometer, Magnetometer, and Compass). Inexpensive smartphones that are equipped with various sensors are opening new opportunities for LBS, especially those services which tackle the road surface condition. Road safety estimation implies a pleasant driving experience and reduces accident rates. Moreover, road conditions, identification including weather, surface changes, and anomalies (e.g. Bumps, Potholes, Ruts, Roughness), introduces a significant challenge. Recently, road surface condition detection became one of the most interesting fields in LBS [1], [2], [6], [8], [10]. Road surface quality characterization and anomaly detection do not only participate in accident avoidance, but they also ensure smooth traffic flows, and protect vehicles from possible damage due to rough roads. In developing countries, it is common to drive along under-repairing roads for several kilometers. One of the issues that face drivers are ruts which are caused by the incomplete road maintenance process. When engineers recycle a road surface by asphalt milling which removes just the surface of the pavement. This is done as a primary step for repairing damage causing ruts; such as the one shown in Figure 1. After the milling operation, the road will be rutted waiting for the next step of fixing. However, due to the lack of budget or proper planning, the next step may not come for several months up to few years. That causes a problem for drivers who do not know about roads under repair and it may lead to accidents or at least major damage to vehicles.

Fig. 1: Road Ruts

In this respect, we propose rutted road-segment alert system to aid in enhancing safe driving trips. At the core of our system, we use two main phases; detection and localization. On the first one, we based our system on crowd-sourcing, using a powerful sensing capability of various sensors equipped with smartphones, (i.e. the accelerometer, compass, and magnetometer) to collect sensory data while vehicles pass over the flat road and ruts. Consequently, our system analyzes these sensor readings to define rut-patterns by machine learning techniques (e.g. random forest, random tree, regression...). On the second one, we focus on localizing those ruts on the map to help in alarm the driver about ruts locations and this is achievable by GPS. We implemented our rutted road-segment alert system on a Sony Xperia C3 Android phone with 5.0.2 (Lollipop) operating system, which has 8GB internal storage, 1GB RAM, Accelerometer, proximity, compass and GPS with A-GPS and GLONASS sensors. Our experiments show that it can provide Ruts localization with a high accuracy up to 99% when using the Random Forest Classifier on a data set of size 100000 sample.

The rest of this paper is organized as follows. Section II

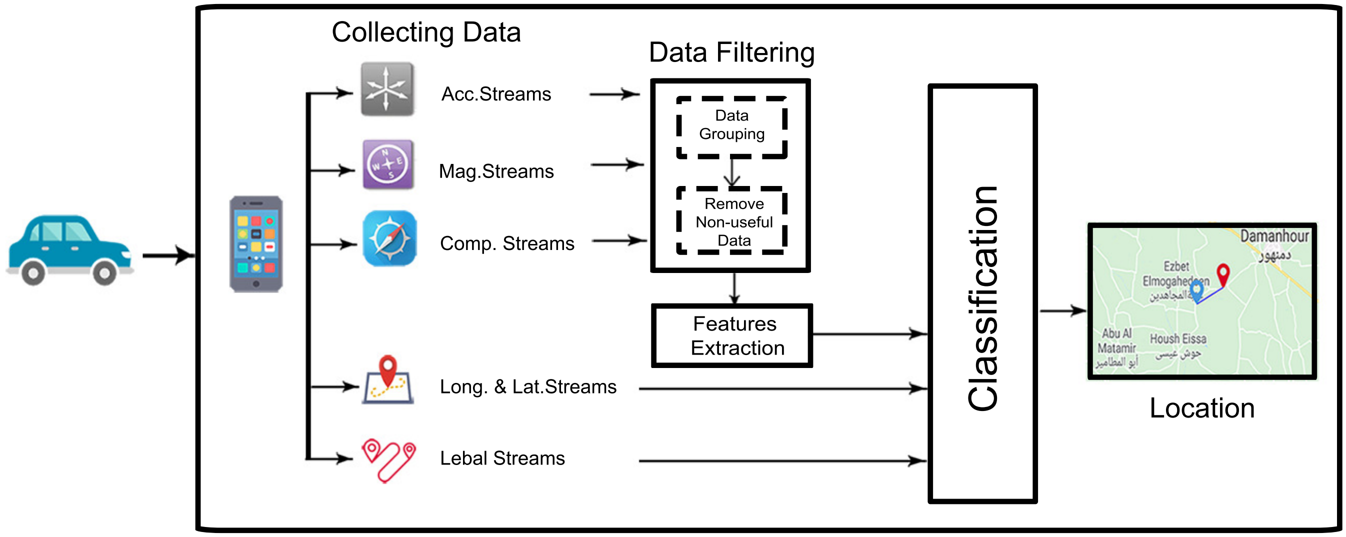


Fig. 2: The Architecture of Our Proposed Rutted Road-Segment Alert System.

