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Vibration vs. vision: best approach for automated pavement distress detection

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Abstract

Roads are the largest component of infrastructure; they directly impact people's life by providing mobility and connectivity. To ensure consistent surface quality, roads must be monitored continuously and repaired when necessary. Presently, authorities spend substantial amount of time, finance and labor for pavement distress detection by employing traditional manual and instrumented methods which are generally tedious, and time-consuming. To overcome these drawbacks, various automated techniques like Ground Penetrating Radar, Laser-Imaging-Systems, etc. are deployed. Recently, image-processing and smartphone-based systems are being devised for pavement distress detection. Here, a vibration-based method using smartphone accelerometer and gyroscope, and a vision-based method using video processing for automated pavement distress detection are designed and compared to identify the more suitable one. Both experiments are performed on same roads and results are validated by manual surveying. Accuracy of vibration-based method for detecting potholes, patches and bumps is found as 80%. Accuracy for detecting cracks, potholes and patches using vision-based method is identified as 84%. An additional effort is taken to estimate the extent of pavement distresses using vision-based approach and validate it using manual stripping method. The study reveals that, vibration-based-analysis is sufficient for routine monitoring purposes whereas vision-based-method is more appropriate for detailed analysis.

Keywords: Pavement distress; Smartphone; Accelerometer; Gyroscope; Video processing; Manual distress survey

1. Introduction

A rapidly developing country like India has relentless demand for good quality infrastructure offering reliable services, and an adequate transportation system. India's road network of over 5,903,293 kilometers is the second largest in the world and almost 65% of freight as well as 80% of passenger traffic are carried by these roads. Therefore, well-maintained roads are mandatory for efficient transportation [1]. To guarantee a high-quality standard for the road network, frequent performance monitoring and maintenance operations are indispensable.

Pavement condition survey is imperative in a structured maintenance and management program. Pavement condition monitoring with proper surveys helps in obtaining critical information on the prevailing state for pavement performance analysis. Roughness, structural adequacy, distress, material durability, drainage adequacy, the extent of past maintenance activities, etc. are primarily evaluated to determine the overall pavement condition [2]. Pavement distress detection is deemed critical since it directly affects the safety as well as the comfort of users. It also helps in optimizing road maintenance activities. Conventionally, manual methods are adopted for pavement distress detection and analysis. Inspectors traverse the roads to measure the distresses. These manual pavement distress analysis methods are tedious, subjective, costly, time-consuming, and labor-intensive [3]. To address these difficulties, various automated technologies such as Ground Penetrating Radar, Laser Road Imaging system, video or image processing, smartphone sensors, etc. are used for pavement distress detection by different transportation agencies and researchers all around the world [4–6].

Among all the aforementioned automated distress detection methods, smartphone sensors, as well as video processing techniques, have gained popularity over the past few decades particularly as other sophisticated methods require particular setups like special lights, lasers, etc. that significantly increase the cost of the survey. However, a comparative study of both methods has not been undertaken by any researchers thus far despite the pressing need to identify the most suitable automated approach to pavement distress detection.

The number of smartphone users is exponentially increasing around the world and numerous researches have been conducted to explore the applicability of smartphones in various walks of transportation engineering, such as traffic congestion studies, travel time estimation, least cost or shortest route identification, vehicle speed monitoring, etc. [7–11]. Sharma et al. developed an innovative distress detection technology that leverages

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microphone sensors present in smartphones [12]. Kyriakou, Christodoulou, and Dimitriou studied the applicability of pitch and roll sensors in smartphones for detection and classification of pavement anomalies by using Artificial Neural Networks [13]. Pothole Patrol system proposed by Eriksson et al. uses a GPS and smartphone accelerometer that is attached to a car's dashboard to detect potholes [14]. Zoysa et al. proposed a system called 'BusNet' that monitors environmental pollution and road surface condition [15]. This system places the smartphones on the roof of public buses. Nericell system developed by Mohan, Padmanabha, and Ramjee utilizes the microphone, GPS, and accelerometer embedded in smartphones to identify potholes and analyze traffic [16]. Kyriakou, Christodoulou, and Dimitriou, utilized smartphone sensors as well as on-board diagnostic devices for pothole detection [17].

Two-dimensional or three-dimensional images and videos are also harnessed in the field of pavement distress detection. Georgopoulos, Loizos, & Fiouda, Ho et al. and Ouyang, Luo, and Zhou, employed digital image processing technique to automatically and objectively determine the type, extent, and severity of cracks on flexible pavements [18–20]. Nienaber, Booysen, and Kroon, and Vigneshwar and Kumar, utilized simple image processing techniques and real-world footages to detect the potholes present on the pavement [21,22]. Lokeshwor, Das, and Goel employed video processing for detecting and quantifying pavement distresses [23,24].

Exploring past research works throws light on the fact that, most of the smartphone-based or video processing based researches have concentrated on detecting a single pavement distress; studies on the combined detection of multiple pavement anomalies are found to be less. Artificial Neural Network approach has not been explored earlier for smartphone-based pavement distress detection.

