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Research Article

Estimating cost of pothole repair from digital images using Stereo Vision and Artificial Neural Network

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ABSTRACT

A significant amount of road maintenance cost goes into pothole repairs. The primary cost factors related to potholes are their size and depth, as larger and thicker potholes incur higher repair costs. However, existing methods for estimating pothole repair in developing countries rely on manual size measurements, which is time consuming, labor intensive, subjective and can lead to poor estimation of repair cost. This paper presents a system that can automatically determine the size of potholes from digital images and estimate the cost of repair.

In this study, the stereo vision method was used to automatically estimate the depths of potholes from digital camera images. A feed-forward backward propagation Artificial Neural Network (ANN) was trained using pothole images acquired using mobile phones. The predicted depths and sizes of the potholes were then used to estimate the quantity of materials required to fill the potholes and subsequently, the cumulative cost of repair. Marking out and manual size measurements were performed for twenty randomly selected potholes in the Ugbowo Campus of the University of Benin, Nigeria. These measurements were compared against the estimated sizes of potholes predicted by the ANN model. A system was developed to automatically compute these material costs and considering other cost components such as transportation, labor, and equipment. Results obtained showed that the mean errors for depth, width and height estimates were 3.403%, 3.789% and 5.2617% respectively. Consequently, the developed system correctly estimated the cost of repair of the potholes considered in this study. A significant contribution of the paper is the speed and convenience of acquiring pothole data using a mobile phones without the need for on spot assessment of potholes or use of relatively more expensive stereoscopic camera setup.

1. Introduction

Potholes are small, bowl-shaped depressions in asphalt pavement surfaces, they have been the major cause of bad roads in tropical regions of many developing countries worldwide. It is typically caused by water weakening the soil in the asphalt pavement probably due to poor drainage and due to the presence of heavy traffic over the affected area. A study has estimated that road injuries will cost the world economy US$1·8 trillion between 2015 and 2030[1]. Many of these accidents are due to potholes[2]. Interestingly, potholes do not only lead to accidents but damage to vehicles and traffic jams safety, repair costs and accident compensation costs [2], [3], [4].

Pothole reparation and maintenance require a detection and estimation system for proper planning of work to be carried out. The patching of potholes is influenced by traffic volume, time to resurfacing, resource availability, and cost-effectiveness. However, without proper calculations and estimation of damages done on the road from collected information, it will be difficult to estimate what it will cost to repair the potholes.

The motivation for this research stems from the pervasive issue of potholes, which significantly contributes to poor road conditions in Nigeria and many developing countries. The consequences are severe, leading to road accidents, injuries, and substantial damages to vehicles, incurring a considerable financial

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burden on drivers. Reports from the Central Bank of Nigeria highlight an annual loss of N133.8 billion due to bad roads, emphasizing the urgent need for effective pothole repairs. Currently, manual measurements and estimations are employed, consuming valuable time and labor. The research recognizes the critical factors influencing pothole patching, such as resource availability, and cost-effectiveness. We seek to address these challenges by leveraging technological advancements, particularly image processing techniques, to estimate pothole repair cost. By leveraging citizens to capture images of potholes using their smartphones and forwarding these images to road maintenance agencies, the cost of repairs can be estimated without incurring additional expenses associated with traditional road inspections. This will ultimately enhance road safety, reduce vehicle damages, and optimize the efficiency of maintenance efforts.

Even though several technologies for pothole detection exists, when planning for pothole repairs, manual inspection of potholes is often done which is time consuming, inconsistent and may lead to wrong estimates of materials required to repair the potholes. This paper presents a system that attempts to solve this problem by automatically determining the estimated cost of repairing a pothole from a digital image acquired using a phone camera using an efficient image processing technique that accurately estimates the quantity materials needed to repair the pothole. The remainder of this paper is structured as follows. In Section 1.1, we provide the theoretical framework for pothole repair, pothole detection methods and the stereovision method. A review of related work is presented in section 1.5. Section 2 contains the methodology for the study. In Section 3, we present the results of the study and discuss them. Section 4 closes with a conclusion of our work.