introduces some recent research related to the road surface conditions localization using mobile phone sensors. SectionIII gives the details about the architecture of our proposed rutted road-segment alert system. We demonstrate the implementation and evaluation of our proposed rutted road-segment alert system in Section IV. Finally, Section V provides conclusions and future work.

II. Related Work

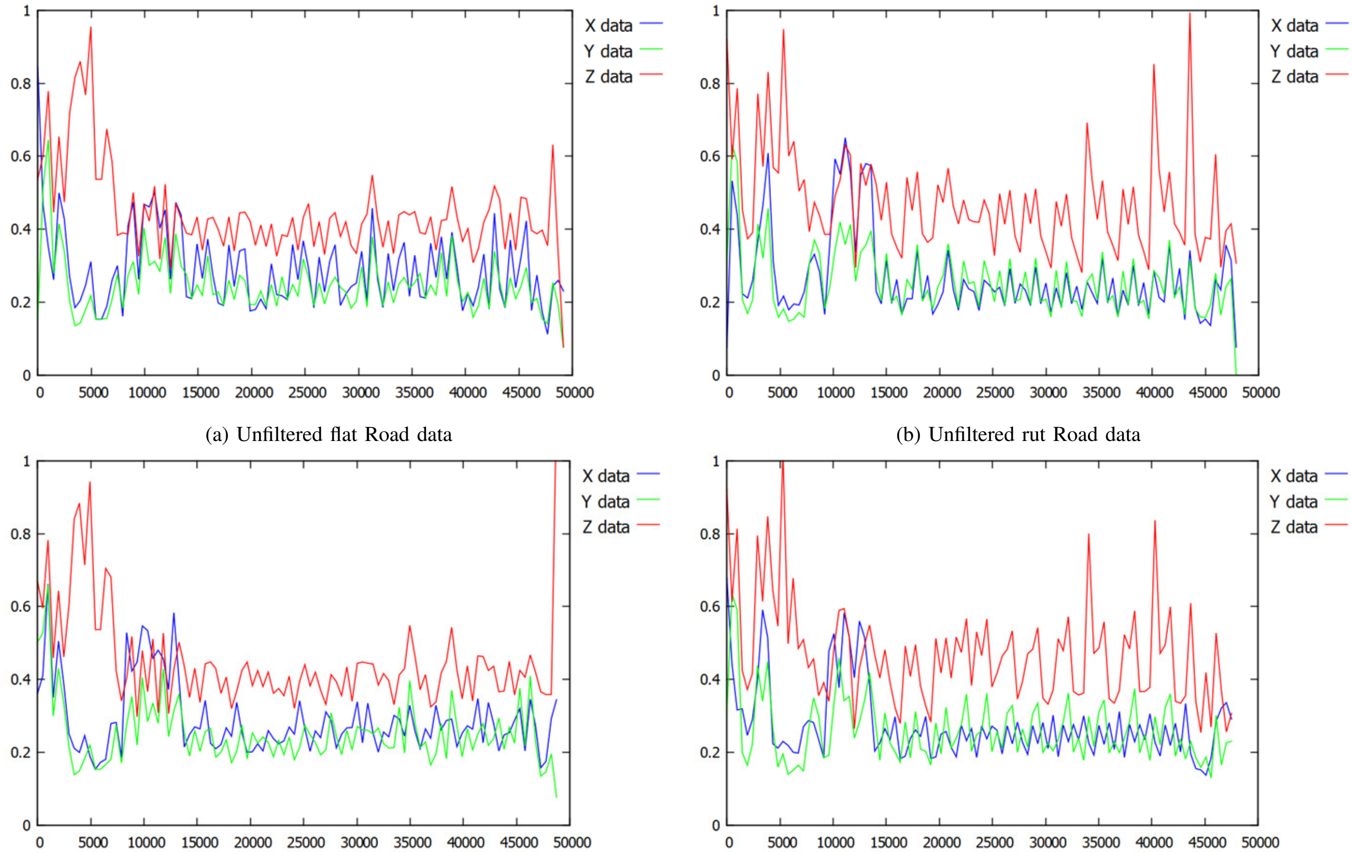
In literature, the spread of sensors-equipped smartphones provided large opportunities for researcher to tackle new as well as existing challenges. In this section, we discuss previous work in road surface conditions and outdoor localization that inspired our proposed system.

