Intelligent Road Surface Quality Evaluation Using Rough Mereology

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***Abstract*—The road surface condition information is very useful for the safety of road users and to inform road administrators for conducting appropriate maintenance. Roughness features of road surface; such as speed bumps and potholes, have bad effects on road users and their vehicles. Usually speed bumps are used to slow motor-vehicle traffic in specific areas in order to increase safety conditions. On the other hand driving over speed bumps at high speeds could cause accidents or be the reason for spinal injury. Therefore informing road users of the position of speed bumps through their journey on the road especially at night or when lighting is poor would be a valuable feature. This paper exploits a mobile sensor computing framework to monitor and assess road surface conditions. The framework measures the changes in the gravity orientation through a gyroscope and the shifts in the accelerometer's indications, both as an assessment for the existence of speed bumps. The proposed classification approach used the theory of rough mereology to rank the modified data in order to make a useful recommendation to road users.**

Keywords*—Intelligent Transportation Systems, Rough Mereology; Rough Inclusion; Speed bump; Road monitoring; Smartphones; Accelerometer; Gyroscope

I. Introduction

Traffic flow metric includes three main parameters; the vehicle, the driver, and the road. Road events, such as speed bumps, potholes, signage, or traffic control devices, can be the source for dramatic changes in the traffic flow. Although the main purpose of using speed bumps is to reduce vehicle's speed for promoting safe driving, they can create long-term problems, as well. They increase the traffic volume in specific areas and as a result they cause noise and reduces the efficiency of emergency vehicles at these areas. Also, speed bumps may cause a jolt and potential personal injury if traversed at high speed, especially for people with various disabilities and chronic pain conditions.

The discovery of anomalous segments of a road that spans thousands of kilometers is a complex and expensive task. Using the new paradigm wireless sensor networks by deploying a number of sensors along the road is costly and hard to be managed. On the other hand, the using of smartphones in Intelligent Transportation Systems (ITS) is gaining popularity as in [1] [2]. In another new approach, researchers developed a functional application on smartphones to define the driving behavior of vehicle's drivers [3]. Developing the suitable road anomalies detection algorithm is important, as a result to the challenges that exist in form of limitation of energy and memory that are exist in smartphones.

Recently, moving motors (vehicles, buses, etc.) provide the means for collecting and transferring data. This concept was introduced in DakNet project in Calcutta [4] which focused on bringing Internet connectivity to developing and rural communities through the use of Wi-Fi boxes that are placed in buses or in any other vehicle. Although DakNet project provides solutions for the deficiency of communication infrastructure, it carries the idea of using transportation for collecting data from the road. BusNet [5] is a multi-objective project that mount sensors within public transport buses to monitor both the environmental pollution and road surface conditions. The use of public transportation solved both the communication and the high-cost problems attached with spreading a large number of sensors to monitor a large area.

Although they are used for automotive safety applications such as automatically opening airbags in crashes, accelerometers are now used to detect different road anomalies. For example , the Pothole Patrol (P2) system [6] that used a custom made device that has 3-axis accelerometers and GPS sensors deployed on a taxi's dashboard and a the back-end of the system the road quality was assessed using a machine-learning approach.

Nericell project [2] was based on previous mentioned approaches, although it avoided the need for installing specialized and potentially expensive monitoring equipment. Nericell focused on the use of smartphones to sense varied road and traffic conditions, such as bumpy roads and noisy traffic. Moreover, Perttunen et al. [7] proposed a pattern recognition system for detecting road surface anomalies. It composed of preprocessing, classification and visualization phases. The road roughness was recognized using embedded-mobile sensors (3-axis accelerometer and GPS). While the acceleration data was analyzed to detect road anomalies, the GPS readings were filtered by the Kalman filter to reduce noisy samples. The anomalies were classified according to the severity of the road into two types; Type 1 that represents small road anomalies, and Type 2 that represents rough road anomalies. Also, authors farmed signals into windows for correction, and analytically compared them with acceleration and GPS readings. Comparing their results with the previous works of [2] authors had reduced the number of false negative detection ratio from 51% to 18%.

Vittorio et al. [8] used a simple application for smartphones that employs a GPS receiver for vehicle's localization and a three axis accelerometer to collect acceleration data due to vehicles motion on road anomalies. The proposed sensing system is automated to monitor road surface quality. The collected signals are automatically transferred to a central server to be analyzed. The application defined any anomaly through calculating the vertical acceleration impulse; which is the difference between the minimum and maximum vertical acceleration values that are related to road events. The detection accuracy was 80% of anomaly events.

This paper investigates the road quality through a computing framework approach. The framework collects specific smartphones's sensors values; the Accelerometer, the Gyroscope, and the GPS to explore road anomalies (currently, detects speed bumps). Differently from all previously presented algorithms, those apply common classification techniques, this paper evaluates the existence of speed bumps along the road using rough mereology theory.

