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# ROADWAY PAVEMENT ROUGHNESS EVALUATION BASED ON SMART-CITY PRINCIPLES, VIBRATION SENSING AND MACHINE LEARNING

Charalambos Kyriakou[1] and Symeon E. Christodoulou[1]
[1]University of Cyprus, Nicosia, Cyprus

## Abstract

The evaluation of roadway networks utilizing contemporary datasets is currently conducted periodically because of the collection methods' cost. Nowadays, the development of smart city-based systems aims to transform city road infrastructure using big data information and communications technology. The proposed system utilizes vehicles, smartphones, onboard diagnostic (OBD) devices and machine learning algorithms. The major contribution of this work is the development of a cost-efficient smart city-based assessment system that evaluates roadway pavement roughness conditions more frequently than current systems. The system's roadway daily information can be utilized by pavement agencies for automating the planning of pavement maintenance.

## Introduction

Current trends in urbanization, economic growth, technological processes and environmental sustainability are the drivers for an urgent need for cities to become 'smarter' in how they manage their infrastructure and resources (Naphade et al., 2011). A smart city is a built-up system that combines data and communication technologies (ICT), and internet of things (IoT) technologies to certify that municipal services and infrastructure are operating accordingly (El-Wakeel et al., 2018). Alternatively, a smart city is an urban area that uses different types of electronic methods and sensors to collect specific data, and information gained from that data is in turn used to manage assets, resources and services efficiently and to improve operations across the city. This includes data collected from citizens, devices, buildings and other urban assets. The final aim of a smart city is to make more efficient use of the public resources, increasing the quality of the services offered to the citizens, while reducing the operational costs of the public administrations (Zanella et al., 2014). With regard to roadway pavement maintenance, this objective can be pursued by the deployment of a smart-city-driven pavement roughness evaluation system utilizing vibration sensors and machine learning.

Poor roadway pavement conditions, such as potholes, patches, rutting, raveling and cracks, can produce costly consequences to municipalities and drivers. For example, in 2011, UK councils paid more than 22 million sterling pounds as compensation to drivers whose cars were damaged by potholes (Xue et al., 2017). Further to reducing such adverse consequences, the development of tools that facilitate the appraisal of roadway conditions and smart-city-based intelligent transportation systems (ITS) would contribute to an increase in driver safety and comfort and a decrease in traffic accidents and vehicle damage (Yi et al., 2015). In fact, according to Fixing America's Surface Transportation (FAST), each US state is required to develop a pavement management system (PMS) to optimize the allocation of available resources and for planning pavement maintenance (Aleadelat et al., 2018).

The international roughness index (IRI) is the most widely used pavement quality index and is considered as a critical pavement condition parameter along with other pavement distresses (potholes, patches, rutting, raveling and cracks) (Ksaibati et al., 1999). According to ASTM E87-06, pavement roughness is defined as 'the deviation of a surface from a true planar surface with characteristic dimensions that affect vehicle dynamics and ride quality. Thus, a high level of profile variation (roughness) can decrease driver safety, and increase, traffic accidents, vehicle damages and operating costs by 4-5% (Islam and Buttlar, 2012). Further, according to Zaabar and Chatti (2014), an increase in IRI of 1m/km increased fuel consumption of passenger cars by 2% to 3% regardless of speed. Additionally, the cost of evaluating IRI varies in the range of $1.4-$6.20 per kilometer (McGhee, 2004). To sum up, the overall cost and maintenance of the PMS equipment are very high which reduce the system's feasibility. Consequently, pavement agencies evaluate roughness roadway quality approximately only once or twice per year because the existing high-end vehicles for the assessment of pavement network cost approximately one million US dollars (Fugro Roadware, 2022). Who, then, assesses pavement conditions between these two evaluations?