A. *Road Surface Conditions*

Recent research focused on the usage of smart phone sensors to detect and classify road surface conditions and anomalies. In [1], the authors proposed a system to detect the crack type and estimate the crack size with smartphones sensors e.g. accelerometer and magnetometer. The type of a crack is determined with a coordinate transmission method based on the direction of the crack, the rotation of the smartphone, and the direction of the road. The size of a crack is estimated by using the camera's convex lens imaging theory. In [2], the authors proposed a method for estimating road surface conditions in snowy areas of Japan by collecting sensors data from Accelerometer, gyro, compass, camera, and GPS. The method can estimate the substance that covers the road surface type, and the road surface shape. In [3], the authors proposed an early warning system detecting speed breakers and bad road conditions and providing the user with an alternative route. In [4], the authors proposed a statistical approach based on smartphone sensors like Accelerometer, Gyroscope and Magnetometer data and GPS information to monitor and detect road surface conditions and abnormalities. In [5], the authors proposed an early warning Crowd-sourcing system that detecting of potholes, road humps, and roads under repair. it transfers the information like type of obstacle, GPS location and the time of detection to the cloud that will process the data and uploaded the processed data to the end-user app. In [6], authors proposed a crowd-sourced system to detect and localize potholes in multi-lane environments. By aggregating accelerometer data from multiple embedded vehicles. In [7], the authors proposed a system uses speed humps, as an indicator of vehicle location and that done when the vehicle passes through the speed hump, it experiences significant fluctuations, which is transferred into a sequence of moving directions of the vehicle to derive real-time location. In [8], the authors proposed an approach to identify dangerous road zones by identifying sudden brakes using standard smartphone accelerometers. Simulator studies show that it affects driver behavior to slow down in dangerous road sections by using in-car feedback. In [9], the authors proposed an early alarm system detects anomalies which include potholes and bumps which are caused by the weather or stresses of traffic and safety-related anomalies which are speed bumps and rumble strips. In [10], the authors proposed a system for detecting bumps by using the accelerometer sensor for identifying the position and height of the road bumps. The system also contains a speed reduction unit to reduce car speed if there is a bump ahead and the driver does not reduce the speed. In [11], the authors proposed a method for detection and characterization of road bumps using the accelerations recorded by the smartphones of drivers of different vehicles. In [12], the authors proposed a smartphone based framework for monitoring speed bumps by using 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.

B. *Outdoor Localization*

Outdoor positioning system researches had mindful to use mobile phone sensors to aiding in promoting GPS readings and get more accurate locations. As in [13], the authors



(a) Unfiltered flat Road data

(b) Unfiltered rut Road data

(c) Filtered flat Road data

(d) Filtered rut Road data

Fig. 3: Effect of flat and rut road on the X, Y, and Z accelerometer data with and without filtering. Moving average with 400 filter window size is used.

present a system to estimate the location and the traveling distance of a vehicle by using the accelerometer, gyroscope, compass sensors. the system is used the intermittent strong GPS signals and data from sensors to build a prediction model and when the GPS signal is weak, the model automatically detected landmarks that detected from inertial sensors data to improve the localization accuracy. In [14], the authors presented a system that uses standard cell phone sensors to provide accurate and low energy outdoor localization suitable for car navigation depending on a dead reckoning localization approach that uses different road landmarks; Like, tunnels, bumps, bridges, and potholes to reset the accumulated error and achieve accurate localization compared with GPS.

