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Design and Implementation of a Vibration-Based Real-Time Internet of Things Framework for Road Condition Monitoring

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ABSTRACT This paper presents a study on the design and implementation of a real-time Internet of Things (IoT) framework for monitoring road conditions. The proposed system incorporates an accelerometer sensor attached to the rear axle of a vehicle to capture vertical acceleration signals resulting from the interaction between the vehicle suspension system and the road surface. These acceleration signals are utilized to determine vertical displacements, which are then used to calculate the International Roughness Index (IRI) as an indicator of road quality. The system comprises a hardware node for acquiring acceleration signals and a remote monitoring system for calculating and visually representing the IRI on a road map. Our results demonstrate that the proposed system is effective in automatically assessing road conditions, with an error in the calculated IRI of less than 3.5%

INDEX TERMS Internet of Things (IoT), road condition assessment, cellular internet, IRI.

I. INTRODUCTION

The modern economy depends on the presence of a robust transportation network as one of its pillars. Any degradation in the roads condition results in a negative impact on the state economy as well as the citizen daily life quality. The low road quality may result in many bad consequences. The severity of car accidents and overall number of casualties are directly related to road low quality conditions. In terms of financial cost, it's estimated that more than 31% of all crash costs are associated with the bad road conditions [1]. According to a report by the American Automobile Association (AAA), one in every ten vehicles sustained a significant damage after hitting a pothole in 2021. The cost of repair per vehicle is around $600 on average with a total cost of around $26.5 billion [2].

Accordingly, highway authorities focus on enhancing the roads pavement quality to reduce car accidents and casualties associated to road quality and to improve driving experience in general. However, without road quality monitoring system, road maintenance is difficult and of less efficiency. One requirement to maintain the roads in an appropriate condition is to utilize a timely monitoring process that enables the road authorities to detect any degradation in the road quality in its initial stages and, thus, allowing them to take measures to reduce or mitigate the negative effect of bad roads and reduce the cost of repair. Also, it is important to have a standard reference to measure the road quality. A commonly used metric is the International Roughness Index (IRI) [3], [4], [5] which is developed by the World Bank as a road quality indicator. The IRI value indicates the road profile status by calculating the vertical displacements in a defined horizontal road segment. Higher value of IRI means that the road surface is not smooth, for example, due to the presence of road anomalies (pathole, bump...etc) or duo to degradation in the quality of pavement.

The IRI measuring techniques can be classified into 4 different classes. Class I is the most accurate one and depends on accurately measuring the elevations at closely spaced points. This class uses several methods, e.g. dipstick, road and level and walking profiler. Although considered to have a highest accuracy, it requires intensive labor work and time. Class II utilizes contact-less measurement techniques such as a laser profile-meter mounted in a vehicle [6], [7]. While this class can cover a larger area, it requires expensive equipment and skilled labor to operate, and its accuracy is lower than that of Class I. Class III (A.K.A Response-based class) depends on measuring the accumulated suspension motion resulting from the interaction between the vehicle and the road. Class III is considered less accurate than the previous two classes, however it requires less complex equipment (transducers such as accelerometers or Inertia measurement Units). Finally, Class IV has the lowest accuracy and gives a qualitative measure of the road condition based on user perception of the ride or visual inspection.

Recently, with the enhancement in electronic devices and the Microelectromechanical system (MEMS) sensors new alternatives for the road profiler vehicle and other costly systems have been found. MEMS accelerometers with high accuracy can be affixed to moving vehicles to record vertical acceleration resulting from the interaction between the vehicle suspension system and the road surface. The vertical displacement can then be calculated from the acceleration signal, using either MEMS accelerometer sensors found in smartphones or dedicated MEMS accelerometers with their processing circuit.

In addition, the current trend of equipping sensor nodes with fully functional internet connectivity has enabled the implementation of fully automated systems based on Internet of Things (IoT) technology in various fields. In such systems, collected signals are automatically transmitted over the internet to a remote server for further analysis. This approach eliminates the need for manual data offloading to the processing platform and eliminates the need for a dedicated operator.

This paper presents an automated system for Road Condition Monitoring (RCM) utilizing IoT technology, with the International Roughness Index (IRI) as the quality indicator. The proposed measuring technique falls in the Class III (response type) category described before. In our approach MEMS accelerometer is affixed to the vehicle's rear axle to capture acceleration signals resulting from the interaction between the road surface and the suspension system. This approach eliminates the influence of the suspension system on shock absorption, resulting in a more accurate estimation of vertical acceleration. The accelerometer is connected to an IoT node based on an STM32F07 ARM microcontroller, equipped with a Global Positioning System (GPS) module and a Long-Term Evolution (LTE) cellular internet module (A.K.A 4th generation cellular communication). The cellular data network provides an infrastructure-less internet connection suitable for the proposed system. Acceleration signals along the three axes, vehicle speed, and location information are transmitted to a monitoring server for storage and IRI calculation. The server visualizes the IRI values in real-time on a Google MAP. The paper details the design of the IoT nodes, the IRI calculation algorithm, and the server architecture. The system's validation includes testing against a scaled road segment with a known surface curvature and real-world scenarios. **The contributions of the paper can be summarized in the following points**:

- Propose a fully automated IoT based response type IRI calculation system.
- Design and manufacture an IoT node responsible of collecting and transmitting the acceleration signal.
- Design and implement a cloud-based server responsible of saving the acceleration signal, calculating the IRI for a given road segment, and visualize the values of the IRI on google map.
- Validate the calculation method using a scaled road model with known IRI value.