1.1. Pothole Repair

Pothole patching is generally performed either as an emergency repair under harsh conditions, or as routine maintenance scheduled for warmer and drier periods. Some of such materials and techniques includes using hot mix asphalt (HMA) and cold mix. For hot mix asphalt (HMA), mix is laid on top of existing asphalt layer(s), making sure that the present or in-place surface is free of major distress and potholes, be reasonably smooth, and clean. After marking the area that needs to be patched, a clean, dry, square-edged hole that extends at least one foot beyond the damaged area is dug. The pothole might then be patched with a light coating of asphalt material, most often applied through spray. The HMA mixture is then carefully placed at the desired location. A single thick lift compacted with a heavier roller produces a higher in-place density than a series of lifts compacted with a vibratory trench compactor.

Many maintenance agencies use the throw-and-go method for repairing potholes. Although not considered the best way to patch potholes, it is the most used method because of its high rate of production. The procedure termed throw-and-roll, is considered a superior alternative to the traditional throw and-go method [5]. The US Department of Transportation conducted a study on the effectiveness of different materials and patching procedures for repairing potholes in asphalt concrete pavements. The study found that cold-mix asphalt (CMA) was the most effective material for pothole repair, but that the durability of the repair was affected by the type of CMA used, the weather conditions, and the quality of the installation [6]. Nicholls *et. al.*, [7] reached a similar conclusion that CMA was the most effective material for pothole repair in most cases, but that other materials, such as cement-based materials and polymer-modified materials, could also be effective in certain conditions. Ipavec, [8] opined that the most durable pothole repairs are those that use a combination of materials and methods that are designed to withstand the specific environmental conditions of the location. A study has demonstrated that the vacuum-assisted method was effective in sealing the cracks and delaminating, and that the repaired potholes were able to withstand the same pressure as the original potholes [9]. Another study found that the composite repair patch was effective in sealing the cracks and preventing further damage, and that the repaired potholes were able to withstand the same pressure as the original potholes[10]. Depending on the pothole and cost considerations, the cold patch method is widely used [11]. The method is illustrated in Figure 1, and it involves the following steps:

1. Clean pothole. Remove large loose rocks and other debris.
2. Pour and spread cold-patch material to a level approximately ½” into pothole.
3. Compact material with hand tamper, car tires or another suitable compaction method.

Figure 1. Cold-patch method for pothole repair [11].

1.2. Pothole Patching Cost

The three main costs for pothole patching are material, labor, and equipment. There may also be some user-delay costs associated with pothole patching operations, as well as associated lane-closure time. The main component of material cost are the aggregates used to fill the pothole. Labor cost on the other hand include personnel cost for patching and traffic control [12]. Cost of equipment largely depends on the method employed to repair the potholes. For instance, for the throw-and-roll, edge seal, and semi-permanent methods, shovels, rakes, or other hand-tools are needed for placing the material.

1.3. Pothole depth detection methods

Analyzing and estimating the depth of potholes is an important project for society, and numerous studies have been conducted to detect and patch potholes, as well as to prevent distress in asphalt pavements. Current methods for pothole depth estimation and analysis include, 3D surface reconstruction methods using 3D laser-based scanning [13], [14] stereovision systems [15], vibration based systems that use accelerometers [16] and image based 2D appearance detection approach [17]. Pothole detection has been an area of interest for researchers and the methods have been classified into vision-based methods, vibration-based methods, and a 3D reconstruction-based methods [18]. However, the purpose for detection is usually to avoid road accidents or improve ride quality[19]

Laser scanning offers outstanding detection performance, compared to the other methods. This approach is able to collect extremely detailed road-surface information using a technique that employs reflected laser pulses to create precise digital models [20]. Laser scanning although more efficient when compared to other image processing techniques, it is relatively more expensive and does not cover a wide area of the asphalt pavement. "Stereo vision systems are used to determine the depth of the pothole from the images taken at the same time but from slightly at different viewpoint situation by using two cameras". Stereo vision have been demonstrated to provide information on the depth potholes without the need for using high cost specialized laser scanners. [21], [22]. A study went beyond detection and depth estimation to predicting and calculating the area of potholes using Mask Region-Based Convolutional Neural Network [23]. Another study applied multilinear regression machine learning approach to predict the number of pixels as an indication of area to compute pothole risk [24]

