MONITORING ROAD SURFACE ANOMALIES TOWARDS DYNAMIC ROAD MAPPING FOR FUTURE SMART CITIES

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Abstract — **The development of Smart Cities aims to transform city infrastructures and services through the use of information and communication technologies. One aspect of Smart City applications is the demand for more efficient and safe transportation systems. Specifically, road anomalies are some of the challenges that contribute to the increase in vehicle damage and decrease in driver safety. In this paper, we propose a road surface condition monitoring system that utilizes low cost MEMS acceleration sensors and GPS receivers within a tablet to detect and localize road surface anomalies. Several types of road information data were collected, analyzed, and processed using statistical and time domain analysis for feature extraction of the various events. We also propose a multi-level decision-tree classifier to precisely distinguish between the events. In addition, the use of the tablet sensors to localize the monitored events is discussed.**

Keywords— Smart cities, intelligent transportation systems, road information monitoring, intra-vehicle sensing, statistical and time domain analysis

I. INTRODUCTION

In light of the increase in global urban population, the demand to maintain organization, accessibility, and efficiency is prompting many cities around the world to implement smarter management systems [1]. A Smart City is an urban system that integrates information and communication technologies (ICT), and Internet of things (loT) technologies to ensure its public services and infrastructure are functioning accordingly [2]. Specifically in infrastructure, the expected growth in urban populations in the next few decades will lead to an increased need in efficient and smart transportation systems [3].

In the current technological era, the aim to develop smart transportation systems that processes data and uses applications to eliminate challenges and encourage sustainability is underway. A development that led to intelligent transportation systems (ITS) intends to save time, money, and energy on an economic, environmental, and social scale [4]. Specifically, ITS involved in detecting road conditions and driver behavior aims to provide a link between people and their vehicles [5, 6].

Clearly, surface road anomalies contribute to a decrease in driver safety and comfort, and an increase in traffic accidents and vehicle damage [7]. Poor road conditions, commonly potholes, manholes and cracks can produce costly consequences. For instance, in 2015 it was estimated that the cost of repairing broken vehicle parts in the United States cost an urban driver between five hundred to one thousand dollars [7, 8]. Similarly, in 2016, the Canadian Automobile Association (CAA) took data from two thousand drivers over five years, and it was estimated that potholes alone cost Canadians $1.4 billion a year [8]. Formerly, authorities monitored the road surface conditions utilizing specific instrumentation merged with simulation software. In addition, manual reporting was adopted as well [9, 10].

On the other hand, the evolution of smart phones and tablets led to their inclusion in the new ITS. The increased number of sensors and the computational capabilities of smart phones and tablets make them suitable to participate in various crowdsensing applications, specifically ones that are used in road information services [5, 11].

Recently, smartphones and tablet devices were used in monitoring and assessing road conditions in the context of building dynamic road mapping that could benefit authorities, road operators, and drivers as well. The current generation of these smart devices is equipped with numerous sensors such as GPS, accelerometers, gyroscopes, magnetometers, barometers and others. Consequently, saved data can be analyzed and processed in order to give valuable information about road conditions and anomalies. In [12], multiple smart phones are utilized in the detection and classification of potholes and drain pits. A 3-axis accelerometer and a GPS receiver were used in anomaly detection and localization. Yi in [5] proposed a system that used a smartphone vertical accelerometer and GPS receiver in detecting and localizing road anomalies. An anomaly indexing algorithm was developed to detect speed bumps, manholes, potholes and deceleration lines. However, the proposed algorithm showed significant results in speed bump detections only. In [13], based on predetermined thresholds, the transverse and vertical accelerations of a smartphone were used together to detect road surface conditions with a data rate of 25-30 Hz. The conditions were classified into four classes: bumps, potholes, rough, and smooth, achieving an overall accuracy of 85.6%. The smartphone GPS receiver was used for event localization. RoADS system proposed in [14] used the smartphone's 3-axis accelerometers and gyroscopes to categorize road anomalies into three groups of severe, mild, and span anomalies achieving an average accuracy of 91%. Road anomaly detection systems based on analyzing the vertical acceleration of multiple smartphones mounted on land vehicles was proposed in [15]. A machine learning technique was adopted to detect whether a land vehicle attended a road anomaly, with an accuracy of 70%. In addition, a GPS receiver was used for localizing the monitored anomalies.