The rest of the paper is organized as follows: First, we review the related work in IoT based Road condition monitoring (RCM) systems in Section II. In Section III presents the theoretical background for IRI calculation and the related work. In Section IV we present the IoT node and monitoring server design. In Section V we present the monitoring server design. The system is validated in Section VI. In Section VII we present the practical experiment setup and the results. Finally, the paper is concluded in Section VIII.

II. RELATED WORK

In this section, we review the techniques used to assess the road condition by calculating the values of the IRI, focusing on the class III (response type) based measurement systems. Due to the lack of the standard reference IRI values which makes the accuracy comparison between different techniques not feasible. The rod-and-level survey technique was first used to calculate the IRI values. This comes in the form of a beam which had a vertical displacement transducer to measure the vertical displacement (hence named Dipstick Profile) and the rod and level techniques. This technique has been acknowledged as a precise and reliable technique and serves as a benchmark for other methodologies [8]. Nevertheless, the deployment of the Dipstick Profile incurs considerable expenses in terms of labor and time. With the advance of sensor and electronic circuits, an automatic profiler for road assessment has been widely used. In these profilers, the dipstick is replaced by a suit of distance sensors like ultrasonic, laser sensor or accelerometer sensor. The profiler comes in the shape of a customized vehicle with onboard computer for data collection and processing [6], [7]. However, such vehicle based profiler considered a costly solution which is only affordable by local authorities. Other affordable approaches depend on photogrammetric technique in which a laser module (or more) is used to mark independent points that can be detected by image processing algorithms to construct a road profile which is used to calculate the road IRI values [9]. Another technique used by the road profiler is to measure the vertical distance form the moving vehicle and the road surface using ultrasonic sensors, which provide a low-cost alternative to other techniques [10]. Depth sensors are also used to estimate the road condition through calculating the value of the IRI from a reconstructed road image. Mahmoudzadeh et al. [11] developed a low cast IRI measurement system where inexpensive RGB-D sensors. The constructed 3D road profile was used to calculate the IRI where an acceptable accuracy was achieved when compared to the standard rod and level technique. Light Imaging, Detection, and Ranging (LiDAR) [12], [13], [14] technology has been recently used to calculate the IRI for a defined segment of the road. The LiDAR sensor is used to construct a a 3D profile for the road segment which can be used to calculate the IRI value of the target road segment.

The vibration-based RCM systems utilize accelerometer sensors to capture the acceleration that occurs during the moving of a vehicle over the targeted to assess the road surface condition. The RCM systems can be categorized into two main categorizes. The first one depends on detecting and identification of road anomalies like pothole, speed bump, crack...etc. These systems utilize the acceleration signals resulting from the interaction between the road surface and the vehicle suspension system to identify the footprints of different road anomalies [15]. The other approach is to use the acceleration signals to calculate a quantitative index (the IRI) that describes the general road condition [5]. Here, our review will focus on the latter approach of calculating the IRI as a road condition index.

Fortunatus et al. [16] compared the performance of a standard inertial profiler with that of Roadroid [17], a smartphone-based application, in estimating ride quality of concrete pavement. While Roadroid underestimated IRI values, there was a linear correlation between IRI measurements obtained from both methods. Aleadelat et al. [18] utilized smartphone accelerometers to obtain acceleration data and applied basic signal processing and pattern recognition techniques to establish a correlation between the measured data and the IRI). This validates the use of variance in acceleration measurements obtained from smartphone sensors for determining IRI. Souza et al. [19] proposed a system for monitoring asphalt pavement quality by treating accelerometer sensor data collected from smartphones as a multi-dimensional time series classification problem. The proposed approach achieved high classification accuracy. Christodoulou et al. [20] introduced a new technique utilizing vibration sensors and smartphone images with the assistance of Artificial Intelligence (AI). The study found that the vibration-based method was effective but not comprehensive enough to cover the entire roadway or detect pavement anomalies not caused by vibrations. To address this, vision-based methods were incorporated into the technique. Rana et al. proposed RCM system that utilizes vibration analysis and considers vehicle suspension and pavement profile reconstruction to calculate IRI. The practical experiments shown promising results in field testing with reasonable accuracy and efficiency.

ALQaydi et al. [21] developed a smartphone application to measure IRI by utilizing low-cost smartphone accelerometer data and incorporating vehicle speed and type, which showed a reasonable correlation with measured IRI data collected using profiler vans.