1.4. Stereo vision Method for Pothole Depth Estimation

Stereo vision involves many processing steps and algorithms which include: Stereo image capture – using a high definition digital camera to capture images of the pothole from two distinct but similar positions; Feature rectification process - finding the sets of corresponding matching points between the two images and aligning them to calculate disparity; finding corresponding points (stereo matching) – using techniques such as Correlation (C), Normalized Cross Correlation (NCC), Sum of Squared Differences (SSD) and Sum of Absolute Differences (SAD) algorithms; and generating fundamental matrix – ensuring that the correctly matched points satisfy epipolar constraints and Mean depth estimation computed using Equation (1) through Equation (3) [25].

$$D_{max} = \max \left[\sum_{i=1}^{m} |I_{nL}\ (i,j) - I_{nR}\ (i,j)| \right] \tag{1}$$

$$D_{min} = \min \left[\sum_{i=1}^{m} |I_{nL}\ (i,j) - I_{nR}\ (i,j)| \right] \tag{2}$$

where I_{nL} and I_{nR} are the inlier points in the left and in the right image respectively.

$$Mean\ depth = \frac{D_{max}+D_{min}}{2} \tag{3}$$

Equation (3) is a convenient way to calculate the magnification (m) without knowing the object length.

Wang et al (2008).

$$m = -\frac{Image\ Distance}{Object\ Distance} \tag{3}$$

The magnitude of the magnification helps to determine if the image size is larger or smaller than the object. Given, manual measurements of the potholes are already taken, using equations above a relationship between the image length and pothole length, which is equal to the relationship between the image breadth and pothole breadth, is obtained. Hence, the size of the object can be derived from the image. The stereo vision algorithm is presented in Table 1.

Table 1. Algorithm for Depth Estimation from Stereo Images

Step	Procedure Input: Stereo Image Pair Output: Mean Depth
1	Read the stereo image pair.
2	Find matching image features between the left and right images.
3	Estimate the fundamental matrix from the corresponding points in the stereo images.
4	Deduce the inlier points from both the left and right images using the estimated fundamental matrix.
5	Find the maximum and minimum disparity among the inlier points to obtain the depth range.
6	Extract interest points' descriptions from the stereo images.
7	Detect Speeded-Up Robust Features (SURF) features in the grayscale images.
8	Obtain the mean depth from the calculated disparity values.
9	Read the stereo image pair.
10	Find matching image features between the left and right images.

1.5. Related Works

An attempt to evaluate pavement distress using 3D depth information from stereo vision was reported in [26]. The authors used a stereo vision-based approach in which the depth of the pothole was based on the disparity of the two similar images captured by the cameras placed in such positions, so that the view of the images looks like two different views of the similar images at different viewpoints. However, for such system to work, the intrinsic and extrinsic parameters of the used camera via camera calibration is required in order to make the rectification process in processing stage before matching the stereo images. An efficient and robust algorithm in depth estimation suitable for mobile robot navigation and obstacle detection in real life applications was proposed by [25]. Using SURF algorithm, the author successfully implemented un-calibrated rectification using inliers to calculate the depth without a disparity map. An inexpensive vision-based method for detecting and assessing the severity of potholes through 2D recognition and 3D reconstruction have been proposed [27]. The results indicate the method's potential in improving automated pothole detection. Another study by explores the use of vibration-based mobile sensing to detect road surface conditions, particularly potholes, using accelerometer data and GPS devices [28]. They successfully identified potholes through a machine-learning approach. Other researchers have recorded success in using ANNs and CNNs for pothole detection. ANN has been used for many other applications such as detecting cattle [29] and skin cancer [30]. For pothole repair, deep learning approaches have been investigated and shown to be effective [31]. A recent study has investigated the critical role of road maintenance in sustaining economic and social development, emphasizing the economic consequences of neglecting road distresses. The study showed that labor-based methods are effective for addressing various road defects. They opined that the abundance of labor can be leveraged upon to improve road maintenance in rural areas. [32] . Another related study explored the application of a state-of-the-art Convolutional Neural Network (CNN) based pothole detection model for the real-world scenario of Bangladeshi streets. The study employed a multiple-case analysis approach, combining various experiments based on video recorded at different environmental conditions and vehicle speeds. The findings demonstrate the superior performance of the AI-based model compared to an expert human evaluator in four out of five cases, with the highest accuracy of 85%. This suggests the potential of using AI-based methods for pothole detection, particularly in regions with limited resources like Bangladesh [33].