Smartphone based systems proposed for detecting and localizing road surface conditions and anomalies lack the ability of being comprehensive systems. These systems focused on describing only one type of anomaly or simply presented general classifications for anomalies based on similarities in their behaviors without distinguishing events from each other [14]. In addition, some systems utilized low data rate sensors which are insufficient for capturing certain features that classify multiple anomaly types [13]. Furthermore, the entire smartphone based road surface monitoring system relied on GPS for localizing the monitored anomalies, which is not sufficiently accurate due to error at high speeds or in urban canyons. Considering GPS signal blockage and multipath, localization errors are dramatically increased in downtown cores and urban areas [16-18].

In this paper, we propose a system that adopt tablet based low cost MEMS accelerometers for monitoring road surface conditions and its embedded GPS receiver for localizing the monitored events. Consequently, to build and assess the system capabilities, we utilized 3 land vehicles to perform more than 25 road trajectories that span multiple road surface conditions and anomalies. In addition, we provide feature extraction techniques using statistical, time and frequency domain analysis. Based on the extracted features, we propose a simple tree-classifier to identify the type of the detected anomaly. This proposed classifier enables the detection of various types of anomalies such as smooth road, potholes, manholes, transverse cracks, decelerating strips, and railroad crossings. In this context, we present and compare the performance of the proposed system over the sensed data using the tablet and integrated navigation system running at 100 Hz and 20 Hz respectively. Highlighting the localization accuracy, we provide results and discuss the capabilities of the tablet and integrated navigation systems in localizing the detected events at a data rate of 1 Hz. This proposed road anomaly monitoring system leads to distinguishing and localizing multiple anomaly types.

II. METHODOLOGY AND SYSTEM CONFIGURATION

In order to design a durable road anomaly monitoring system we considered many aspects. Firstly, as shown in Figure 1.

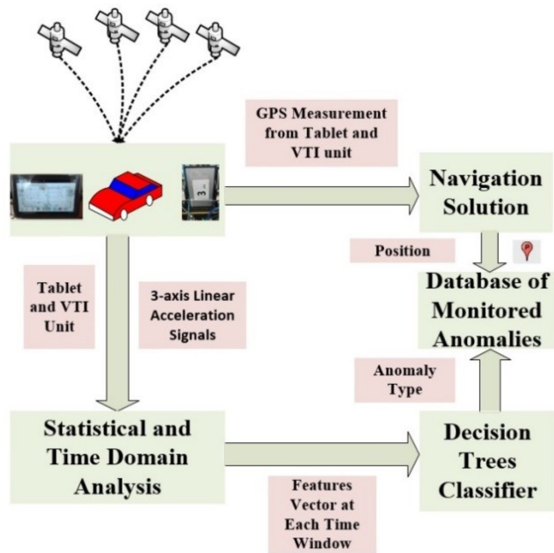


Figure 1: Road surface anomalies proposed monitoring system.

The linear acceleration data of the tablet was collected at the fastest rate, which is approximately equal to 100 Hz. Also, for assessing the tablet capabilities for anomaly localization we used an integrated positioning unit to compare the performance of them together. After the data was collected, extensive statistical and time domain analyses were carried out at each time window of 1 second. Consequently, based on the gathered features we adopted a simple and efficient decision-tree classifier to determine the type of anomaly detected. As a first classification step, we classify the road condition into two classes: smooth road driving and anomaly road driving. Afterwards, based on the nature of the event, we classify the anomalies into two sub-classes: single sided or double-sided event. Single sided anomalies (potholes and manholes) are attended by either the right wheels or the left wheels of a land vehicle, while double sided events (transverse cracks, deceleration strips, and railroad crossings) are attended by all 4 wheels of a land vehicle. Each sub-class has also been subdivided to distinguish each road anomaly from the others. The detection, classification, and sub-classification of road anomalies are held based on multiple extracted features for each event. Features include peak-to-peak thresholds, RMS, standard deviation, variance, normalization of the 3-axis linear acceleration, zero and threshold crossing rates, and cross correlation between the vertical and transversal linear acceleration. Once an event is detected and classified, a GPS based location is labelled to each event. Finally, a record of the detected and localized event is used to update a database that maintains the event type and location.

III. Experimental Analysis and Results

A. Experimental Setup and Trajectory Planning

In this section, we describe the equipment and the approach used in our trajectories. Through the multiple sensors shown in Figure 2, to assess our proposed system we utilized a Samsung Galaxy Note GT-N8010 Tablet, VTI integrated positioning unit developed by Trusted Positioning Inc., and MiVue 388 Dash Cam. For the tablet, we used its MEMS grade LSM330DLC 3-axis accelerometers at an approximate data rate of 100 Hz for trajectories involving linear acceleration data collection. In addition, we used the built-in GPS receiver of the tablet for positioning and localization. The VTI integrated positioning unit was adopted at a data rate of 20 Hz and it was used for data collection and providing an integrated navigation solution for the trajectories. Moreover, we used the camera for marking the ground truth of the attended anomalies through the recorded trajectories.