Chatterjee et al. [22] developed a RCM technique that utilizes 3D pavement data to train Machine Learning (ML) models on low-cost vehicle-mounted smartphone sensor data. The model generates distress values as outputs, which can be utilized for estimating the value of the IRI. The effectiveness of the technique is supported by a high correlation peak between IRI estimations produced from multiple runs along the same route. Shohel et al. [23] proposed a method to determine the IRI of a pavement surface using conventional vehicles and smartphones by employing the grey box model algorithm and the quarter-car vehicle model. The results demonstrate that smartphones can be used to determine pavement IRI with reasonable accuracy An algorithm was developed by Zhang et al. [24] to calculate the International Roughness Index (IRI) using acceleration values obtained from smartphone sensors. This algorithm also identified physical parameters associated with a quarter-scale vehicle model and established a relationship between acceleration, IRI, and profile elevation. It was observed that incorporating dynamic characteristics of vehicles improved the accuracy of this method for measuring road conditions. Most of the Previous research studies have utilized the smartphone sensor suite, including the accelerometer and Inertial Measurement Unit (IMU), for the collection of acceleration signals and their transmission to a monitoring platform. However, the vertical displacement determined from the acceleration signal obtained from the smartphone sensor does not accurately reflect the actual displacement resulting from the interaction between the car wheels and road surface. This discrepancy is due to the placement of the smartphone, which is typically located on or within the car dashboard. This location places the vehicle suspension system between the accelerometer and wheel, resulting in absorption of much of the vibration caused by interaction between vehicle and road surface. Consequently, calculated IRI values are generally lower than actual values [5]. Furthermore, the acceleration signals captured by the smartphone are contingent upon the position and orientation of the device, thereby diminishing the dependability and consistency of the recorded data.

To overcome this challenge, other techniques utilize dedicated sensors attached directly to the vehicle suspension systems, and connected to stand alone processing unit [5], [25], [26], [27]. Tomiyama et al. developed a vibration-based RCM where two piezoelectric accelerometers are affixed to the car suspension system. The accelerometers are connected to an onboard computer through a transducer where the IRI values are calculated. The measurements obtained from this method are compared with those obtained from a standard profiler vehicle. Eshkabilov et al. [27] conducted a validation study of an accelerometer-based RCM system by comparing the IRI values derived from high-precision accelerometer data collected from the front axle of a vehicle to those obtained via the standard rod and level method for a specific road segment. The primary objective of [25], [27] investigation was to assess the accuracy of the vibration-based RCM, rather than developing an automated IRI calculation system. In [26], Du et al. developed a regression method to model the variation in the z axis, resulted from the interaction between the road surface and the vehicle suspension system, and the value of the IRI for a defined road segment. To enhance the accuracy of the proposed model, several accelerometers are affixed to the rear wheels of a mobile vehicle. The acceleration data, along with location details, are conveyed through a Zigbee module to a data processing software, which applies the regression model to estimate the IRI value. AbdelRaheem et al. developed a drive-by IRI measurement and visualization technique using both dedicated accelerometer attached to the car rear axle and on board smartphone. The dedicated accelerometer is attached to an onboard processing and communication node. Two different designs were proposed; the first used Raspberry Pi 3 Model B (RPi) single board computer and 4G cellular Internet Universal Serial Bus (USB) stick while the second used ARM STM32F104 microcontroller and a cellular Internet developing board along with GPS module in both approaches. The data were relayed to a remote server where the values of the IRI were calculated and visualized.

Notwithstanding the fact that these systems overcame the precision issue encountered in smartphone-based methods, they exhibit an incomplete automation feature whereby the gathered data are either preserved in an onboard computer or necessitate manual transfer to the processing server for further evaluation. The present study introduces an initial design aiming at addressing the challenges encountered in vibration-based RCM systems. The proposed solution is a fully automated IoT-based vibration-based RCM system that minimizes operator intervention while facilitating automatic transmission, storage, and calculation of the International Roughness Index (IRI) for visualization on a server. Additionally, the proposed system is well-suited for crowd-sensing and can be readily deployed on a fleet of buses or other types of vehicles to achieve maximum coverage of roadways.

III. INTERNATIONAL ROUGHNESS INDEX (IRI)

In this section, we present a background on road monitoring systems and the calculation model of the IRI used in our experiment.

The IRI is adopted by the World Bank as a standard indicator for road roughness. The vertical displacement of the road profile of a defined horizontal road segment gives the IRI value in this segment in unit of m/km. As mentioned before, road profiler may be used to measure the IRI. However, this is not always efficient given the cost and the availability of this solution. Alternatively, the acceleration signals generated from the interaction between the road surface and the moving vehicle which is acquired using accelerometer sensor can be used to calculate the vertical displacement of the road and then used to calculate the IRI [5], [28]. Moreover, the pattern of the acceleration signal can be used to detect and classify different road anomalies, including cracks, potholes and speed bumps [15], [29], [30], [31].

The IRI is calculated by summing the vertical road segment profile (distance in the z axis) and dividing it by the segment length. For a road profile shown in Fig. 2, if the sampling time instant t_x where $x \in 0, 1, 2, \ldots, n$, the vertical displacement v_{h_x} between samples $x-1$ and x is calculated as:

$$v_{h_x} = |h_x - h_{x-1}|. \tag{1}$$

The IRI for this road profile is calculated as

$$IRI = \sum_{x=1}^{N} \frac{v_{h_x}}{d}, \tag{2}$$

where d is the target road segment length, and N is the number of samples.