In the present explorative work, an attempt is made to detect multiple pavement distresses such as potholes, cracks, bumps, and patches by applying smartphone sensor-based vibration analysis as well as video processing. The accuracy of both the methods is checked and validated by comparing the results with that of manual distress survey. An effort is also taken to estimate the extent of each of the pavement distresses using video processing. To validate the results, the area and length of the distresses considered for the study are estimated manually by stripping method, and the results are compared with that of the video processing method. Both vibration-based and vision-based analysis are performed on the same road network, and the accuracy of the methods is compared with a motive to identify the ideal and practical approach for automated pavement distress detection. The distresses detected by both the methods are incorporated into a GIS platform to develop geotagged distress maps that can be used not only to visualize the pavement condition data effectively but also for prioritizing the pavement rehabilitation needs.

2. Study approach

The major steps involved in the present study are depicted in Fig. 1.

2.1. Delineation of the study area

As the primary objective of the current work is to compare two automated pavement distress detection techniques, viz. vibration-based and vision-based methods, both the experiments are conducted on the same road stretch, and the results are comparatively analyzed. The experimental road stretches taken up for the present study are situated inside the National Institute of Technology Tiruchirappalli campus, the total length of which is 6.2 km. However, as the vibration-based method is employed using Artificial Neural Network technique, it warrants more amount of data for training the network. Therefore, smartphone-based vibration data is collected for 19 roads having a total length of 15.25 km within Tiruchirappalli district, TamilNadu state of South India for training the ANN model. Fig. 2 and Fig. 3 shows the study road stretches selected for training the ANN model and for comparing the two automated methods, respectively.

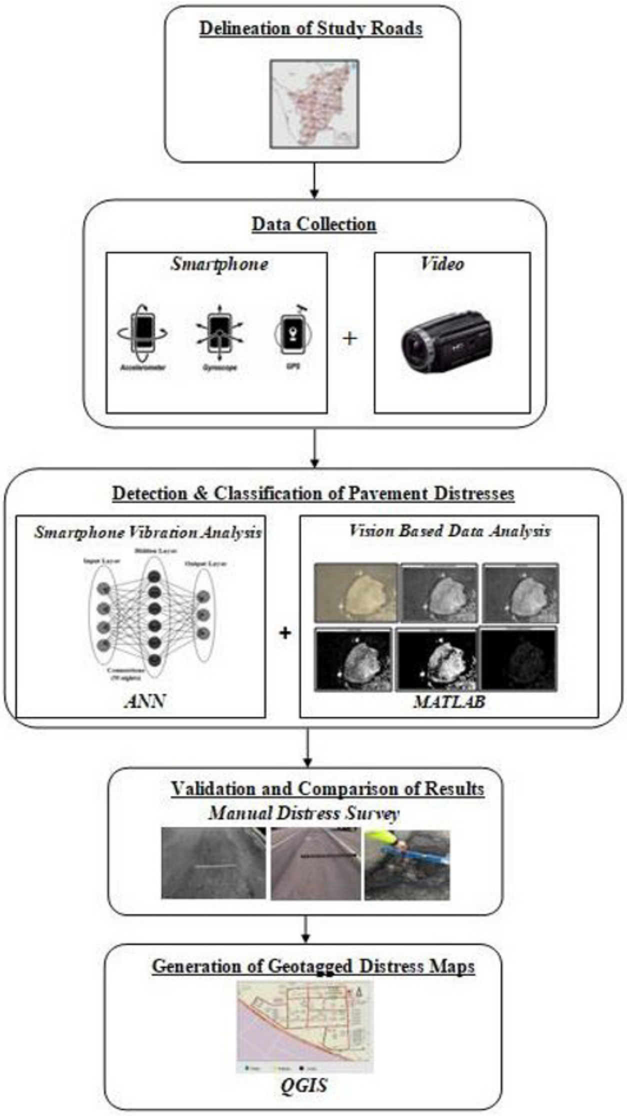

Fig. 1. Schematic of study approach.

2.2. Data collection

Smartphone-based data, as well as video-based data, are collected for the present work.

2.2.1. Vibration-based data

The smartphone is mounted using a GPS holder on the windshield of the car, as shown in Fig. 4, with its accelerometer, gyroscope, and GPS sensors turned on. The video camera of the smartphone

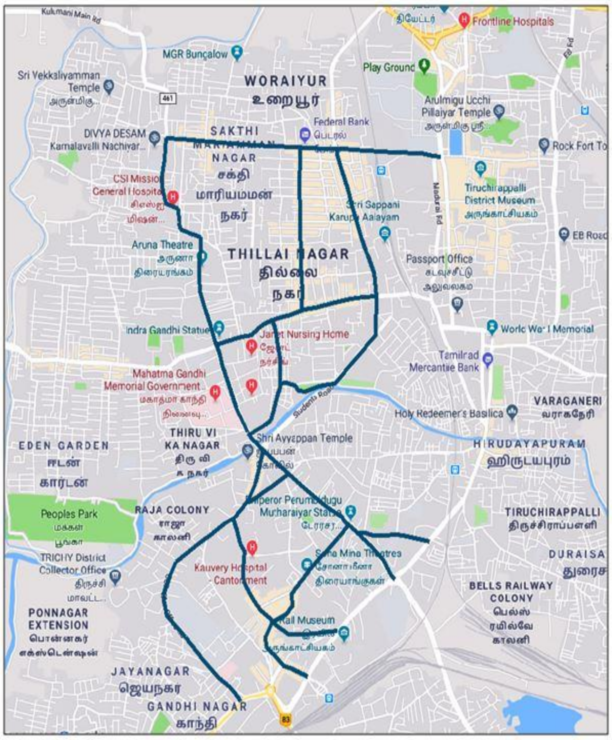

Fig. 2. Study roads for training the ANN model.