Comparatively, the evolution of smart devices, the increased number and the low cost of sensors found in smartphones make them suitable for various crowdsourcing applications, specifically ones that are used in road information services (Wahlström et al., 2017). More specifically, the current generation of smartphones is equipped with numerous sensors such as Global Positioning System (GPS), accelerometers, gyroscopes, and others, which could save data that can be analyzed and processed to give valuable information about road conditions and anomalies (Kyriakou & Christodoulou, 2017). Further, smartphones can be used in monitoring roadway pavements conditions in the context of building dynamic roadway network mappings that could benefit pavement authorities and drivers alike (Kyriakou & Christodoulou, 2021).

This primary key contribution of this research is to address the high-cost low-frequency pavement monitoring systems (mentioned in existing technologies) by developing a smart-city-based pavement roughness surface condition system (Figure 1), having as a principal goal the development of a low-cost vibration-based data acquisition and a reliable five-class roughness system for the classification of pavement roughness levels (instead of two or three categories mentioned in the literature). The proposed system architecture has been already field-tested for the evaluation of roughness conditions and the classification of five rating categories.

Further to this short introduction, a literature review section presents brief overviews of past and ongoing work related to the development of a roughness evaluation system for roadway pavements by use of smart devices. A section on the proposed system presents the data collection system and the analysis method, while the results and discussion sections include the processes and tools used to evaluate roughness levels of roadways based on the sensed data. The paper concludes with key findings and with an outline of future work.

*Figure 1: Smart city-based pavement roughness evaluation system*

## Literature review

In developed countries, pavement agencies utilize specialized hardware and software for the evaluation of roadway networks, which are hosted on expensive high-end vehicles (Wolters et al., 2011). These specialized platforms typically use machine vision and laser technologies, and they can provide a reliable standard rating system for pavement networks (AASHTO, 1993). The costs related to existing technologies are comprised of several components (e.g., data collection, database set-up, software, training and personnel costs, consulting services) and the typical combined unit cost of pavement imaging analysis ranges from $15 to $52 per kilometer (McGhee, 2004). Because of this high unit cost, the evaluation of pavement networks is typically conducted no more than twice a year.

In such an evaluation process, crucial is the stages related to data collection, classification, and spatial mapping of pavement conditions. Alternatively, the concept of ‘citizen sensing’ which takes advantage of smartphones’ sensors has been employed by scientists because of its low-cost, high efficiency and high scalability. Smartphones also remove the need to deploy special sensors and specialized vehicles. For that reason, a plethora of research has already published works on low-cost pavement condition assessment using smartphones, threshold algorithms, and machine learning and related work is discussed below.

Bhoraskar et al. (2012) proposed a non-intrusive method that used smartphones’ sensors. The researchers were interested in identifying braking events, assuming that frequent braking is an indication of congested traffic conditions and bumps on the road to characterize the type of the road. They applied machine learning techniques (k-means clustering) to classify data and helped the system to adapt to changing factors such as the condition of the roadway, and Support Vector Machines (SVM) to further improve the negative rates of their system’s accuracy.

Seraj et al. (2014) monitored pavement surface conditions utilizing smartphones equipped with GPS, accelerometers, and gyroscopes. Their system implemented wavelet decomposition analysis for signal processing of sensor signals and SVM for anomaly detection and classification. They obtained a consistent accuracy of ~90% on detecting severe anomalies.

Chen et al. (2014) proposed a crowdsourcing-based road surface monitoring system that detected road potholes and evaluate road roughness levels using their hardware modules mounted on distributed vehicles. These modules used low-end accelerometers and GPS devices to obtain vibration pattern, location, and vehicle velocity. Their results showed that the system can detect road potholes with up to 90% accuracy and evaluate road roughness levels correctly, even with some interferences from small bumps or potholes.

Allouch et al. (2017) created an Android application that predicts the quality of the road based on a tri-axial accelerometer and a gyroscope, mapping such results on a geographical map using GPS. A decision-tree classifier was applied to the training data to classify roadway networks, with their experimental results showing consistent accuracy of ~98%.

Li and Goldberg (2018) presented a crowdsourcing system for road surface assessment utilizing smartphones. The built-in smartphones' GPS receiver and accelerometer were used to capture spatial series of the geo-referenced Z-axis accelerations of the road surface. Field tests demonstrated that the roadway condition could be effectively identified, and the transient events could be detected and located by mining the crowdsourced data.