To calculate the IRI, it is required to calculate the vertical displacement at each sampling instant and the travel distance between the time samples. Here, we adopt the IRI calculation model used in [28].

A. VERTICAL DISPLACEMENT CALCULATION

The acceleration a along the three axis (x, y, z) are measured using the accelerometer. The vertical displacement for the road segment d between samples $(0, n)$ can be calculated as follows:

$$V_h = \int_t \left(\int_t |a_v| \, dt \right) dt \tag{3}$$

and hence

$$IRI = \frac{\int_t \left(\int_t |a_v| \, dt \right) dt}{d}. \tag{4}$$

B. TRAVEL DISTANCE CALCULATION

The distance between two points p_1 and p_2 can be calculated from the longitude and latitude coordinates obtained from the GPS using the Haversine formula as shown in (5) at the bottom of this page, where ϕ_1 and λ_1 are point p_1 latitude and longitude respectively while ϕ_2, and λ_2 are those of point p_2 and R is the Earth's radius.

C. PRACTICAL CONSIDERATION IN IRI CALCULATION

The basic elements of the IRI computing model are the accumulative vertical displacement values from the longitudinal profile and the overall distance (road segment) of the measurement as shown in (4). The recorded data from accelerometer sensors are discrete samples (accelerations along three axes

$$d = 2 \cdot R \cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + \cos(\phi_1) \cdot \cos(\phi_2) \sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right) \tag{5}$$

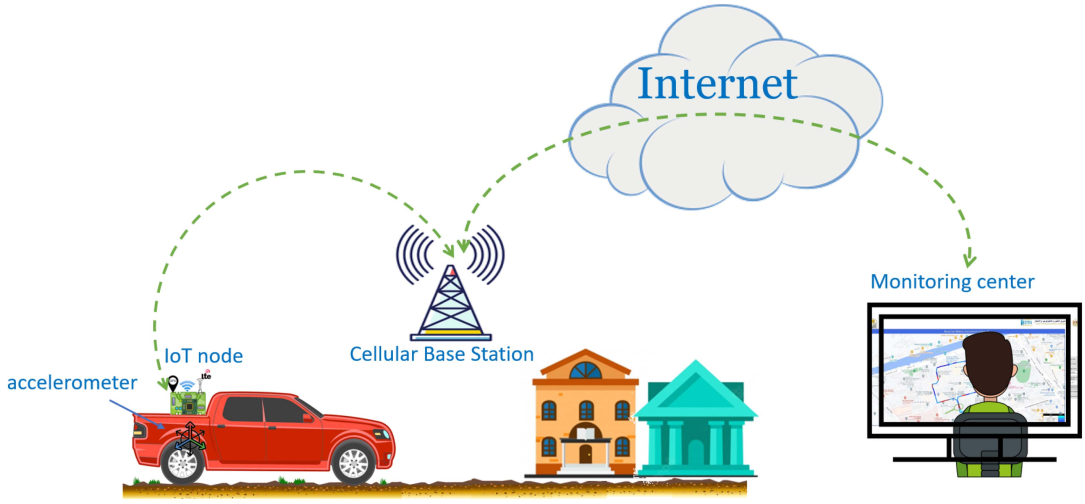


FIGURE 1. Proposed system overview.

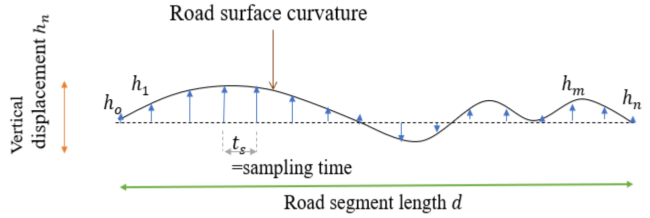


FIGURE 2. IRI calculation.

a_x, a_y and a_z) with sampling time interval dt. Because of the non-perfect sensor alignment, the vertical acceleration (a_v) may appear in all directions of the tri-axial acceleration data recorded. Therefore, the Z-axis acceleration data from the accelerometer cannot be considered the only component of the vertical acceleration. In the acquisition process, and as suggested by [28] we set the system to start recording acceleration data in the normal position, and is kept stationary for more than 5 sec. When the car is stationary, the acceleration data is corrected so that the acceleration is only along Z-axis with a value equals to 1 g (g is gravity acceleration) according to the following:

$$\overline{A_x} \cdot \overline{A_x} + \overline{A_y} \cdot \overline{A_y} + \overline{A_z} \cdot \overline{A_z} = 1 \tag{6}$$

Where $\overline{A_x}$, $\overline{A_y}$ and $\overline{A_z}$ are the average values of the acceleration signal in the x, y, and z axes in the first five seconds. The vertical acceleration (a_v) can be driven from any tri-axial acceleration output A $= (A_x, A_y, A_z)$ by projecting the vector A onto the reference vector $\bar{A} = (\overline{A_x}, \overline{A_y}, \overline{A_z})$, acquired at the beginning of the sampling process. This can be expressed mathematically as:

$$\alpha_v = \frac{A \cdot \bar{A}}{|\bar{A}|} = \frac{A_x \cdot \overline{A_x} + A_y \cdot \overline{A_y} + A_z \cdot \overline{A_z}}{\sqrt{\overline{A_x} \cdot \overline{A_x} + \overline{A_y} \cdot \overline{A_y} + \overline{A_z} \cdot \overline{A_z}}}, \tag{7}$$

$$\alpha_v = \frac{A \cdot \bar{A}}{|\bar{A}|} = A_x \cdot \overline{A_x} + A_y \cdot \overline{A_y} + A_z \cdot \overline{A_z}. \tag{8}$$