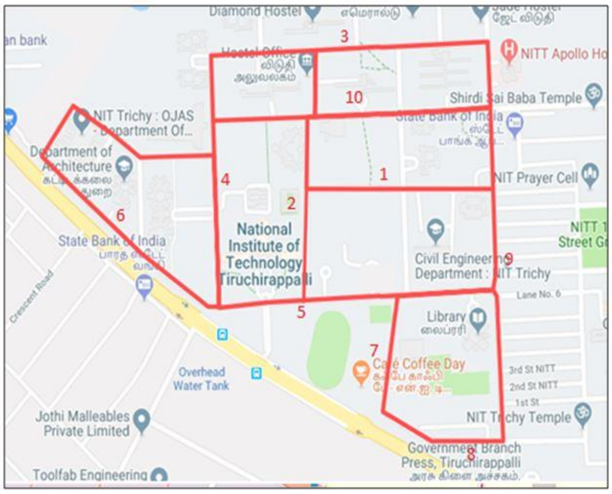

Fig. 3. Study roads for comparing vibration-based and vision-based methods.

is kept active throughout the experiment to visually verify the existence of all the pavement distresses detected by the sensor data. The smartphone accelerometer captures the linear accelerations along all the three axes as the vehicle is driven. The X, Y and Z axes correspond to longitudinal, lateral and vertical accelerations, respectively. The gyroscope sensor is used to measure the rate of rotation in each direction. The collected data pertains to both uni-dimensional parameters such as X, Y, Z accelerations, speed, etc. and two-dimensional indicators such as the smartphone's roll, pitch and yaw values that can be correlated with the corresponding values of the host car. Since, the roll of the car indicates its acceleration differential between the left and right front wheels, and the pitch of the car indicates its acceleration differential between front and rear wheels, both roll and pitch in tandem elucidate how the host car is off-balance. The sensor data is collected at a frequency of 5 readings per second, and the speed of the vehicle is tried to be maintained within 40-60 km/hr. The location data is also collected using the GPS module present in the smartphones.

Fig. 4. Data collection setup for vibration-based approach.

2.2.2. *Vision-based data*

Data on the pavement surface is collected by mounting a camera on the rear end of the car. The car model used is Tata Indica, and the camera is a Sony Handycam of 8.9 MP resolution. The video of the pavement surface is captured when the vehicle is moving at a speed of 10-15 km/hr. Fig. 5 shows the data collection setup for vision-based approach. For this, an arrangement consisting of a horizontal pipe of 2.2 m length and a vertical pipe of 1 m height is fabricated. The two rods are fastened using nuts and bolts. The pipe is extended from the car to avoid overlapping with the body of the car and also to capture the video of the road stretches without inclination.

2.3. *Detection and classification of pavement distress:*

2.3.1. *Vibration-based method*

An attempt is made to detect patches, bumps, cracks, and potholes using smartphone vibration-based approach. An Artificial Neural Network (ANN) is modeled using a Python script to serve this purpose. The complete data collection was performed at a sampling rate of 5 readings/s. Initially, the model is trained by utilizing the data collected for 19 roads with a total length of 15.25 km within Tiruchirappalli district. The time-stamped smartphone based accelerometer and gyroscopic data corresponding to the various distresses present in these road stretches are deployed for training the model. Almost 5690 readings were utilized for the training and testing purpose. Following this, the raw vibration data collected for the 10 study roads within National Institute of Technology Tiruchirappalli campus, with a total length of 6.2 km is given as input to the ANN model to detect and classify the

Fig. 5. Data collection setup for vision-based approach.

pavement distresses. Almost 1758 readings were utilized for the validation purpose. Therefore, almost 70% of the total data were used for the training and testing purpose and almost 30% of the total data were used for the validation purpose.

2.3.2. Vision-based method

The distresses detected using this approach are patches, cracks, and potholes. The video processing is performed using a MATLAB script. Initially, the videos of the road stretch collected are converted into image frames, and the noise present in the images is removed. The images are further enhanced, and an attempt is made to classify the pavement distresses according to the image texture and shape factor. Additional steps are also taken to identify the extent of the different pavement anomalies.

2.4. Validation and comparison of results

The results of both the methods are validated by conducting a manual distress survey of the study roads. The accuracy of both the methods in identifying each distress is quantified and compared. The length of the pavement cracks is measured manually, and it is compared with that obtained from the vision-based method. Similarly, a tracing of the potholes and patches is taken on a chart paper, and the area is calculated using the stripping method. This is compared with the area obtained using a vision-based approach to find out the accuracy of automated detection of the extent of pavement distresses.