Moazzam et al., [34] utilizes Kinect sensors to collect pavement depth images and calculate pothole volume. While cost-effective, further research is needed to improve the error rate associated with this novel infrared technology-based measurement method. A system was proposed that leverages a smartphone's built-in sensors, including acceleration, rotation angle, and rotation speed, to detect potholes on the road. The system employs a Random Forest (RF) based machine learning model trained on collected sensor data [35]. A study attempted to address the challenge of automating the detection of potholes in asphalt pavement images. The method involved resizing, grayscale conversion, histogram equalization, thresholding, and edge detection, followed by morphological operations and median filtering to extract relative pothole shapes. A stereoscopic camera technique was utilized to enhance accuracy and estimate the depth or volume of the pothole, which can be valuable for assessing the amount of asphalt material needed for repair [36]. The work of [36] has a similar objective with this paper but differs in the aspect of how the digital image is acquired. The method in this paper did not involve the use of the relatively more expensive stereoscopic camera setup. Rather, images acquired using digital cameras of mobile phones were used. Another gap is that whereas there is a large collection of pothole data suitable for detection purpose [37], there is scarcity of data containing pairs of pothole images (left and right) suitable for depth estimation using stereo vision.

2. Methodology

The development workflow for the cost estimation of pothole repair system is presented in Figure 3; the process involved data acquisition, modeling, and system implementation.

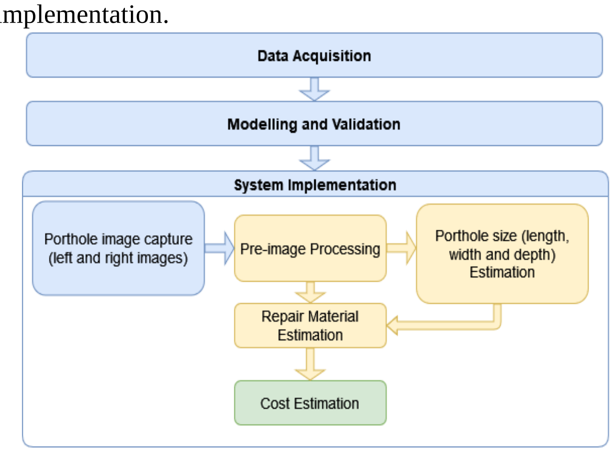


Figure 3. Development workflow for the cost estimation of pothole repair system

2.1. Data acquisition, validation and processing

In this study, twenty (20) randomly selected samples of potholes with different sizes and shapes were manually measured using measuring tape and ruler, recording the length (cm), breadth (cm), and various depth (cm) around the corners of each pothole. All pothole samples were acquired in the Ugbowo campus of the University of Benin, Nigeria. Figure 2 shows sample images of the manual measurement procedure on potholes in the study area.

Figure 2. Pothole samples showing the marking out and manual measurement procedure.

A measuring plastic bucket filled with sand and fine granite was used to measure the volume of asphalts required to patch each pothole. The substitute materials were used instead of asphalt to reduce material handling cost during the research. The repair procedure adopted for this research is presented in these five steps:

1. Measure the Pothole Dimensions
2. Calculate the Volume of the Pothole (m^3)
3. Determine Asphalt Density (lb/ft^3 or kg/m^3)
4. Calculate Asphalt Quantity by dividing the pothole's volume by the density
5. Carry out repair

2.2. ANN modelling, training, prediction and Validation

ANN was selected for length and width estimation due to its simplicity and flexibility for training data and biasing weights to obtain the best possible goodness of fit model. This was done with the aid of MATLAB.

For ANN modeling and prediction, six (6) input variables were required namely, the pothole (length (cm), breadth (cm), depth1 (cm), depth2 (cm), depth3 (cm) and depth4 (cm)). The output or target variable is the volume (liters) of asphalt required to fill the pothole.