TABLE 1 IRI Values Classification and Visualization Colors

IRI range	Description	Color code
IRI < 0.7	Very Smooth	
0.7≤ IRI < 1.5	Smooth	
1.5≤ IRI < 3	Fair	
3≤ IRI < 5	Rough	
5≤ IRI	Very Rough	

The vertical acceleration (a_v) should be calculated for each acceleration sample, after that we can calculate the vertical displacement V_h using numerical integration of the vertical acceleration (a_v) according to summation trapezoidal integration as follows:

$$\int_a^b f(t)dt \approx \sum_{k=1}^{N} \frac{f\left(t_{k-1}\right) + f\left(t_k\right)}{2} \Delta t_k, \tag{9}$$

where

$$\Delta t_k = \left(t_k - t_{k-1}\right).$$

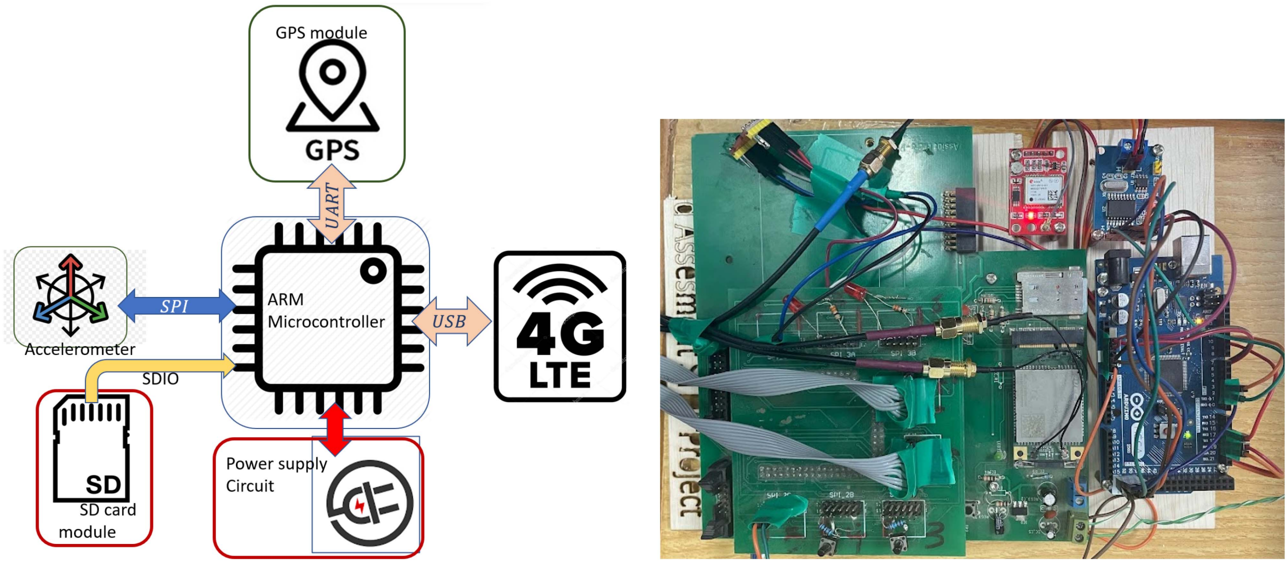
where N is the total number of acceleration samples. Equation 3 becomes as follows:

$$V_h \approx \sum_{k=1}^{N} \left(\sum_{k=1}^{N} \frac{f\left(t_{k-1}\right) + f\left(t_k\right)}{2} \Delta t_k \right) \Delta t_k. \tag{10}$$

The total travel distance can be calculated using equation (5) then we use the IRI equation as follows:

$$\text{IRI} = \frac{V_h}{d}. \tag{11}$$

The condition of the road pavement can be classified to five different level according to the value of the IRI [32]. Table 1 shows the relation between the IRI range of values and the



(a) (b)

FIGURE 3. IoT node (a) building blocks (b) actual implementation.

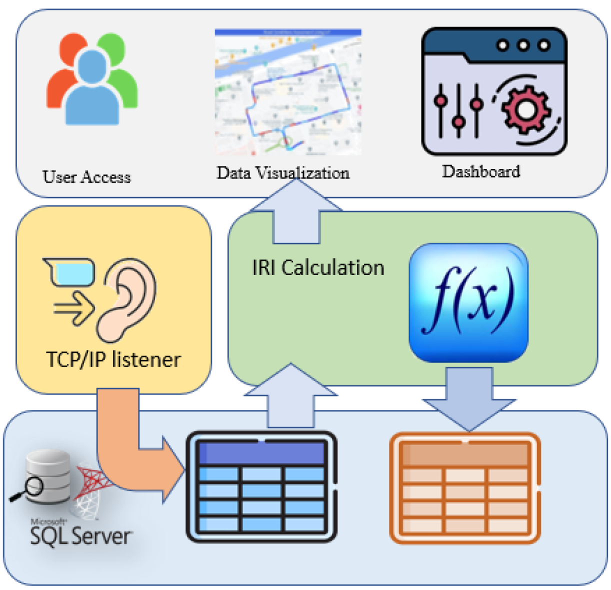


FIGURE 4. Proposed system server architecture.