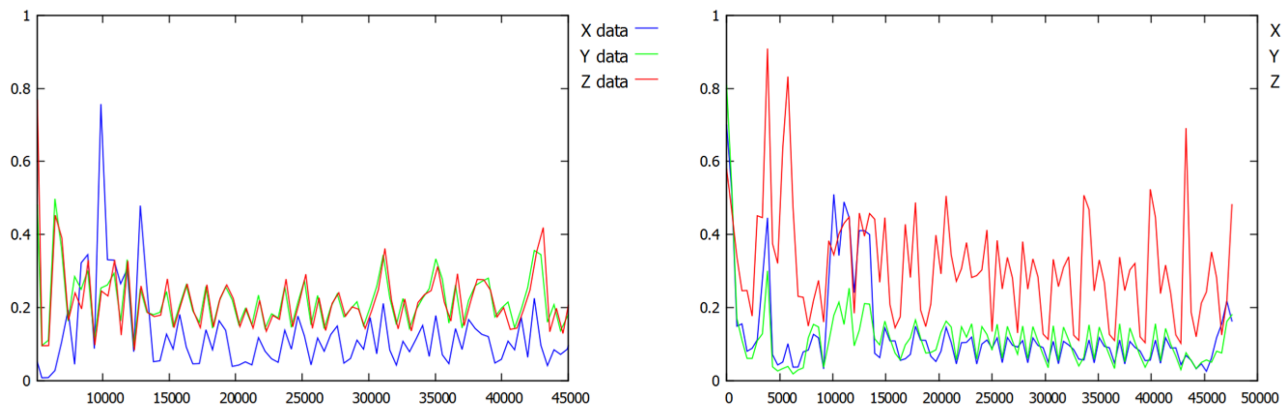
Although these approaches and systems accomplished an acceptable accuracy in previous fields, none of these approaches recognizes ruts from milling pavement operation on roads under construction, which will be the purpose of our proposed rutted road-segment alert system based on mobile phone sensors to detect and localize the ruts, thus drivers will be able to early observe while crossing them.

III.SYSTEM ARCHITECTURE

In this section, we shed the light on our rutted road-segment alert system architecture that notifies the drivers that they are approaching rutted part of the road. That will save them from the dangers that they may go through if the ruts suddenly appeared under their wheels. We use crowd-sourcing to detect the ruts first, then our system localizes them on the map. Therefore, when a driver is moving towards a rut, his smartphone will warn him. Our proposed rutted road-segment alert system architecture is illustrated in Figure 2. The system is made up of five main stages that are: Collection of raw sensory data, filtering of sensory data, features extraction, classification, and localization. The functionality of these stages are as follows; the first three stages specify the dataset construction step, the fourth specifies the detection of ruts, and the last one specifies the localization process. In this section, we describe each of these stages of our rutted road-segment alert system.

A. Selected Sensory Data

Our rutted road-segment alert system collects data from mobile phone built-in sensors, including the accelerometer, magnetometer, compass, and GPS sensors to provide early rut locations. To collect data for training and performance evaluation (testing), we designed and implemented an Android data collection application. This app was installed on a Sony Xperia C3 Android smartphone. When launched, the application records 10 readings per second of all sensors related data each automatically. The application allows human interaction at the data collection phase. Thus, labels indicating flat roads, under construction roads and ground truth can be defined. These labels are used for training in the learning phase. The raw sensory data is stored as a 10-tuple denoted by (A_x, A_y, A_z, M_x, M_y, M_z, Comp, long, lat, label); where, (A_x, A_y,



(a) Flat variance

(b) Rut variance

Fig. 4: Comparing flat and rut variance in the x-axis, y-axis, and z-axis gravity acceleration.

A_z) and (M_x, M_y, M_z) symbolize the 3D accelerometer and magnetometer readings respectively, comp stands for compass reading, (long, lat) stand for the longitude and the latitude readings obtained by the GPS and "label" stands for the ground truth (i.e. flat and rutted). Among these features, accelerometer readings are considered the main indicator of road anomalies as discussed in previous approaches e.g. [1], [6], [11] because the accelerometer provides detailed information about phone movement without depending on any external signal sources. To further illustrate the disturbance due to ruts than flat, we get the variance in the x-axis, y-axis, and z-axis gravity acceleration. The highest variance is also in the z-axis compared to the other axes as shown in Figure 4b. On the other hand, flat variance doesn't significantly differ in gravity acceleration axes as shown in Figure 4a.

On the contrary, the accelerometer readings on a flat road do not show such severe disturbance in gravity acceleration axes as shown in Figure 3a. However, it has been well documented e.g. [13] that the noise collateralize with the data measured from the accelerometer sensor will generate a drift in the final estimated parameter that degrades the performance. There are many factors that may affect accelerometer readings causing these noises such as user interactions, wind from opened windows, gravity and others.