The remainder of this paper is organized as follows. Section II provides a brief explanation of the rough mereology concept. Section III describes the proposed road quality assessment framework along with presenting the details of its phases. Section IV presents experimental results and discussion. Finally, Section V points out the concluding remarks and discusses future work directions.

II. Preliminaries: Rough Mereology

Rough Mereology (RM) introduced the notion of "a part to a degree". The degree is expressed in a real number existing within the interval [0; 1]. RM is occupied with a class of similarity relations among objects which are expressed as a ternary predicate called rough inclusion $\mu(x, y, r)$, read as: The object x is a part in object y to a degree of r ($r \in [0; 1]$). Rough inclusions can be induced in continuous t-norms form as in Equation 1 , that represents the minimum t-norm [9]. Moreover rough inclusion can be defined by means of residual implications of continuous t-norm [9]. In a continuous t-norm t, the residual implication $x \Rightarrow_t y$ is a mapping from the $[0, 1]^2$ into [0, 1] defined as Equation 2 [10]:

$$M(x, y) = min\{x, y\} \tag{1}$$

$$x \Rightarrow_t y = max\{z : T(x, z) \leq y\} \tag{2}$$

Then,

$$\mu_T(x, y, r) \Leftrightarrow x \Rightarrow_T y \geq r \tag{3}$$

Also, the rough inclusion function $\mu(x, y, r)$ can be obtained from indiscernibility set $IND(u, v) = A - DIS(u, v)$, where $DIS(u, v)$ represents discernibility for objects u, and v in the following equation (Equation 4):

$$\mu_h(x, y, r) = \frac{|IND(x, y)|}{|A|} \geq r \tag{4}$$

where:

$|IND(x, y)|$ is the cardinality of set $IND(x, y)$,

$IND(x, y) = a \in A, a(x) = a(y)$, and

$|A|$ is the cardinality of set $A(where, A = xUy)$.

III. The Proposed Intelligent Road Surface Condition Monitoring System

The proposed intelligent road surface condition monitoring system seeks to investigate the road quality. Figure 1 illustrates a scenario of main phases of the system. The data acquisition phase starts by a mobile application attached to a vehicle to detect the presence of road anomalies. Data acquisition phase collects triple sensors values; the Accelerometer, the Gyroscope, and the GPS. The main intention of using the gyroscope, which represents variation around gravity rotation, is to confirm the acceleration readings for indicating road anomalies. Rough mereology phase is used to rank the modified data in order to make a useful recommendation to road user

The following subsections will describe in more details the proposed road surface conditions monitoring phases.

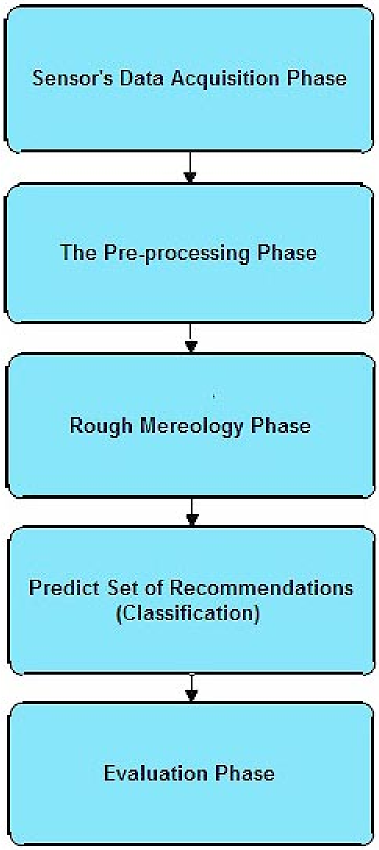

Fig. 1: The proposed intelligent road surface condition monitoring system

A. Sensor's Data Acquisition Phase

Alike the approach used in [11], the data acquisition process has been done by using Windows-based smartphone (Nokia Lumia 820) that was placed inside a Chevrolet Aveo vehicle. Readings of road surface conditions were gathered using both accelerometer and gyroscope sensors. Also the GPS was recorded for a further research to indicate dangerous segments of the road. The sensors gathered data along the vehicle path. The collected data were stored locally within the mobile device memory. Also, the GPS coordinates of the manually marked road bumps points are kept within the memory.

The application is not dedicated only for Lumia 820 device, another version was developed to work on android based phones. While Figure 3 shows the real-life data acquisition, Figure 2 shows the data acquisition framework. It starts by checking the existence of accelerometer and gyroscope sensors. then, the application initializes a timer to start receiving sensors data. For saving mobile memory space, specific readings were pre-processed before being stored, like optimizing the time structure in the log files by putting the difference against a certain time stated at the beginning of the file. Another pre-processed optimization is done over sensors readings; for example, the readings of the gyroscope are appended to the device memory if the current sensed rotation rate (in radians/s) is greater than a certain threshold (representing a stationary vehicle). Once the user stops the data acquisition, the application dumps the log files exist within the memory into the attached microSD card.