2.5. Generation of geo-tagged distress maps

The pavement distresses detected by vibration-based as well as vision-based methods are exported to QGIS platform, and geo-tagged maps are prepared.

3. Vibration-based pavement distress detection

In the present work, an attempt is made to deploy the readings captured using smartphone sensors to detect various pavement distresses. The events considered in the study are patches, bumps, cracks, and potholes. Artificial Neural Network (ANN) approach is selected for the present work since it has some major advantages like ease of usage, ability to model non-linear or complex relations, etc. ANN is a computational model that is analogous to the biological characteristics that simulate the decision processes in the brain. This method is helpful to estimate unknown functions depending upon the numerous input values [25]. Multilayer Feed-forward Neural Network (MFNN) is one of the most widely used kinds of Artificial Neural Network. It consists of three different layers (input, hidden, and output) of interconnected neurons. The received signals are processed by each neuron, and as per a well-defined activation function, the output is produced, and the same is transmitted to the neurons present in the upcoming layers through specific connections that define the network topology. Each of these connections is associated with a particular weight that is intended to either amplify or reduce the input.

In a "supervised approach" like MFNN, when a broad set of input as well as output data is fed, the training procedure modulates the various weights to deliver an acceptable output. The results generated should be comparable to the output provided for the training. Levenberg-Marquardt is the most common training algorithm, and the corresponding error is evaluated by analysing the Mean Square Error (MSE) [26]. Fig. 6 depicts the internal skeleton of the building phase of an ANN model. It is clear that this method works on the principle of predicting the output by analyzing the trends of the input data. The training phase is usually performed with the aid of a back propagation model that permits the network to adjust the weights in a reverse direction by simultaneously distributing and minimizing the errors in the various neurons for each iteration.

For training the ANN, smartphone sensor data is collected from 19 roads having a total length of 15.25 km within Tiruchirappalli district. The smartphone sensor data and pavement distresses are given as the input and the output, respectively, of the ANN considered for the study, as shown in Fig. 7. The ANN deployed for the present study consists of 6 neurons in the input layer, 10 neurons in the hidden layer and 5 neurons in the output layer. h_1, h_2, etc. in Fig. 7 indicate the neurons of the hidden layer. The 6 neurons in the input layer are forward acceleration, lateral acceleration, vertical acceleration, vehicle pitch, vehicle roll and vehicle yaw. The 5 neurons in the output layer are no defects, potholes, patches, cracks and, bumps. The ANN is trained for each case of distress and then trained with all four individual distresses in tandem. For each case, 70% of the data is utilized for training and the rest 30% of data is divided in half for testing as well as validation. Training sample is used for the learning process of the neural network and the test sample is used for analyzing the accuracy of the classifier. While training the ANN, different IDs are given for different events, as shown in Table 1.

A test dataset consisting of distresses whose location is known is given as input and the obtained result is analyzed. The result from the ANN for a sample data is shown in Fig. 8. This sample data consists of 48 events including, 12 bumps, 17 patches, 9 potholes, 3 cracks and 7 no defects. Out of this, 38 events are detected correctly by the ANN model. Even though all the bumps are detected by the ANN model, two patches are incorrectly identified as bumps. Six patches are also detected as no defect regions. Out of the three cracks, only one is detected by the model and one no defect area is wrongly identified as a crack.

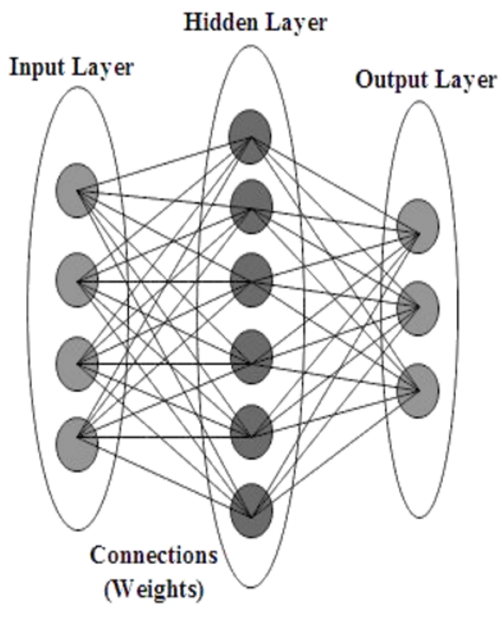

Fig. 6. Layers of MLPANN.

Similarly, the data for the whole 15.25 km road is used and the required network is trained. The final ANN model developed is identified to have an overall accuracy of 83%. Once the ANN model is trained, the data collected for the roads within NIT Tiruchirappalli campus is given as the input and the distresses present on the study roads are detected. The distresses detected are linked with the location data collected using the GPS module present in the smartphone and the whole data is exported to a QGIS platform. Finally, the geo-tagged map for all the ten study roads is prepared, as shown in Fig. 9.