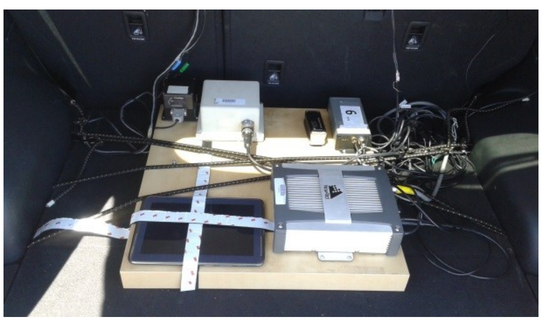


Figure 2: Testbed mounted in one of the land vehicles utilized for 25 trajectories.

For the trajectory planning, we used the previously mentioned setup for holding more than 25 trajectories. In these trajectories, we utilized one sedan Nissan Sentra and two crossover SUVs (Toyota Venza and Hyundai Tucson). The position of the testbed was placed in different spots through the three car models used (on the front passenger seat, in the trunk, and at the center of the car). In the trajectories, we attended multiple roads in Kingston, ON, Canada that spanned various road types and anomalies. Some of the trajectories were used in building the proposed anomaly detection system and the others were adopted for the system testing purposes.

B. Results and Discussion

To assess the capabilities of our proposed system, we used the experimental setup explained in section III. A for more than 25 trajectories. The most significant road anomalies detected were the manholes, potholes, transverse cracks, railroad crossings, and deceleration strips. The orientation of the tablet and VTI unit were aligned with the vertical linear acceleration in the +Z direction, the longitudinal and transverse linear accelerations in the +Y and +X directions, respectively. However, the data collected from the tablet was only used for building and assessing the event detection portion of the road monitoring proposed system. The comparison between the tablet and VTI data from multiple road anomalies and conditions showed that the VTI data lacks rich features, which can be used to identify and classify each event. This is because of the lower resolution of the VTI unit (20 Hz). Figures 3 and 4 show the 3-axis linear acceleration for the tablet and VTI unit during a severe pothole event. Statistical and time domain analysis showed that there are many distinguishing features that can be extracted from the tablet data for each anomaly type.

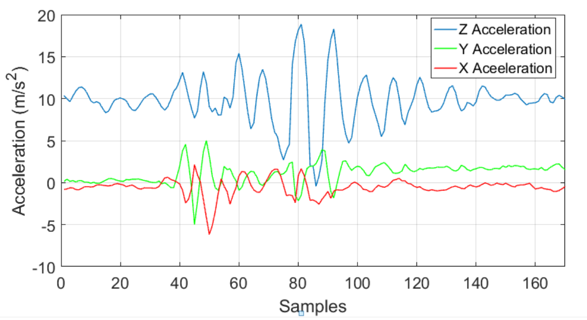


Figure 3: 3-axis linear acceleration of the (**tablet**) data during a (**pothole**) driving event.

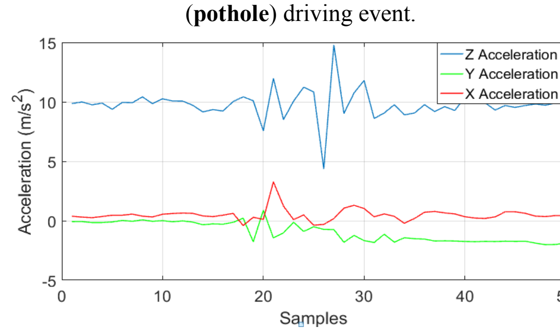
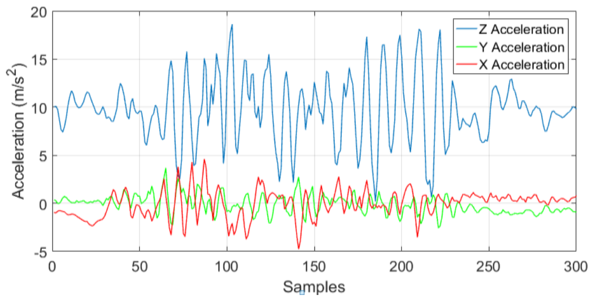


Figure 4: 3-axis linear acceleration of the (**VTI**) data during a (**pothole**) driving event.

