Pavement Pothole Detection and Severity Measurement Using Laser Imaging

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Abstract**—** Over the years, Automated Image Analysis Systems (AIAS) have been developed for pavement surface analysis and management. The cameras used by most of the AIAS are based on Charge-Coupled Device (CCD) image sensors where a visible ray is projected. However, the quality of the images captured by the CCD cameras was limited by the inconsistent illumination and shadows caused by sunlight. To enhance the CCD image quality, a high-power artificial lighting system has been used, which requires a complicated lighting system and a significant power source. In this paper, we will introduce an efficient and more economical approach for pavement distress inspection by using laser imaging. After the pavement images are captured, regions corresponding to potholes are represented by a matrix of square tiles and the estimated shape of the pothole is determined. The vertical, horizontal distress measures, the total number of distress tiles and the depth index information are calculated providing input to a three-layer feed-forward neural network for pothole severity and crack type classification. The proposed analysis algorithm is capable of enhancing the pavement image, extracting the pothole from background and analyzing its severity. To validate the system, actual pavement pictures were taken from pavements both in highway and local roads. The experimental results demonstrated that the proposed model works well for pothole and crack detection.

Index Terms**—** Pavement distress detection, laser, Pothole, neural network.

I. INTRODUCTION

Automatic detection of potholes on the pavement surface is an important issue and has great significance for the purpose of road maintenance. To help pavement engineers to maintain roads in the best possible condition at the lowest cost, Pavement Management System (PMS) has been widely implemented by most public road agencies [1]. Pavement pothole information is one of the key elements needed for the PMS. The information was collected through visual surveys until the early 1980's. However, the visual surveys are subjective, inconsistent, tedious and often dangerous. Thus, during the last three decades, significant efforts have been made to develop methods to automatically collect pavement images and extract pothole information with varying levels of success.

Acosta et al. [2] developed a low cost system which automatically analyzes pavement images captured from video or film recordings. The system allows the identification, classification, and quantification of commonly occurring pavement distress types in terms of severity and extent. Once pavement distress is identified, quantified, and classified, the system can be combined with rating procedures to obtain a quantitative measure of pavement condition. However, distress identification and classification is currently limited to distress types that can be quantified by width, length, geometry, or area covered by the distress.

Mraz et al. [3] introduced a statistical filtering method to enhance crack images more effectively. In their method the image of grayscale target is captured under the same ambient temperature and lighting conditions as those of the crack imaging operation. The total noise in a given region of the image is calculated using the noise in the image of the Grayscale wedge of the corresponding intensity. They concluded that the new method enhanced the pavement images by improving pixel intensity contrast between the crack and the surrounding area.

Despite such efforts the Automated Image Analysis System has suffered from the presence of shadow and often failed to meet the accuracy level required by agencies. In 2005, a new Laser Road Imaging System (LRIS) was developed, which utilizes a laser to illuminate the pavement surface and a line scan camera to capture an image under laser frequency [4]. The images of LRIS are free from shadows under consistent laser illumination.

The real world environment is highly unstructured and dynamic, therefore, any algorithm for pothole detection have certain advantages and limitations. The main objective of this paper is to propose a laser-based optical system for pothole detection on roads. The proposed method consists of an active light source that projects a line pattern of laser beams onto the pavement surface, a camera for capturing images, and the image processing algorithms that identify the potholes, as shown in Figure 1. Following the pothole/crack detection, a feed-forward neural network is used to determine its severity and crack type. The experimental results demonstrate that the proposed system is more economical, accurate and efficient compared with earlier methods.

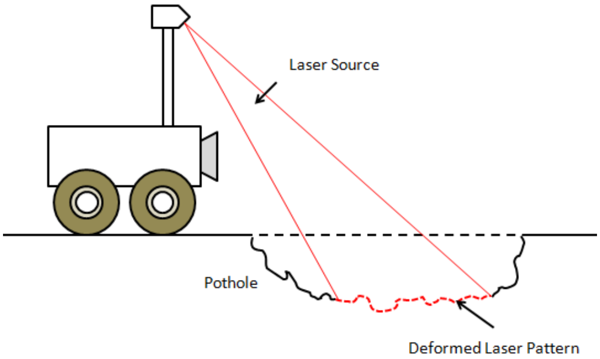


Figure 1 An example of how the structured light deforms when a pothole is detected

II. IMAGE ANALYSIS TECHNIQUES FOR POTHOLE DETECTION

The main aim of the image processing module is to extract laser color regions in the image. After extracting the laser line from the background, the resulting image is searched for any deformation in the shape of the laser line pattern. This section describes different image processing techniques for detecting potholes using a laser pattern.

2.1 Multi-window median filtering

The removal of impulse noise is an important issue in pothole detection. After the video sequences are captured as image frames, the frames are scanned to detect the laser line. The laser line is affected by the superposition of a certain amount of undesired external lighting.

A multi-window median filter is applied in the initial step to perform noise reduction in an image. The standard median (MED) filter is a well-known nonlinear filter that eliminates the noise and performs well in the smooth region of an image. Since the detection of pavement distress involves the detection of liner structures in the pavement image, a multi-stage median filter which uses 4 directional median values as represented by masks in Figure 2, is considered.

1	1	1

	1	
	1	
	1	

		1
	1	
1		

1		
	1	
		1

Figure 2 Four masks used for filtering

The multi-stage median filter could be used to reduce the noise while preserving much of the detail in the 2-D image and produces comparable results with the standard median filter.

2.2 Tile partitioning

2.2.1 Thresholding

Image tiling starts with binarizing the image using a thresholding operation. Thresholding is a widely used technique for image segmentation and feature extraction. In many applications of image processing, the gray levels of pixels belonging to the object are substantially different from the pixels belonging to the background. During the thresholding process, individual pixels in an image are marked as “object” pixels if their value is greater than some threshold value and as “background” pixels if lower. In this paper, a laser line pixel is given a value of “0” while a background pixel is given a value of “1”. Finally, a binary output image is created, as shown in Figure 3.