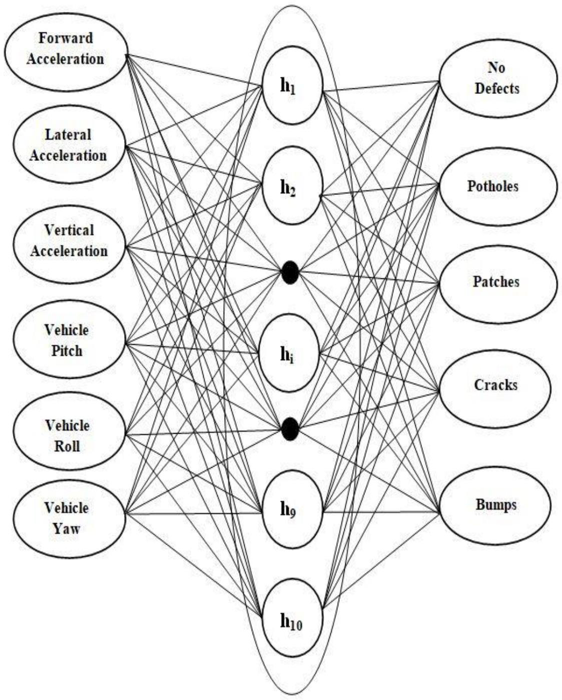

Fig. 7. ANN architecture for pavement distress detection.

Table 1
Distress and ID.

ID	Event
1	Bump
2	Patch
3	Pothole
4	Crack
5	No Defect

4. Vision-based pavement distress detection

Vision-based pavement distress detection is performed on the same set of roads within NIT Tiruchirappalli campus where vibration-based experiment was conducted earlier. Potholes, patches and cracks are the distresses considered for vision-based distress detection in the present work. A MATLAB script is used to employ the video processing. The major steps involved in vision-based pavement distress detection are, converting the videos into image frames, image pre-processing, identifying and tracking the images consisting of pavement distresses and classifying the distresses detected. An additional effort is made to estimate the extent and severities of the distresses detected.

4.1. Video to image frames

Initially, the image frames are extracted from the video data at a frequency of 5 frames per second.

4.2. Preprocessing

Preprocessing is performed to remove the noise present in the image. The basic preprocessing steps performed are shown in Fig. 10 with the help of a sample image of a pothole.

RGB to Grayscale: Initially, the RGB images are converted to grayscale images and which are then filtered to enhance the features.

Filtering: Median filtering is the filtering technique employed in this study. Median filter runs through every pixel of the image, and replaces each pixel with the median of the neighboring values. It aids in reducing the noise of the image to some extent.

Binary Image: Once the filtering is performed, the grayscale image is converted to a black and white image so that the area of interest is represented using white pixels and the other areas are represented using black pixels. This can be considered as a form of reverse contrast stretching. Contrast stretching is changing the range of intensities of pixels from the original range to a higher range. Here, the intensity range of 0-255 of grayscale image is converted to 0-1 for the black and white image. In the present work, Otsu’s method is deployed to perform the binary thresholding. Otsu's thresholding is performed by iterating through all the possible threshold values and from this; a measure of spread for the pixel levels at each side of the threshold is calculated. It chooses a threshold that minimizes the intraclass variance of the thresholded black and white pixels. This helps in identifying the pixels that either falls in foreground or background.

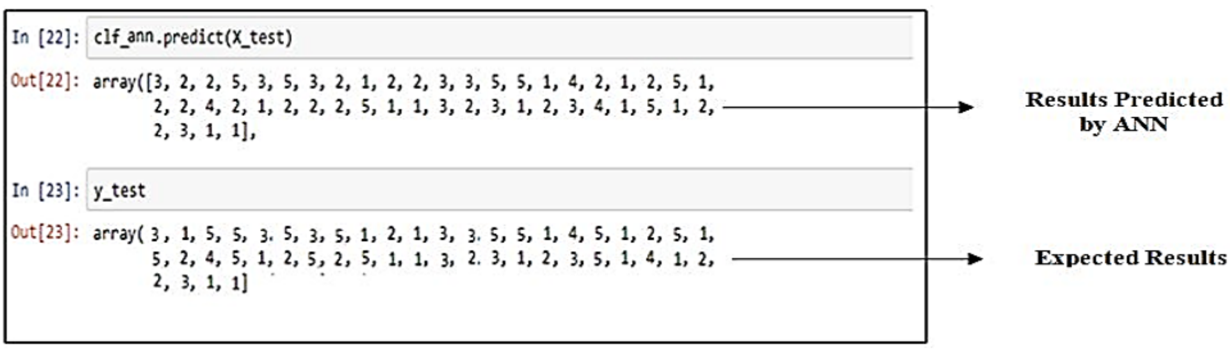

Fig. 8. Validation result of vibration-based pavement distress detection.

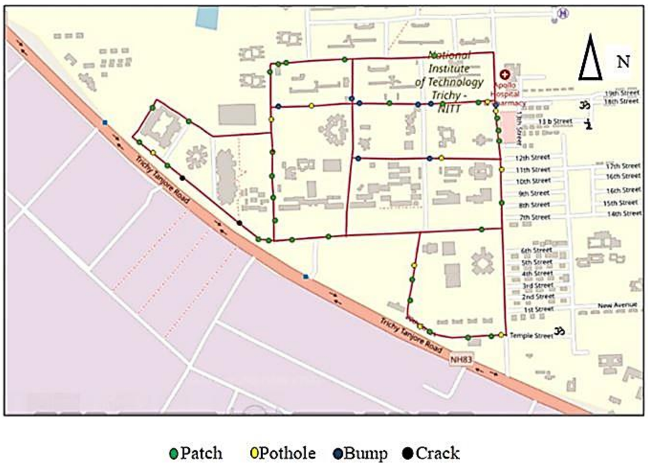

Fig. 9. Distresses detected using vibration-based analysis.