Kyriakou et al (2017, 2018, 2019, 2021) proposed a low-cost data-driven framework on the use of typical vehicles, typical smartphones, on-board diagnostic (OBD) devices and unsupervised and supervised machine learning for the detection, classification, and rating pavement surfaces. They utilized robust regression analysis, artificial neural networks (ANN), bagged tree classification model and k-medoids clustering to analyze smartphone and gyroscope data. The proposed system was field-tested, with accuracy levels higher than 90%, and it is currently expanded to include a bigger number of pavement surface anomalies.

A summary of the methods and related characteristics, as reported in the literature, is shown in Table 1.

*Table 1: Comparison of related smart city-based research in pavement roughness evaluation*

| Researcher | Roughness Assessment | Anomaly Detection | Classification Method |
|---|---|---|---|
| Bhoraskar et al. (2012) | Smooth Bumpy | Bumps Accuracy ~90% | K-means clustering & SVM |
| Seraj et al. (2014) | Transversal, Mild, Severe, | No | Wavelet decomposition analysis, SVM |
| Chen et al. (2014) | Excellent, Good, Qualified, Unqualified | Potholes Accuracy: ~90% | Gaussian Mixture Model (GMM) algorithm |
| Allouch et al. (2017) | Smooth Potholed | Potholes Accuracy: 98.6% | C4.5 Decision Trees |
| Li and Goldberg (2018) | Good, Moderate, Bad | Pothole Accuracy: ~92% | Threshold |
| Kyriakou et al (2017, 2018,2019, 2021) | No | Cracks, Raveling, Rutting, Patching and Potholes Accuracy: ~98% | Robust Regression, ANN, Bagged Trees, K-medoids |

# Methodological setup

## System overview and data collection

The paper focuses on the evaluation of pavement roughness and the development of a six-class roughness scale according to Sayers et al. (1986). Vehicle and smartphone data were collected from nine different roadway sections (highways, new pavements, older pavements, maintained unpaved roads, damaged pavements, rough unpaved roads) of ~10 Km total distance (~18320 total data points; ~20 data points per GPS location ~916 total GPS locations). The system utilizes data from a typical vehicle and smartphone, and server-based unsupervised machine learning algorithms to analyze the acquired data. The processed information on the pavement roughness levels of GPS locations data is then disseminated to pavement agencies.

The data collection was performed on urban roads using a car (Nissan Qashqai (2011), a smartphone (Samsung Galaxy S8) fitted with the DashCommand$^{TM}$ application and an OBD II Bluetooth reader (ELM 327). Vehicle and smartphone (mounted on the car's windshield) data were transmitted through the smartphone application to a data server for storing and processing via Bluetooth and a digital cellular connection. The collected dataset is collected at intervals of 0.1 seconds (sampling rate of 10 Hz) and for visually verifying the roughness pavement condition, the smartphone had also its video camera and GPS active for recording the pavement network travelled.

## System design

Mathematically, the proposed system is based on rigid-body dynamics and the ability to express any three-dimensional rotation as a combination of yaw, pitch, and roll rotations. GPS location, vehicle speed, frame time between the last two readings and vehicle pitch were recorded through the smartphone application and by utilizing equations (1) and (2) the height difference was calculated between two sensor readings (Figure 2).

$$x = v * t \tag{1}$$

x = distance between the last two sensor readings (sampling rate 10 Hz)

v = vehicle speed (Km/hr)

t = time between the last two sensor readings (ms)

$$h = \tan(\theta) * x \tag{2}$$

h = height difference between the last two sensor readings

θ = vehicle pitch (Â°)

x = distance between the last two sensor readings


*Figure 2: Calculation of road profile*

### Feature Extraction

Feature extraction is the process of dimensionality reduction, by which an initial set of raw data is reduced to more manageable groups for processing. The research presented herein examined several time-domain features as data aggregators: the maximum, the mean, the standard deviation, and the variance of the height difference between the last two sensor signal readings at each GPS location. For example, a maximum analysis was performed for each geographical point (thus, the 20 raw data per GPS location were converted into a single data – 18320/20 = 916 data) in which analysis each GPS location is characterized by the maximum analysis of the observed raw signal data.