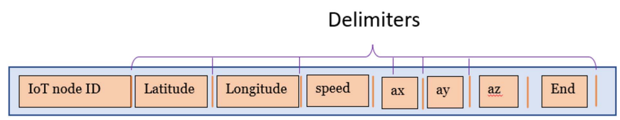


FIGURE 5. Packet format sent from IoT node to the monitoring server.

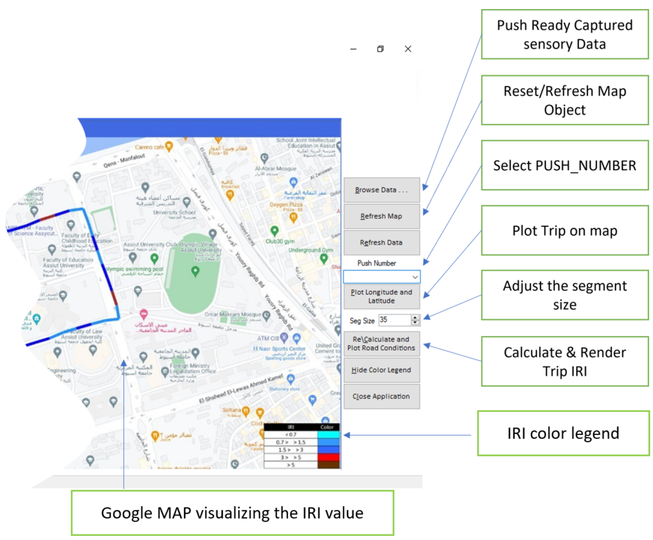


FIGURE 6. Proposed system user interface control panel.

road condition, along with the color scheme utilized for visualizing the IRI value on Google Maps used later in our system user interface.

IV. IOT NODE DESIGN

In this section we describe the design and the implementation details of the IoT node installed in the vehicle.

The IoT node consists of the following main components:

- *Processing Unit:* The main processing unit is STM32F407 ARM Cortex M4 microcontroller. It is responsible for collecting the data from the accelerometer sensor and GPS and transmit them to the central monitoring server.
- *Accelerometer Sensor:* The ADXL355 module is digital, low Drift, low power, low Noise, and 3-Axis MEMS accelerometers that provides a Sigma-Delta ADC of 20-bit,

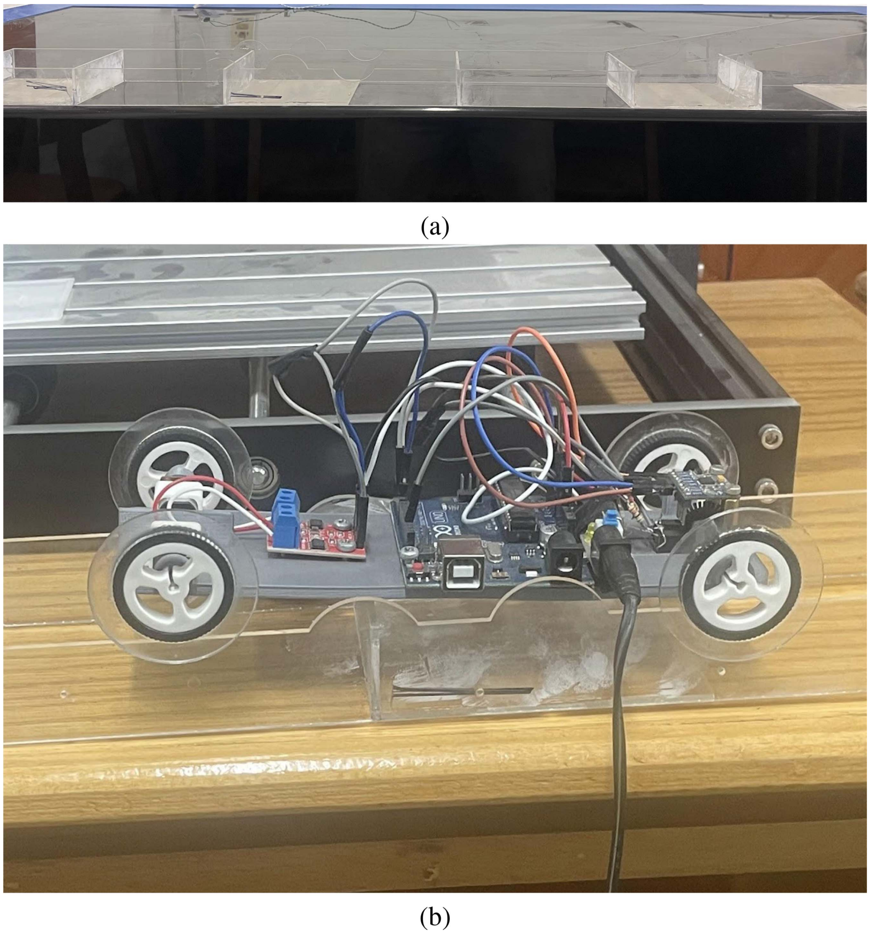


FIGURE 7. (a) The test road model (b) the scaled test vehicle.