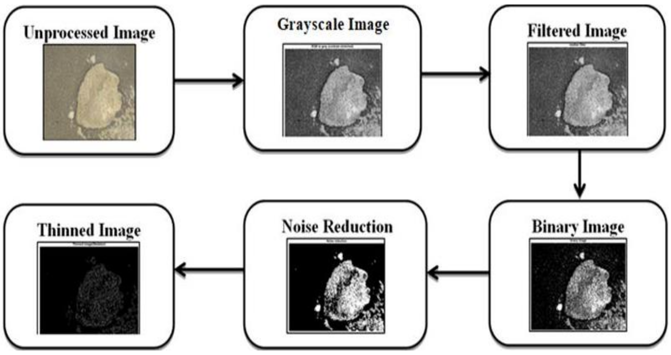

Fig. 10. Preprocessing steps.

Noise Removal: When the image is converted from a grayscale to a black and white, there are possibilities of inaccuracies in identifying the threshold for conversion. This might result in the formation of discontinuities in the distressed areas or formation of noise in the image. To avoid this, a neighborhood of 5 x 5 pixels around each pixel is checked and if the majority of pixels are black, the pixel considered is converted to black and vice versa.

Thinning: The next operation performed is thinning. It is a morphological operation that removes selected foreground pixels from the binary image. It creates a skeleton of the distressed area by removing pixels on the boundaries so that the complexity of the image is reduced. This also helps to remove the isolated pixels or their small clusters.

4.3. Identifying and tracking the images with distresses

Since videos are converted into frames at a frequency of five frames per second, a video clip of even one minute comprises of 300 frames. Thus, it is necessary to restrict the number of video frames to reduce the computation time. This can be achieved by identifying the video frames that are suspected of containing any distress and removing all the other frames. This will also help in quickly predicting the general condition of road as per the total number of video frames with distress. For this, initially, the total area of pixels representing distressed areas is calculated by multiplying the total number of white pixels with the area of a single pixel. If the area obtained is greater than or equal to 177 cm², then that image is identified to be having a distress. This logic was developed by Lokeshwor, Das, and Goel, 2013 after conducting experiments on 200 frames with distress and 100 frames without distress [24]. Once a pavement distress is detected, the corresponding region is tracked in the subsequent frames until it leaves the viewport.

4.4. Classification of distresses

Classification of frames having potholes, patches and cracks is done based on a set of visual properties. The visual properties considered for the present study are image texture, shape factor and dimension. An image texture is defined as a set of metrics calculated to quantify the perceived texture of any image. Image texture provides the information regarding the spatial arrangement of color or intensities in an image or selected region of an image. In the present work, the spatial arrangement of the pixel intensities in the image is analyzed. The image texture of a pothole, crack and patch varies from that of the distress-free areas. However, the contrast variation of a pothole is much higher than that of a patch. Therefore, Standard Deviation (SD) of the pixel intensities is analyzed for the required purpose. Fig. 12 shows a raw and preprocessed image frame that consists of both pothole and a patch. The image after preprocessing clearly shows that the contrast variation within the pothole is high when compared to the patch. Shape factors are dimensionless quantities used in image analysis that numerically describes the shape of an object, independent of its size. Shape factors are calculated from measured dimensions, such as chord lengths, diameter, area, centroid, perimeter, circularity, etc. It is assumed that, the shape of the pothole or a patch is approximately circular and that of a crack is approximately elongated. Therefore, the shape factor is analyzed in terms of circularity (CIRC) and circularity varies depending upon the surface area and perimeter. The third factor considered in the analysis is dimension. The dimensions of an object in a digital image represent its length and width. It is usually measured in pixels. The width of a patch or pothole will be more than that of cracks. Therefore, the average width (W) of the distressed regions is analyzed.

All frames that are identified to have a distress are categorized into frames with potholes, patches and cracks. The classification is performed if the image complies with any of the following categories [23]:

If SD ≥ 10 & CIRC ≥ 0.10 & W ≥ 60mm - Pothole
If 5 ≤ SD > 10 & CIRC ≥ 0.40 & W ≥ 60mm - Patch
If SD ≥ 5 & CIRC ≤ 0.30 & W < 60mm - Crack

where, SD = standard deviation of pixel intensities; CIRC = circularity of the distress; W = average width of the distress.

Fig. 11 shows an example of a patch detected using MATLAB.

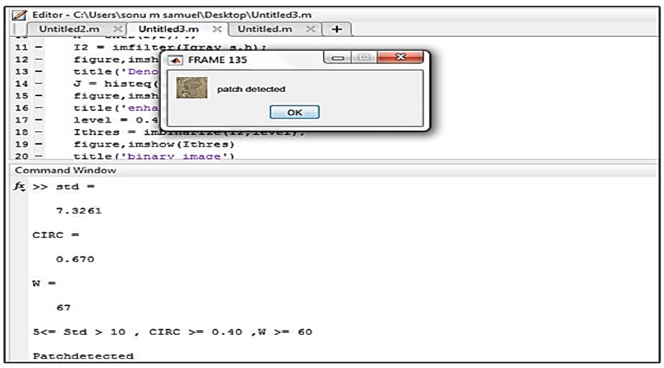

Fig. 11. Distress detection example.