The most work presented in literature, e.g. [13], [12], [2] tackled this issue by combining the accelerometer readings with gyroscope ones and several filtering techniques to eliminate the noises out of the data. That achieved acceptable results when we used in our contribution to confronting the noise-caused drift. We combined accelerometer with magnetometer and compass readings, then apply a moving average filter.

B. Data Filtering

During this stage sensors data and ground truth labels are processed in two main phases. Firstly data at the beginning of the file should be trimmed because sensors take a few seconds to reach stability and get accurate readings. Secondly, we apply the moving average filter which is mainly used for eliminating unwanted noisy data from the intended data.

The moving average is a method for smoothing an array of sampled data. It takes m samples of input at a time and computes the average of them. The same process is repeated starting from the next datum and the consecutive averages replaces the original data in the upcoming processing. The noise removal effect of the moving average filter on our flat and rut data illustrates as shown in Figures 3c and 3d. At this point, data are ready for the feature extraction stage.

C. Features Extraction

A set of features is needed in order to provide training data to the classifier that we will use later in ruts detection. We use each sample of sensors readings represented by a single value as a feature. Thus, for the multi-value data, i.e. the accelerometer data has three components along the x, y, and z directions; we consider each of them individually as a feature to extract a plentiful set of features.

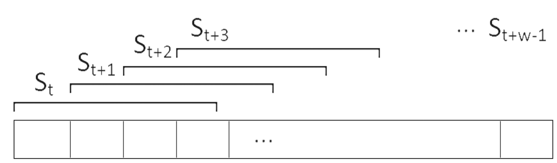


Fig. 5: Overlapping windows

The sampling rate at which the sensors record the data is high. Therefore, a single sample is too short to capture the vibration pattern caused by a rut. Multiple consecutive samples should be treated as a single entry in order to represent the anticipated pattern. We extract features by dividing sensing data using an overlapping sliding window of arbitrary size w as shown in Figure 5. The readings inside the sliding window starting at time t as in Equation 1

$$S = (s_t, s_{t_{+1}}, ..., s_{t_{+w_{-1}}}) \tag{1}$$

Where S is for slide window, t for time, and W for window.

A lot of features are used in our rutted road-segment alert model including the mean, median, variance, maximum, skewness and standard deviation of the readings within the

	$RandomForest$								
	20000 $Samples$			50000 $Samples$			100000 $Samples$		
	$FW^{*} = 100$	$FW = 400$	$FW = 800$	$FW = 100$	$FW = 400$	$FW = 800$	$FW = 100$	$FW = 400$	$FW = 800$
$W^{**} = 100$	88.18 %	89.81%	91.32%	92.65 %	93.73%	93.89%	99.872%	99.873%	99.879%
$W = 400$	93.13%	93.66%	93.77%	96.12%	97.96%	98.11%	99.959%	99.964%	99.966%
$W = 600$	95.30%	95.61%	95.92%	98.43%	98.71%	98.88%	99.972%	99.973%	99.967%

TABLE I: Random Forest Classification Accuracy. * Filter Window size. ** Data Window slide.

Mean	AVG ($\sum x_i$)
Variance	VAR ($\sum x_i$)
Standard Deviation	$\sqrt{VAR(\sum x_i)}$
Skewness	3(Mean-Median) / StD*

TABLE II: Features Calculation (* Standard Deviation).

sliding window as shown in Table II. Each feature can be calculated by Equation 2

$$F = Q(s) \tag{2}$$

where Q is a function that represents the samples inside each of a window.

	Features			
	F_{11}	F_{12}	...	F_{1n}
	F_{21}	F_{22}	...	F_{2n}
Cases	.	.	...	.
	.	.	...	.
	F_{m1}	F_{m2}	...	F_{mn}

TABLE III: Features Matrix

The features that resulted from the accelerometer, Magnetometer and compass are combined into single matrix called feature matrix as shown in Table III to be supplied into the classification tool, matrix rows represent the combined feature vectors.