### Clustering

Upon completion of the feature extraction process, the data was fed into unsupervised machine learning algorithms for clustering analysis. Clustering is one of the main analytical methods in data mining and it is of wide use and great importance. It is an unsupervised machine learning technique that divides the data into several groups such that data points in the same group are similar to each other, and data points in different groups are dissimilar. The widespread clustering methods can be classified into five categories: partitioning, hierarchical, density-based, grid-based, and model-based methods. Partitional clustering techniques are the most well-known and commonly used clustering methods. They create one-level partitioning of the data points, and the most widely partitioning methods are the k-means and the k-medoids method and their variations (fuzzy clustering and GMM clustering).

Firstly, K-means is the most popular partition-based clustering algorithm, and it uses a centroid, defined as the mean of a group of points, as its key parameter. It should be noted that a cluster's centroid rarely corresponds to an actual data point. Secondly, the K-medoids algorithm attempts to determine k partitions from n objects, with each cluster represented by one of the objects in the cluster. In contrast to the k-means clustering algorithm, instead of taking the mean value of the object in a cluster as a reference point, the method utilizes the medoid which is the most centrally located object in a cluster. Thirdly, Fuzzy clustering generalizes partition clustering methods (such as k-means and medoid) by allowing individual data to be partially classified into more than one cluster (Chattopadhyay et al., 2011). This technique was originally introduced by Jim Bezdek (1981) as an improvement on earlier clustering methods. It is a soft clustering method, where each data point is allocated a probability score to belong to that cluster. Finally, GMM clustering is a probabilistic model for representing normally distributed subpopulations within an overall population. A GMM is parameterized by two types of values, the mixture component weights, and the component means and variances/covariances.

## Results and discussion

At first, the smartphone-based data were fed into k-means, k-medoids, fuzzy and GMM clustering algorithms for unsupervised machine learning. Then, an evaluation of the goodness of fit for each clustering method was performed and the most suitable was selected.

### K-means clustering (case-study dataset)

First, the k-means algorithm randomly selected k points as initial centroids and then all data points were assigned to the closest centroid. After that, it recomputed the centroid of each cluster based on the assignment of points to the clusters, and it repeated the previous steps until the computed centroids in two successive iterations did not change. The objective of the k-means clustering was to minimize the Euclidean sums of square deviations of objects from the cluster mean.

Advantages of k-means:

- Scaled to large data sets.
- Guaranteed convergence.
- Generalized to clusters of different shapes and sizes, such as elliptical clusters.

Disadvantages of k-means:

- Difficult to cluster data where clusters were of varying sizes and densities.
- The algorithm was sensitive to outliers, since an object with an extremely large value may substantially distort the distribution of the data.
- The method required several passes on the entire dataset, which can make the whole process computationally expensive and time-consuming.

### K-medoids clustering (case-study dataset)

At first, the algorithm selected k initial candidate medoids. Then the distance of each non-selected point from the closest candidate medoid was calculated and this distance was summed overall points. The algorithm's cost represented the cost of the current selection, and all possible swaps of a non-selected point for a selected one were considered. The cost of each selection was calculated and the configuration with the lowest cost was selected.

Advantages:

- The algorithm was more robust than the k-means because it minimized a sum of dissimilarities instead of the sum of squared Euclidean distances.
- K-medoids clustering was faster than k-means clustering because the k-medoids algorithm required the computation of the distance between every pair of objects only once and used this distance at every stage of iteration.
- The method was less sensitive to outliers than other partitioning algorithms.

Disadvantages:

- It was not suitable for clustering non-spherical groups of objects because it used compactness as clustering criteria instead of connectivity (minimization of the distances between non-medoid objects and the medoid).

**Fuzzy clustering (case-study dataset)**

First, the algorithm calculated the cluster centers and assigned the data points to these centers using a form of Euclidean distance such that the process was continuously repeated until the cluster centers stabilized Then, the algorithm assigned a value to the data points for the clusters within a range of 0 to 1, and a parameter in the range [1,n] which determined the degree of fuzziness in the clusters (Raju et al., 2008).