To train the network, 70% of the total data collected was employed and the feed-forward back propagation model was used. The progress of the network training was monitored using the mean square error of regression (MSEREG). MSEREG is a network performance function. It measures network performance as the weight of sum of two factors: the mean squared error and the mean squared weight and biased values. The network generation process divides the input data into training data sets, validation and testing. For this study, 70% of the data collected was employed to perform the network training, 15% for validating the network while the remaining 15% was used to test the performance of the network. The feed forward back propagation model and the hyperbolic tangent sigmoid function were used for the ANN. To optimize the ANN model for predicting the volume of asphalt needed to fill potholes, the configuration included six input variables representing pothole dimensions, 20 hidden neurons, and one training output. The output layer was configured with 20 nodes. During the training process, weights and bias of the network were interconnected using feed-forward propagation. Errors generated were looped back into the training process for minimization and eventual elimination. Specifically, the number of hidden neurons per layer was increased to 20 to address the limited available data essential for this training and the network's complexity. This comprehensive configuration aimed at enhancing the model's accuracy and robustness in asphalt volume prediction. Data divisioning was carried using the random algorithm while the training process was achieved using the Levenberg - Marquardt algorithm. The Mean Square Error (MSE) was used to analyze the performance of the model.

2.3 System Implementation

The developed system was sub-divided into five functional parts; pothole image capture, Image processing of the pothole image, depth, breadth and length estimation from the pothole image, Material estimation and cost estimation.

Pothole Image Capture: The pothole images were capture using a 20 mega pixel camera. An image capturing position of at least 5ft was maintained with left and right images captured one after the other. The image processing toolbox in MATLAB was used to pre-process the acquired pothole images by resizing, converting to grayscale and pair the left and right images for further analysis. After the preprocessing, the stereo vision method was used to estimate the depths while the trained ANN model was used to estimate the lengths and widths of the processed pothole images.

Material Estimation (Quantity of Asphalt required to fill pothole): A mathematical model was generated when using ANN tool to analyze the pothole data gathered from manual measurement of the pothole samples, this model shows the relationship between the depth of a pothole and the volume of asphalt required to fill the pothole. Hence, once the depth of the pothole is extracted from the image using stereo vision algorithm, the depth is placed as an input into this model generated by the ANN tool and therefore the quantity of asphalt required to fill the pothole is estimated.

Cost Estimation: Using MATLAB programming language, a program was generated which takes into consideration the cost of transportation in carrying the required materials to the site, the cost of man labor expended during the pothole repair and the cost of asphalt used in the pothole repair process. The software was then programmed to add up the necessary parameters and output the total cost required to repair the desired pothole. The flowchart for the program is presented in Figure 4.

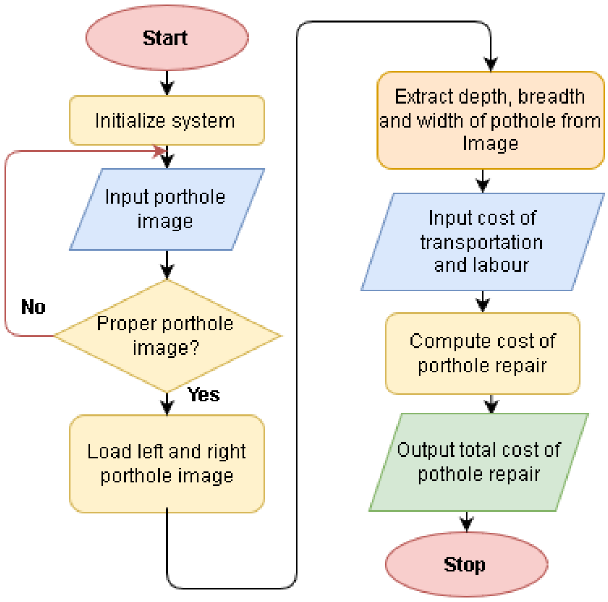


Figure 4. Flowchart of estimated cost of pothole repair system.

3. Results and Discussion

The data obtained from pothole samples after manual measurements and corresponding quantity of materials needed for repair is presented in Table 2. The maximum depth is the most important depth measurement because it indicates how bad the pothole is and is a major determinant of the cost of repair. Secondly, since the pothole will be excavated to the maximum depth, it is a determinant of the quantity of material needed to repair the pothole. The computed values for materials required was obtained by computing the volume of pothole using a rectangular cross section defined by the length and breadth measurements.

3.1. Performance of the ANN model for pothole size estimation

Figure 5 represents the performance curve of the developed ANN model. It is a plot of MSE for each iteration. A goodness of fit of R = 0.9543 was obtained. This indicates that the model produced by the trained network is efficient for predicting the size of the potholes from the input variables.

Table 2. Pothole measurements and predicted pothole depth used as input parameters for ANN training.