D. Classification

We classify our rutted road-segment alert system features into 4 classes, e.g. flat, start rut, rut, and end rut. This classifying stage will group similar samples into one class to identify the start and end of the rutted road. The training data is prepared with the knowledge of the start and end points of the rutted road and with the usage of the GPS to get the latitude and longitude readings of those points. After training, the model is able to classify new data and extract the start and end points of ruts. These points are located on the map to early notify the drivers when they are approaching any of the detected ruts. The classification model uses a machine learning in which the core classifier is Random Forest from WEKA [15] named as "classifiers.tress.RandomForest." We used a set of classifiers on our preliminary experiments as using decision tree, logistic regression, random tree and random forest. For all experiments, the random forest has outperformed the previously mentioned classifiers which illustrate the reason of using it in our proposed model. Our model was trained using a 10-folds Cross Validation testing method. In Section IV, we illustrate the experimental setup besides the performance results of our proposed model.

IV. Evaluation

In order to evaluate the performance of our rutted road-segment alert system, we run the experimentation described in this section.

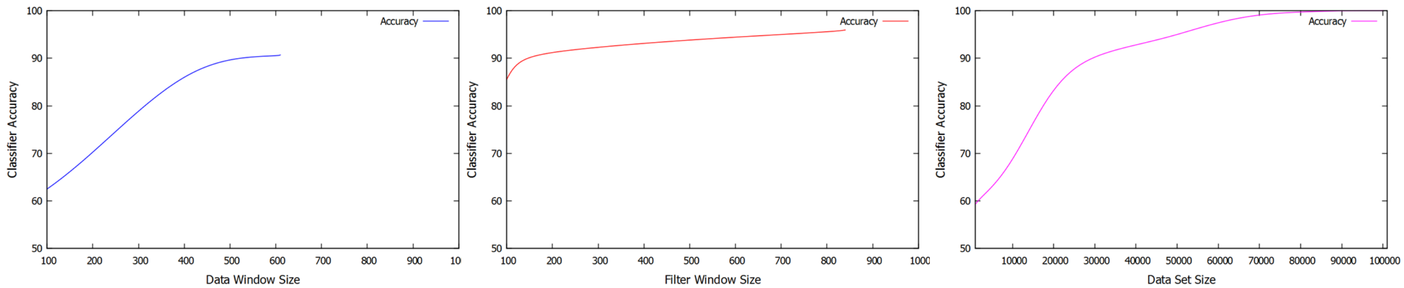
A. Experimentation Setup

We implement and evaluate our rutted road-segment alert model on a Sony Xperia C3 Android phone with 5.0.2 (Lollipop) operating system, which has 8 GB internal storage, 1 GB RAM, Accelerometer, proximity, compass and GPS with A-GPS and GLONASS sensors. One user was engaged in this work, carrying the application on an Xperia C3 during daily regular way from home to work then back to home again. the experiment was accomplished on any location of Abu Almatamir - Damnhour Agricultural Road that covering a road length of 50 km of which 12 km are ruts, collecting a data set of 10000 seconds as 10 readings per second for the experimentation. The features extracted from the dataset depend on two main factors. The first one is the sliding Window size of the dataset that affects the quality of rut vibration pattern capturing. While the second is window size of data used in the filtering process and that should achieve noise removal without losing the information contained in the data. A cross-validation with 10-folds had proved for our model that it is suitable to get the best performing classifier for system than other testing methods. Classification results are presented in the next section.

B. Results Discussion

	$LogisticRegression$		
	$FW^{*} = 10$	$FW = 100$	$FW = 300$
$W^{**} = 50$	59.33 %	59.86%	60.19%
$W = 100$	62.20%	62.56%	63.11%
$W = 400$	88.87%	90.04%	90.47%
$W = 600$	90.26%	90.46%	90.68%

TABLE IV: Logistic Regression Classification Accuracy. * Filter Window size. ** Data Window Slide.



(a) Parameter 1: Data Window Size

(b) Parameter 2: Filter Window Size

(c) Parameter 3: Data Set Size

Fig. 6: Classifier Accuracy Improvement Responding to Three Parameters.

To evaluate the proposed approach, we applied our model to different classifiers like Random Forest, and Logistic Regression, as we before mentioned, to come up with the classifier that gives the higher accuracy. An in-depth look at the Tables I and IV highlights that the random forest classifier outperformed other classifiers for our ruts warning model regarding the highest accuracy.