Advantages:

- It didn't force every object into a specific cluster.
- Gave the best results for the overlapped data set and was comparatively better than the k-means algorithm.

Disadvantages:

- There was much more information to be interpreted.
- The membership of a data point in a cluster depended directly on the membership values of other cluster centers, and this sometimes produced undesirable results.
- Euclidean distance measures could unequally weigh underlying factors.

**GMM clustering (case-study dataset)**

At first, GMM assumed there was a certain number of Gaussian distributions, and that each of these distributions represented a cluster. Hence the GMM tended to group the data points belonging to a single distribution together. Thus, for a given set of data points, GMM identified the probability of each data point belonging to each of these distributions.

Advantages:

- The model did not require which subpopulation the data belongs to.
- It allowed the model to learn the subpopulations automatically.
- GMM were more robust than K-Means.

Disadvantages:

- GMM tended to be slower than K-Means because it takes more iterations to reach convergence.

**Silhouette Score**

With regard to appraising how well the obtained configurations fit the original data, Kaufman and Rousseeuw (1990) defined a set of values called silhouettes that provide key information about the goodness of fit. One summary statistic is the average value of the silhouette value across all objects, while the maximum average silhouette across all values of clusters is the Silhouette Score. A Silhouette Score above 0.51 denotes that a reasonable or a strong structure has been found. In the case-study dataset, the system's best results were obtained when clustering with the k-medoids algorithm (Table 2). As ground truth for verifying the method's detection accuracy, the smartphone's recorder video was used.

*Table 2: Silhouette Score*

| Machine Learning | Silhouette Score |
|---|---|
| K-means clustering | 0.60 |
| K-medoids | 0.66 |
| Fuzzy clustering | 0.59 |
| GMM clustering | 0.55 |

The outcome of the k-medoids machine learning algorithm and the resulting pavement roughness condition scores were classified (Table 3) as per the Pavement Roughness Scale (Sayers et al., 1986) and then spatially mapped.

*Table 3: K-medoids Pavement Roughness Scale (Sayers et al., 1986)*

| Roughness Rating | Road Class | Data |
|---|---|---|
| 1 | Highways | 508 |
| 2 | New pavements | 210 |
| 3 | Older pavements | 104 |
| 4 | Maintained unpaved roads | 41 |
| 5 | Damaged pavements | 37 |
| 6 | Rough unpaved roads | 16 |

**Limitations**

As perceived limitations of the method are:

1. A less objective system roughness evaluation rather than the standardized evaluation system used (IRI rating system).
2. The range of roughness distresses detected (only those causing vibration of the vehicle).
3. The missing roughness distresses not on the vehicle's wheel path (to be solved using participatory sensing).
4. Due to the limited accuracy of the built-in smartphone GPS receiver, a high accuracy positioning result cannot be guaranteed. However, Li and Goldberg (2018) noted that Broadcom Limited (a global semiconductor leader) designed a more accurate GPS chip (BCM47755), which enables 30-centimetre positioning accuracy and 50%

fewer battery drains for the current generation of smartphones (released in 2018).

## Conclusions

The research contribution is the development of a system that automatically assesses the quality of the pavements based on an accelerometer, a gyroscope, a GPS and a clustering method, maps the existence of roadway anomalies and saved all sensed data for reinforcement learning through participatory sensing of multiple probe vehicles. The suggested system has the advantages of being low-cost and highly scalable, as the numbers of smartphone users increase day by day. Further, the smartphone-based approach is worthwhile because it removes the need to deploy special sensors and specialized vehicles. Furthermore, the system does not require any expertise in pavement condition assessment. Moreover, the proposed roughness evaluation system is currently field-tested with multiple probe vehicles, smartphones, and more kilometers of roadway network for increasing the accuracy of the system and finetuning the data aggregation and unsupervised machine learning clustering. In conclusion, the developed smart-city-based pavement evaluation system allows speedier and continuous evaluations of the roadway networks.

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