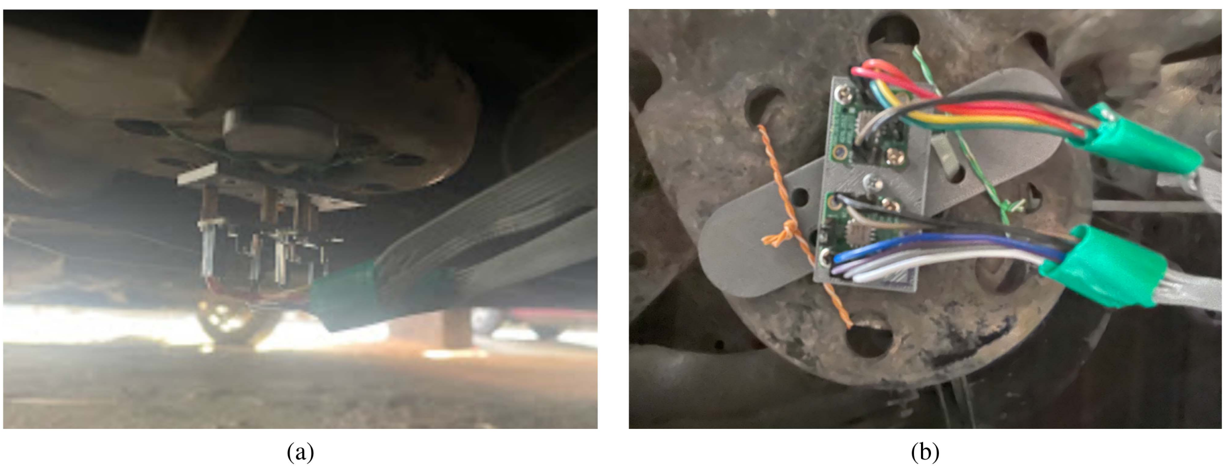


FIGURE 8. Installation of the accelerometer in the rear car axle (a) Horizontal plan (b) vertical plan.

to digitize the analog acceleration signal. The module is able to record the acceleration signals in the x, y and z axes at different output data rates between 4 kHz and 3.9 Hz. The module is equipped with an internal low-pass, filter to limit the bandwidth to 1.5 kHz.

- *GPS Module:* The GY-NEO6MV2 board featuring u-blox 6 GPS module is used to acquire the location (latitude and longitude) of the vehicle. The module interfaces with the microcontroller using UART connection.

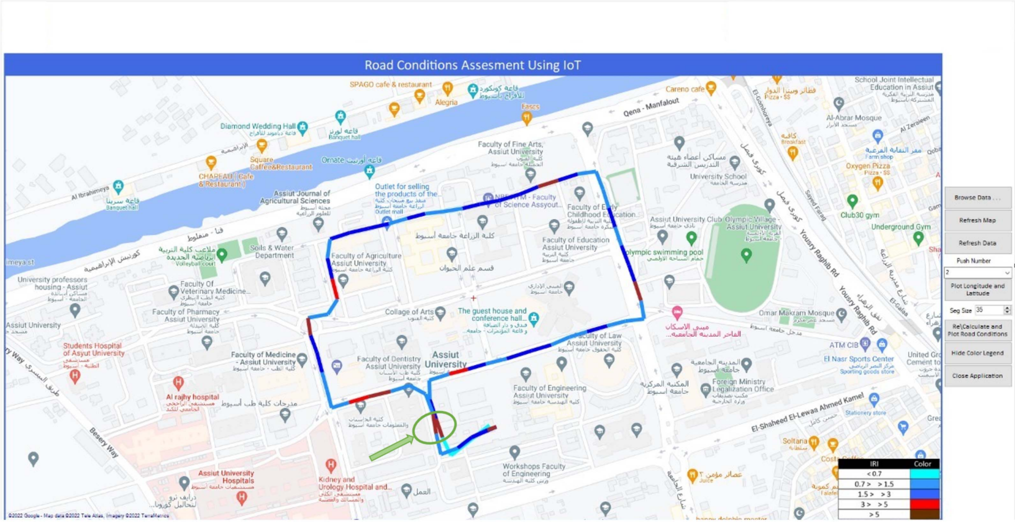


FIGURE 9. **Monitoring server user interface shown visualized IRI values on the integrated Google Map.**

- *Cellular Internet Module:* The IoT node is equipped with cellular internet connectivity to communicate with the remote server. The IoT uses Quectel EC20 module which communicates with the Microcontroller using OTG USB interface.