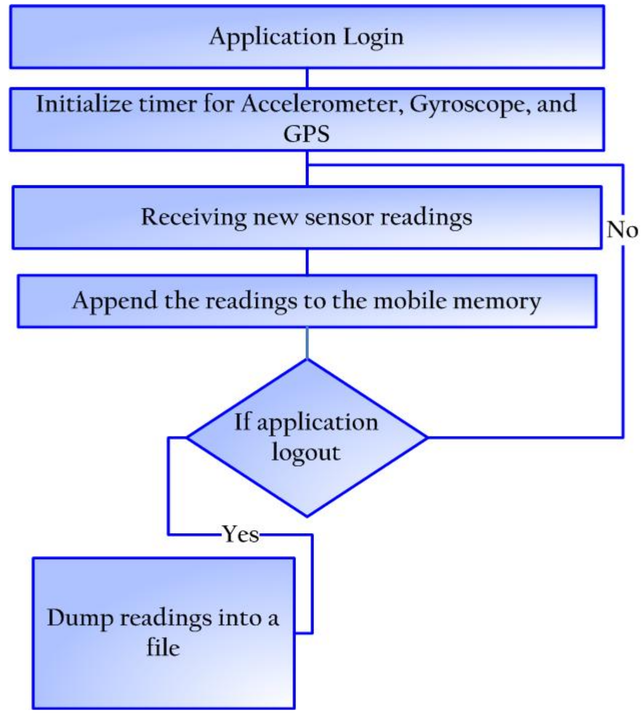

Fig. 2: Data Acquisition Phase

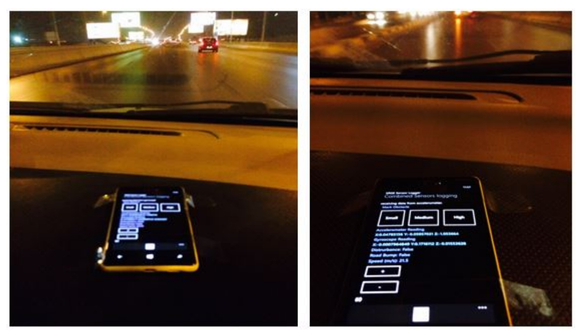

Fig. 3: Real-life Data Acquisition Phase

B. The Pre-processing Phase

The data was collected as tuple form $< SensorType, X - coordinate, Y - coordinate, Z - coordinate, time(in\ millisecond) >$. The gyroscope readings have been converted from radians form into degrees form in order to enhance the scatter point curve (as the once shown in figure 4).

C. Rough Mereology Phase

The role of the rough mereology phase is to rank the modified data in order to make a useful recommendation (the

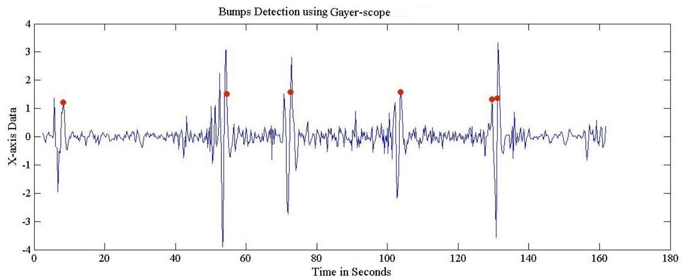

Fig. 4: Gyroscope gravity readings around X-axis

existence of a speed bump) to user. This ranking uses the equations of rough mereology that are described in Section 2. The returned result of this phase is a similarity matrix of items. Figure 5 demonstrates the procedure to establish that similarity matrix.