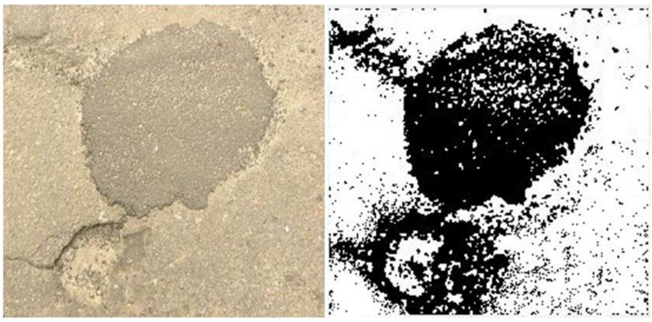

Fig. 12. Image frame with patch and pothole (a) raw image and (b) preprocessed image.

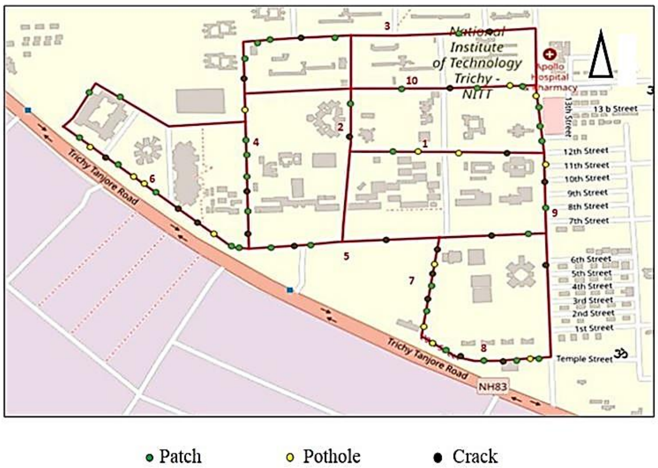

Fig. 13. Distresses detected using vision-based method.

Area of potholes, patches and the length of cracks are also determined by multiplying the total number of white pixels present in the corresponding pixels with the area of a single pixel. The area of one pixel is found to be 0.1236 mm^2. The frame numbers of the images corresponding to the areas having distresses is matched with the location data collected using the smartphone. For example, since 5 frames are extracted per second, if a pothole is detected in the 55^{th} frame of a video of 2 minutes, the event will have been encountered in the 11^{th} second. The latitude and longitude corresponding to the 11^{th} second of smartphone-based location data is matched to the respective distress. This synchronized data is exported to a QGIS environment and the maps are prepared, as shown in Fig. 13.

5. Validation and comparison of results

Manual distress survey is additionally performed for all the ten study road stretches. For vibration-based method, the location data of the distress is also identified by deploying the GPS in the smartphone. In vision-based method, five frames are extracted in one second. The frame number of the image containing distress is recognized and the corresponding time is identified. This is matched with the corresponding location that is collected using the smartphone GPS. The location data of the distresses identified using vibration as well as vision based distress detection method is matched with that of the manual distress survey. The true positives of vibration-based and vision-based distress detection survey when compared to the manual distress survey and the consolidated results are shown in Table 2.

The accuracy in detecting each individual distress using both the methods is also compared and shown in Table 3.

It is evident that, the accuracy of both the methods used for pothole detection is 90%. However, the accuracy for detecting patches and cracks is more for vision-based method. Out of 29 cracks, only three are detected by vibration-based method. Cracks are mostly identified on the sides of roads during manual survey and the variation in sensor reading is too feeble to detect cracks. Even though the overall accuracy of vibration-based distress detection method is just 58 %, if cracks are not considered for the study, the accuracy is increased to 80 %. Bumps are detected only by using vibration-based method and all the 10 bumps present in the study roads are detected by the smartphone sensors. Even when bumps are not detected using vision-based method, the overall accuracy is found to be 75 % and when bumps are not considered, the accuracy is further increased to 84 %. The reason for the lower accuracy for the vibration-based method is that, it is able to detect only those distresses which are along the wheel path. Since the field of view for the vision-based method is more, a higher accuracy is attained by this method.

An attempt is also made to validate the dimensions of the distresses detected using vision- based method. To do so, some typical distresses are traced over a chart paper and the area is determined by stripping method. A series of strips are created on the drawing sheet by drawing a series of parallel lines at regular, fixed intervals. The width of the strip is chosen according to the

Table 2
Consolidated results of pavement distress detection.