S/N	Length (cm)	Breadth (cm)	Depth1 (cm)	Depth2 (cm)	Depth3 (cm)	Depth4 (cm)	Mean Depth (cm)	Max Depth (cm)	Measured Repair material (m3)	Computed Repair Material (m3)
1	37.0	20.0	3.0	3.7	3.2	3.4	3.325	3.70	2.5	2.738
2	35.0	30.0	4.2	7.2	4.0	4.0	4.85	7.20	5.0	7.560
3	85.0	81.0	7.0	7.5	7.0	7.0	7.125	7.50	30	51.638
4	49.0	74.0	2.2	2.5	2.5	2.2	2.35	2.50	20	9.065
5	100.0	72.0	2.6	3.0	4.3	4.8	3.675	4.80	35	34.560
6	53.0	51.0	4.2	3.2	5.0	3.5	3.975	5.00	9.0	13.515
7	35.0	31.0	3.8	3.0	3.8	3.0	3.4	3.80	3.5	4.123
8	83.0	75.5	5.0	2.5	3.0	6.0	4.125	6.00	2.5	37.599
9	64.0	61.0	2.5	2.0	2.0	2.0	2.125	2.50	7.5	9.760
10	115.0	30.0	4.7	1.5	2.0	6.0	3.55	6.00	2.65	20.700
11	42.0	36.5	1.5	1.5	1.5	1.5	1.5	1.50	5.5	2.300
12	58.0	66.5	2.8	6.0	2.5	2.5	3.4375	6.00	1.2	23.142
13	52.0	42.7	2.5	2.0	1.8	2.0	2.075	2.50	7.0	5.551
14	42.0	36.5	1.5	1.5	1.5	1.5	1.5	1.50	7.5	2.300
15	30.0	28.0	2.0	2.0	2.5	2.8	2.325	2.80	3.0	2.352
16	60.0	58.0	3.0	3.5	3.0	2.8	3.075	3.50	7.5	12.180
17	40.0	42.0	2.0	2.6	3.0	2.0	2.4	3.00	6.0	5.040
18	21.0	22.0	4.0	4.5	4.5	4.0	4.25	4.50	2.4	2.079
19	50.0	72.0	3.0	2.0	2.0	3.0	2.5	3.00	2.1	10.800
20	21.0	20.0	3.0	3.6	3.7	3.5	3.45	3.70	2.3	1.554

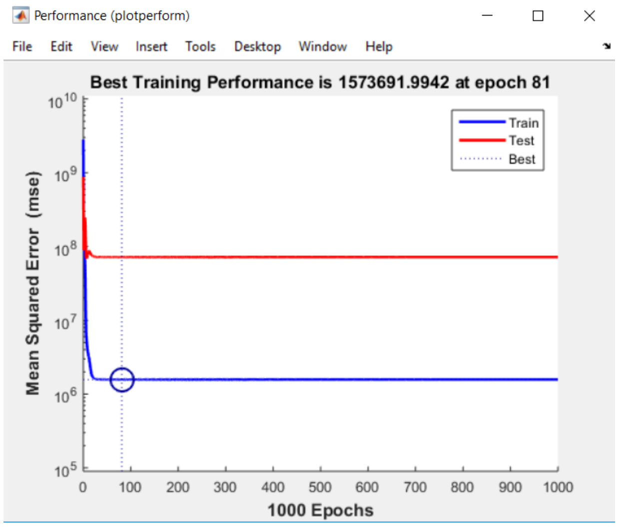


Figure 5. Performance curve of the ANN model.

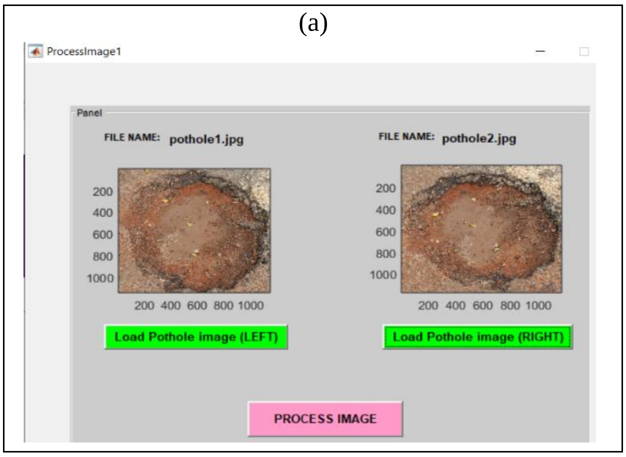
The computed mean errors are presented in Table 3. The errors show that the model predicts length and breadth of potholes better than depth. This result is as expected due to the limitations of the depth estimation technique and data acquisition method used. This results agrees with review of the state of the art methods for pothole detection was conducted in [37]. They opined that classical 2-D image processing-based approaches have serious limitations. However, the performance is acceptable for quick and cost-effective estimation purposes.