As we mentioned previously, the performance of our rutted road-segment alert system varies according to two factors. The first one is the window of Data and the other is the window of moving average. These factors significantly affect the accuracy of the classifier it illustrated in the case of the logistic regression classifier in Table IV and the case of the random forest classifier in Table I. This denotes that the classifier accuracy increases from 60% to 90% according to the growth of the data window size from 100 to 600 samples at features extraction as shown in Figure 6a. Also, when the data window size in the filtering process, using moving average filter, increases from 100 to 400 samples, the accuracy increases from 70% to 95% as illustrated in Figure 6b. However, another factor that can significantly enhance the performance of our system is the training data set size. We applied Random Forest classifier on data sets contain 20000 samples, 50000 samples and 100000 samples as shown in Table I. The results shows that the accuracy significantly increases with growth of the dataset as illustrated in Figure 6c.

V. Conclusion and Future Work

The safety of the vehicles is threatened when traveling on roads contain unsigned anomalies. Our system, when installed on his smart phone, notifies the driver that he is approaching a rutted part of the road, so that, he can slow down and be prepared for probable motion instability. We implemented an application for the Android operated smartphones that collect sensors data with labels using crowd-sourcing. We used the data to train logistic regression and random forest models and got classification accuracy up to 90% and 99% respectively when the models were tested on new data. We showed that increasing the training data set size affects the classification accuracy significantly. The detected rutted road segments are localized on the map, thus using the GPS location of the driver, our system can realize the near anomaly and issue an alert. This is done with no need for any additional devices, only the driver's smartphone.

For the future work, we plan to use lager data set collected by multiple android phones of different specifications. Furthermore, we will expand the system to cover a wider network of roads connecting numerous cities.

References

[1] Kong, Yingying, et al. "Detecting Type and Size of Road Crack with the Smartphone." Computational Science and Engineering (CSE) and Embedded and Ubiquitous Computing (EUC). IEEE, 2017.

[2] Piao, Bin, et al. "Estimating Road Surface Condition Using Crowdsourcing." Information Search, Integration, and Personlization. Springer, Cham, 2017.

[3] Vimalkumar, K., R. E. Vinodhini, and R. Archanaa. "An Early Detection-Warning System to Identify Speed Breakers and Bumpy Roads Using Sensors In Smartphones." International Journal of Electrical and Computer Engineering (IJECE), 2017.

[4] Alqudah, Yazan A., and Belal H. Sababha. "On the analysis of road surface conditions using embedded smartphone sensors." Information and Communication Systems (ICICS). IEEE, 2017.

[5] Kaur, Vinaydeep, et al. "Crowd-sourcing based android application for structural health monitoring and data analytics of roads using cloud computing." Innovative Mechanisms for Industry Applications (ICIMIA), 2017.

[6] Fox, Andrew, et al. "Multi-Lane Pothole Detection from Crowdsourced Undersampled Vehicle Sensor Data." IEEE Transactions on Mobile Computing, 2017.

[7] Chen, Qiuxia, et al. "A Speed Hump Sensing Approach to Global Positioning in Urban Cities without Gps Signals." Smart Computing (SMARTCOMP), 2017 IEEE International Conference on. IEEE, 2017.

[8] Dunlop, Mark D., et al. "Using smartphones in cities to crowdsource dangerous road sections and give effective in-car warnings." Proceedings of the SEACHI 2016 on Smart Cities for Better Living with HCI and UX. ACM, 2016.

[9] Wang, Ru-Yu, Yi-Ta Chuang, and Chih-Wei Yi. "A crowdsourcing-based road anomaly classification system." Network Operations and Management Symposium (APNOMS). IEEE, 2016.

[10] Daraghmi, Yousef-Awwad, and Motaz Daadoo. "Intelligent Smartphone based system for detecting speed bumps and reducing car speed." MATEC Web of Conferences, 2016.

[11] Mukherjee, Abhijit, and Subhra Majhi. "Characterisation of road bumps using smartphones." European Transport Research Review 8.2 (2016).

[12] Mohamed, Adham, et al. "RoadMonitor: an intelligent road surface condition monitoring system." Intelligent Systems' 2014. Springer, Cham, 2015.

[13] Bo, Cheng, et al. "SmartLoc: sensing landmarks silently for smartphone-based metropolitan localization." EURASIP Journal on Wireless Communications and Networking 2016.

[14] Aly, Heba, and Moustafa Youssef. "Dejavu: an accurate energy-efficient outdoor localization system." Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems. ACM, 2013.

[15] Hall, Mark, et al. "The WEKA data mining software: an update." ACM SIGKDD explorations newsletter 11.1 (2009).