Road no.	Number of distresses										
	Potholes			Cracks			Patches			Bumps	
	Manual distress survey	Vibration-based method	Vision-based method	Manual distress survey	Vibration-based method	Vision-based method	Manual distress survey	Vibration-based method	Vision-based method	Manual distress survey	Vibration-based method
1	2	1	2	2	0	1	1	0	1	3	3
2	1	0	0	2	0	1	1	0	1	1	1
3	0	0	0	2	0	2	4	4	4	0	0
4	2	1	1	4	0	2	5	5	5	1	1
5	4	5	4	4	2	3	6	2	4	0	0
6	3	4	3	5	1	4	5	1	3	0	0
7	2	1	2	4	0	3	2	2	2	0	0
8	2	2	2	2	0	2	4	3	4	0	0
9	2	2	2	2	0	2	4	4	4	1	1
10	1	1	1	2	0	2	3	3	3	4	4

Table 3
Accuracy of detection of individual distresses: vibration vs. vision method.

Distress	Vibration-based method (%)	Vision-based method (%)
Potholes	90	90
Patches	69	89
Cracks	10	76
Bumps	100	-

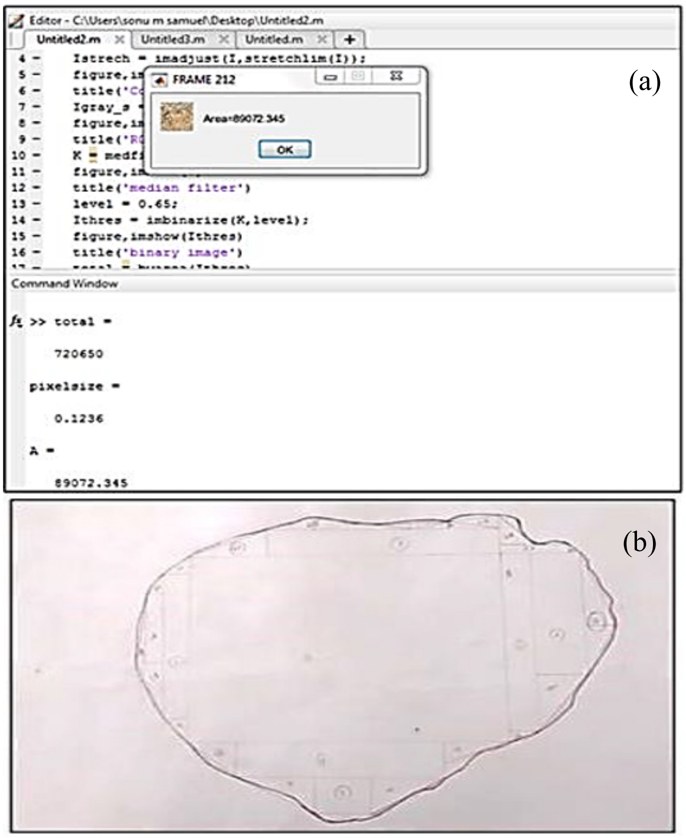

Fig. 14. Determination of area using (a) vision-based method and (b) manual method.

scale. The length of each strip within the boundaries of the distress is measured along a centerline and the sum of these distances is multiplied by the equivalent field distance. This is again multiplied by the width of the strip to obtain the area of the distress. The area determined by both methods is compared and validated.Fig. 14(a) and Fig. 14(b) show the area of a same pothole detected using video processing and stripping method.

The area determined by the manual method is 897.23 cm^2 and that by video processing is 890.72 cm^2.

6. Conclusions

The study presents two automated low-cost methodologies for determining pavement distresses. The first is the smartphone sensor-based distress detection technique. An ANN model is developed to detect road bumps, potholes, cracks and patches. This innovative application using a smartphone can be integrated with an automobile to evaluate the overall road condition. Pavement maintenance agencies can enrich the condition and improve the operation of road networks with the aid of a smartphone-based Pavement Management System. The second method is based on image processing. MATLAB coding is used to detect and classify potholes, patches and cracks from video data of the pavement.

Even though both the methods have the advantages of low-cost cost and adequate accuracy, the vision-based method is found to be more effective than vibration-based method as the latter detects only those distresses that are along the wheel path. However, the smartphone-based pavement distress detection methodology is applicable in both daytime as well as nighttime but image processing requires artificial lighting during nighttime. Since video processing is associated with heavy computational loads, it is very time-consuming. Therefore, the best option is for authorities to deploy vibration-based technique for collecting routine pavement condition data and for the maintenance work that warrants a high level of accuracy, the vision-based approach can be employed. Another possibility is to use the combination of vision and vibration method. In such a case, both the methods would complement each other and to some extent, it will also help in overcoming the disadvantages of using individually. Although the automated techniques like vibration based and vision based analysis can never entirely replace conventional manual distress detection methods, they do provide an opportunity to obtain a general idea of the condition of the pavement. Linking the data to a GIS platform and generating data rich maps will help pavement engineers, policy makers and planners to properly allocate and utilize the available funds for developing an optimal plan for cost-effective corrective measures.

The current investigative research work can be extended further by developing a smartphone application using these automated techniques that will make the process more user-friendly and efficient. The accuracy of the experiment shall be further improved by conducting the experiment in a denser sampling rate. Advanced techniques like Convolutional Neural Networks, ANN- Fuzzy hybrid techniques etc. may also be applied for vibration based pavement distress detection. A GPS navigation system can also be developed to automatically alert and forewarn road users about the approaching distresses in their path of travel.

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