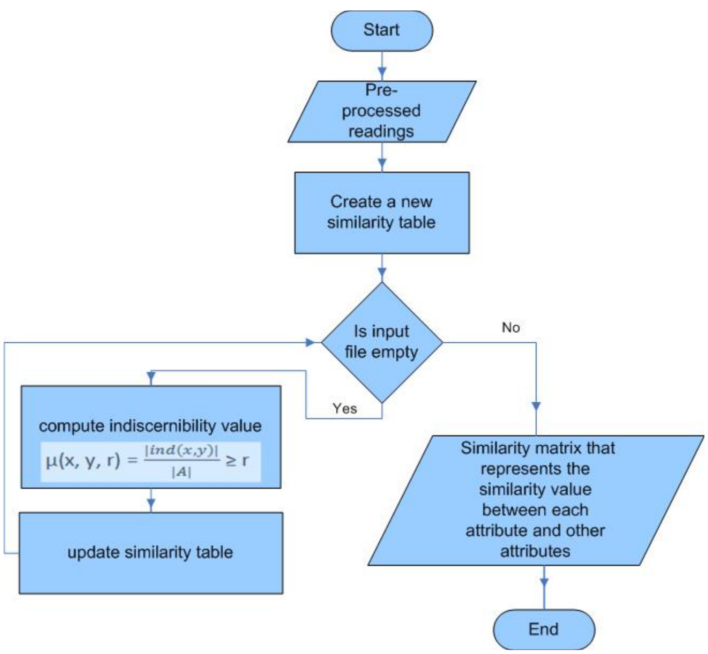

Fig. 5: Rough Mereology recommendation phase

D. Predict Set of Recommendations(Classification)

This paper applies the same methodology of [12], that in order to get the top-N recommendation it uses three prediction equations (Equation 5, Equation 6, Equation 7) and compute the recommendation value obtained from each equation.

The general item-based prediction is presented by Equation 1; that for a user-item pair (u, i) the prediction is composed of a weighted sum of the all $u's$ ratings for the item most similar to i [13], where the $itemSim(i, j)$ is obtained from the Pearson Correlation Coefficient alias Adjusted-Cosine Similarity [13].

$$pred(u, i) = \frac{\sum_{j \in ratedItems(u)} itemSim(i, j).r_{ui}}{\sum_{j \in ratedItems(u)} |itemSim(i, j)|} \quad (5)$$

Equation 6 [14] represents the use of recommendation agent that receives the similarity symmetric table from another matching agent and the collected readings and compute the recommended value for decision attribute. The $sim(i, j)$ represents the computed similarity value that performed by the matching agent of attribute i to another attribute j.

$$pred(u, i) = \frac{\sum_{j \in ratedItems(u)} (sim(i, j).r_{ui})}{\sum_{j \in ratedItems(u)} (sim(i, j)} \quad (6)$$

While equation 7 represents prediction rate in the weighted sum form [14], where $pred(u, i)$ represents the predicted vote for item i calculated for reading u, $\overline{r_u}$ the average rating of the collected readings.

$$pred(u, i) = \overline{r_u} + \frac{\sum_{j \in ratedItems(u)} itemSim(i, j).(r_{ui} - \overline{r_j})}{\sum_{j \in ratedItems(u)} (itemSim(i, j))} \quad (7)$$

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The pre-processed data is sent to an intelligent multi-agent recommender system model [12] in order to evaluate the classification quality of the proposed framework. Evaluation criteria is mainly based on the computation of both the recall and precision statistical equations (Equation 8 and Equation 9 [15], respectively). Statistical precision measurement method adopts the MAE (Mean Absolute Error) in order to measure the recommendation quality [16]. MAE is a commonly used recommendation quality measurement method. MAE calculates the irrelevance between the recommendation value predicted by the speed bump's recommender system and the actual evaluation value. Each pair of interest predicted rank is represented as $< pi; q >$, where pi is the system predicted value and qi is the user evaluation value. Based on the entire set of $< pi; q >$ pairs, MAE calculates the absolute error value $|pi - qi|$ and the sum of all the absolute error value; see equation 10.

$$Recall = \frac{\#of \ correct \ positives}{total \ \#of \ positives} \quad (8)$$

$$Precision = \frac{\#of \ correct \ positives}{\#of \ correct \ positives + \#of \ false \ positives} \quad (9)$$

$$MAE = \frac{\sum_{i=1}^{N} |p_i - q_i|}{N} \quad (10)$$

Through the manual annotation of bump places we recognized that it is always lies in the gyroscope readings in [10, 30] degrees.

TABLE I: Accuracy indication

	speed bump	Not a speed bump
Positive	300 (True Positive)	1523 (False Negative)
Negative	98 (True Negative)	199 (False Positive)

According to classification rates obtained in Table 1, the precision of rough mereology in speed bumps classification reached to 0.754, while the recall statistical evaluation reached 0.165. Therefore the rough mereology as a classification algorithm provides total accuracy equals 75% with MAE= 8.36%.

Classification based on rough mereology does not provide promising results as the work of [8], but on the other hand, it still produces better results than the one obtained in [7]

V. Conclusion and Future Directions

Usually sensory-based smartphones offer opportunities to build useful applications. For maximizing the benefits of these opportunities, this paper represents a framework of an application for monitoring road surface conditions in terms of speed bumps. A pre-processing phase was applied on the collected readings. Although previous road monitoring algorithms apply common classification techniques, this paper tries to evaluate the existence of speed bumps along the road using rough mereology theory. The classification accuracy was not as expected but it reached to a satisfactory value. As a future work we aim to improve the speed bumps' detection algorithm through trying other machine learning classifiers.

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