  In this design the accelerometer acquires the acceleration signals with a sampling rate of 125 sample/sec. then sends them to the microcontroller over Serial Peripheral Interface (SPI) interface. The microcontroller timestamps these signals and transmit them to the monitoring server using the 4G module along with the speed of the vehicle and its current position acquired form the GPS module. The timestamped signals are recorded on the SD card as a backup in the case that the internet connection is lost. In the latter case, the signals are then transmitted upon restoring the internet service. Additionally, the IoT node obtain the vehicle speed from the vehicle computer using Controller Area Network (CAN) bus.[1] Fig. 3 shows the block diagram of the IoT node and its hardware implementation.

V. MONITORING SERVER

In this section the building blocks for the proposed monitoring server' front and back-end are presented in addition to the details function of each part and the communication protocol between the server and the IoT node. The server architecture and its main components are shown in Fig. 4.

The proposed monitoring server consists of a number of building blocks as follows:

- *Data Collection:* This function is carried out through an asynchronous multi-client server. The main functions of this server are:
  1) Collecting data from the IoT nodes
  2) Parsing the received messages from the nodes and storing them in a database
  3) Visualizing the received packets for debugging issues

  To implement these functions, we used Microsoft SQL server as a database Management system in addition to Microsoft Management Studio Express to manually handle the received data.
- *Data communication:* The server is equipped with a TCP/IP listener function that enables the server to receive the data from the internet over a predefined port number. The received data include the acceleration signals along the three dimensions x, y, and z, the vehicle position using the latitude and longitude values received form the GPS. The value of each field is stored in the IoT node in float format (4 B). This results in a total payload of data equals 28 B per packet. The sampling rate equals 125 sample/sec. This gives a total data of around 3.9 kB/sec (14 MB/hr). As it can be noticed, the total amount of data transmitted in one hour of driving is not significant which emphasises the feasibility of using the real-time monitoring system over off-line counterparts. A specific packet format is used between the IoT node and the server as shown in Fig. 5.
- *Data Storing:* The proposed system uses SQL server to manage and store the received sensory data. The sensory data are delimited fields contain (lan,lon, speed, ax1,ay1,az1). All experiments' sensory data are stored in the database and identified by a PUSH_NUMBER to enable the IRI visualizer to handle many experiments through selecting the required PUSH_NUMBER form its Graphical User Interface (GUI).
- *IRI Calculation:* Using the received data, the server calculates the IRI for different road segments according to the steps mentioned in Section III.

[1] While the vehicle speed was continuously recorded, it was stored for further analysis but not used for our calculations.

- *IRI visualization:* The IRI values for different road segment are visualized on a road map using Google map API (GMAP) plug-in embedded in the server web page.

IRI calculation and visualization are implemented by C#.Net to implement the proposed algorithm. Fig. 6 shows the User Interface (UI) of the monitoring server. The UI allows the user to control the road segment length, adjust the sampling rate, and choose the experiment ID to visualize from those stored in the database.

VI. SYSTEM VALIDATION

To validate the proposed system, a scaled prototype car and a road model were used. The road model includes simulated road artifacts such as bumps and humps (as shown in Fig. 7). The goal of this step was to assess the accuracy of the proposed technique by comparing the measured IRI obtained from the acceleration signal of the moving scaled vehicle with the IRI value calculated from the geometry of the road.

The accelerometer was installed in the rear side of the vehicle model which was allowed to move at constant speed along the road. The acceleration data were recorded along the road then fed to the IRI calculation algorithm described in Section III-C. The error between the measured and calculated IRI was nearly 3.48%.

VII. PRACTICAL EXPERIMENT SETUP

In this section, we describe the experimental setup used to test our system.

The accelerometer sensor[2] is fixed on the car rear axle such that its x direction is aligned with the direction of the car and the z direction is aligned with the car suspension system movement. The recorded vertical acceleration is in a perpendicular direction to the road surface. The IoT node is fixed at the rear seat where the accelerometer is connected to the SPI port of the microcontroller through a ribbon cable. The installation of the accelerometer sensors is depicted in Fig. 8.

Before starting the data collection, we check that the connection between the monitoring server and the IoT node is established successfully. At the start of the experiment, the car is stopped for 5 secs while recording the acceleration signals to calibrate the vertical acceleration direction as mentioned in Section III and according to the guidelines of [28]. During the ride the car speed is maintained constant, as possible, at 40 km/h during the experiment. If the car passed over the same road segment more than one time the corresponding sampled signals are averaged. The acquired data were sent to the monitoring server over the cellular internet. Upon receiving the data, the server stores them in the database and visualizes the IRI on the integrated google map view as shown in Fig. 9. As shown in the figure, some of the road segments have higher values of IRI mainly because the presence of road anomalies, more specifically speed bumps.

VIII. CONCLUSION

In this paper, we presented the initial result of using a fully automated road assessment technique that is based on Internet of Things technology. The acceleration signals from a sensor attached to the vehicle suspension system are acquired and transmitted to a monitoring server via IoT node along with the position of the vehicle. In the monitoring server, the value of the IRI for a defined road segment is calculated and visualized in the Google Map window integrated in the server. The study shows the feasibility of the proposed system to automatically assess the condition of the road. In the future work we will investigate the effect of the vehicle speed on the accuracy of the calculated IRI. Also, the data from two acceloremeters aligned with the car direction is used to eliminate the effect of road slope on the calculated IRI values.

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