Table 3. Mean Error

Parameter	Mean Error (%)
Depth	5.262
Breadth	3.789
Length	3.403

3.2. The developed System

The developed system was shown to correctly executes the breadth and length estimation program immediately after stereo vision method has been processed and the depth of the pothole displayed. The pothole images after being analyzed using stereo vision method outputs the processed images as shown in Figure 5.



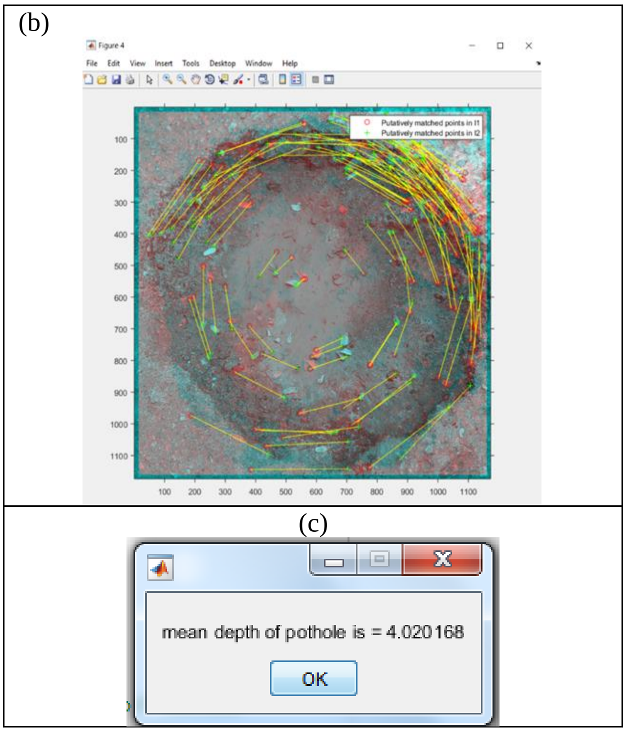


Figure 5. (a) Input pothole images, (b) Processed images of pothole sample and (c) Dialog box of computed mean of pothole

After the image has been analyzed, the basic matrix representing the inlier points is used to estimate the pothole image's mean depth; this result is then exported to the MATLAB workspace and output in a dialog box as shown in Figure 6. The software's final window is the cost estimation window (Figure 6). It gives the user the choice to input other costs that affect the repair of potholes i.e. (transport, equipment and labor), also the depth, breadth and length of the pothole obtained in the previous window is used to calculate the total amount of asphaltic material required. A major limitation of the stereo vision method is that it cannot accurately predict depth of potholes that contain water or debris. Similarly, unevenly shaped potholes have varying depths.

4. Conclusion

The goal of this paper which is to present efforts towards automatically measuring and analyzing potholes with a simple image of the pothole for the purpose cost estimation of pothole repair/patching was achieved. The system presented in this paper proved useful in the estimation of asphalt required to repair a pothole. The results show that the system provides some cost and time savings because it is faster to acquire digital images than for personnel to manually estimate the magnitude of potholes.

In comparison to manual approaches, this system is faster and easier at gathering the data required for maintaining pothole-ridden roads. It also calculates the cost of pothole repair and maintenance while using less labor. Additionally, the subjectivity issue is addressed, and since the acquired digital images can be reviewed again, the system may be evaluated by human employees. The implication of this system is that it will make it easier to efficiently plan the maintenance of damaged roads in a given state or country. The method described in this paper is cost effective compared to using stereoscopic camera setups because the images are acquired using the camera of mobile phones. Future work will involve the implementation of the system using the python programming language. In addition, more work will be done to acquire more pothole images and measurements from geographically dispersed locations to improve the pothole size and depth prediction models.

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