Some data sets collected from the trajectories were used for building the detection algorithm, and others were used for testing it. A total of 68 events and anomalies were attended for the training trajectories using the previously mentioned 3 land vehicles. The attended anomalies are 32 manholes, 18 potholes, 6 deceleration strips, 3 railroad crossings and 9 transverse cracks. The motivation behind using multiple land vehicles and trajectories is that the driver is not attending the same events with the same behavior and speed every time. Also, vehicles' model and size affects the behavior of the anomaly over the sensed acceleration data which creates challenges in anomaly detection. The highest accuracy achieved is 100 % true positive of the railroad crossing. This is due to the significant behavior of the anomaly over the acceleration data as shown in Figure 5. The lowest accuracy achieved is 66 %, which is achieved by the deceleration strips as sensing such anomaly might be mixed with smooth road driving for big-wheeled land vehicles.

Figure 5: 3-axis linear acceleration of the (**tablet**) data



during (**railroad crossing**) driving.

Across 68 attended events, the anomaly detection and classification algorithm was able to successfully detect and classify 59 anomalies achieving average accuracy of 86.7 % of true positives. The main reason for not detecting an event is because some larger land vehicles are more stable and do not vibrate as much through certain types of anomalies. Regarding wrong event classifications, some anomalies have similar behaviors over the sensed acceleration data or due to how the event is attended. Typically, potholes and manholes are often confused. Likewise, transverse cracks and deceleration strips can be mistaken for each other as well. The presented results show higher average accuracy by approximately 17% than the results in [15]. In [19], the average true positive rate achieved was 85%, however, they only classified the monitored anomalies into “safe” or “dangerous” events. Such classification lacks description of the nature of the monitored events. “Roads” presented in [14] classified events into severe, mild and span classes achieving a true positive rate of 91% but they also lack the highly detailed classification of road events.

Table 1: Types of attended anomalies and their corresponding True Positives, False Positives, and False Negatives.

Anomaly Type	Number of Attended Anomalies	True Positive	False Positive	False Negative
Manhole	32	28	4	4
Pothole	6	6	0	1
Paved Pothole	12	10	2	2
Deceleration Strip	6	4	2	2
Rail Road Track (two adjacent tracks)	3	3	0	0
Transverse Crack	9	8	1	2

Considering robust monitoring for road anomalies, an efficient and adequate localization for each anomaly should be present. In our proposed system, we utilized the embedded GPS receiver of the tablet and the integrated navigation solution provided by the VTI unit. Both systems provide localization of the monitored events at a data rate of 1 Hz. Figure 6 shows the navigation solution of both systems in an urban area of Kingston, ON, Canada.

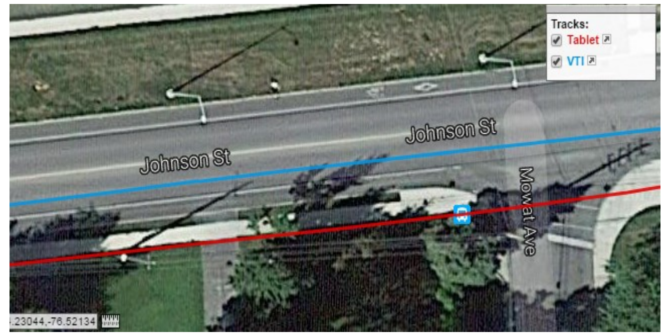


Figure 6: Navigation solution for the tablet (red) and VTI (blue).

The solution of the integrated positioning system of the VTI (blue) provides a better solution than the one provided by the tablet’s GPS receiver (red). In the case of the VTI unit, the solution is continuous and within the right lane of the street, while the tablet solution drifts out of the street leading to increased errors in localizing the monitored events. In addition, for downtown and urban cores, the land vehicle speeds can reach 50 km/h, such speed can limit the localization resolution to approximately 14 meters. This resolution is not sufficient for precisely localizing the road anomalies, as in 14 meters many anomalies could be present specifically in deteriorated roads. In order to ensure rigorous and robust localization, integrated positioning systems should be adopted at higher data rates to assure solution continuity and higher localization resolutions.

IV. Conclusion

In this paper, a road surface condition monitoring system was proposed and presented. The data of 25 trajectories were collected using a tablet and VTI unit utilizing three land vehicles across Kingston, ON, Canada. A feature extraction technique using statistical and time domain analysis was used at each time window to provide sufficient descriptions of each type of road anomaly. Also, a decision-tree based classifier was adopted to precisely classify each monitored event achieving an average accuracy of approximately 87% of true positives. In addition, with the aid of the GPS receiver and integrated positioning system, a location was labeled for each monitored event with updates to a database of the monitored events. Ultimately, this system maximizes benefits for the developing ITS, enabling dynamic mapping for the roads of future smart cities.

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