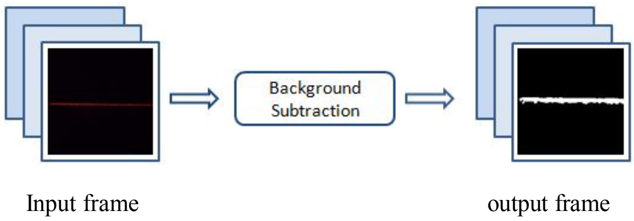


Figure 3 Image thresholding (Background Subtraction)

Due to the strong concentration of the laser source, noise such as shadow, lane marks, oil stains etc. will barely influence the thresholding results. A simple global segmentation method will be practical for this type of application. Here we used a common thresholding algorithm known as Otsu’s method [5] for automatic thresholding. Otsu’s method which is based on the statistics of gray level histograms is a well accepted method for image thresholding. It selects the global optimal threshold by maximizing the between-class variance. The average of these local threshold values is selected to be the global threshold value for the segmentation. The process leads to a lower threshold value which would effectively reduce the misclassification caused by low gray value noises. After an appropriate threshold value is determined, the pixels with gray level below the threshold are classified as distress pixels and pixels with gray level value exceeding the threshold are assigned to the background.

2.2.2 Noise removal

In this step, morphological closing is applied in order to fill small holes, bridge the thin gaps in the binary image, connect nearby laser line pixels without changing the laser line area significantly, and smooth the boundaries. Morphological closing involves dilation followed by erosion as commonly specified by the following equation

$$A \cdot B = (A \oplus B) \ominus B \tag{1}$$

Here we used a line structuring element B of size 20 pixels for the closing operation.

The noise in the binary image is reduced by labeling connected components and counting the number of connected pixels. The operation scans the image and groups them together into components based on pixel connectivity, *i.e.* all pixels in a connected component share similar pixel intensity values and are connected with each other. Let Y represent a connected component contained in a set A and assume that a point p of Y is known. The following iterative expression yields all the elements of Y :

$$X_k = (X_{k-1} \oplus B) \cap A \qquad k=1, 2, 3 \ldots \qquad (2)$$

Where $X_0 = p$, and B is a suitable structuring element. The algorithm converges when $X_k = X_{k-1}$, leading to $Y = X_k$. This algorithm is applicable to any finite number of connected components contained in A, assuming that a point is known in each connected component.

Based on the number of pixels in a connected component, any connected components less than a pre-defined value would be considered as noise and removed from the image.

2.2.3 Tile partitioning

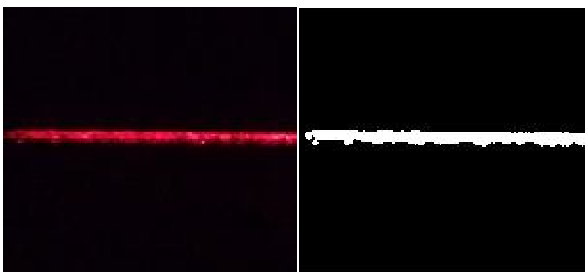
The method proposed in this paper relies on sub-images of pavement rather than pixels. The output image from the previous step is divided into 625 sub-images called "tiles". Each tile is 40x40 pixels which covers a 2x2 inch block on the pavement surface. The tile-based method significantly reduces the computational complexity relative to pixel-based computations. As a result, it is less affected by background noise because a few noise pixels alone would not be sufficient for a tile to be classified as a pothole tile.

After the binary image is sub-divided into square tiles, each tile is classified as either a laser line tile or non-laser line tile. The decision to classify a tile as a laser line tile is based on the global mean value versus the local mean value of each tile. Any tile that has a mean value lower than the global mean value is considered as a laser line tile and would be labeled "1", otherwise it would be labeled with "0". In this way, a tile-based matrix is generated.

3. Laser line deformation detection approach

The laser line in the pothole area of the image produces a visible contour of a deformed pattern. For example, the projection of a laser line onto a plane area produces a pattern with a different shape than the projection of a laser line onto a ball. The deformation of the laser pattern can reveal the presence of the pothole.

In order to detect the deformation of the laser line, a template matching method is used. A predefined laser line template is generated as shown in Figure 4. The input frames are then compared with the predefined template frame to detect the deformation.



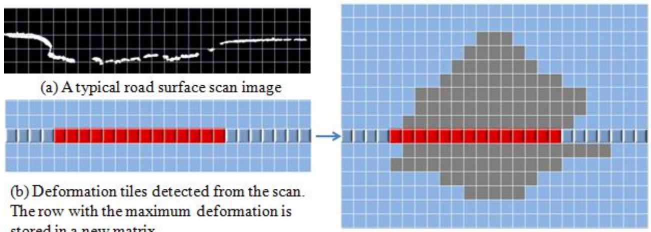
(a) Original image (b) Tile representation

Figure 4 Template laser line

3.1 Template matching method

3.1.1 Pothole shape estimation

After the tile partitioning step, each frame is compared with the template frame, tile by tile, for any deformation. We introduce a simple mechanism to distinguish the deformation of the laser line caused by an obstacle rather than a pothole. The number of tiles in each row that differ between the input frame and the template frame are calculated. If the row that has the maximum deformation of 1's is above the row that has the maximum deformation of 0's, the laser line would be intersecting an obstacle in the scene. Otherwise, we determine this row to be an actual deformed tile row due to a pothole. The row is stored in a new matrix as the first row. This matching process will continue until no further deformation is detected. All rows that qualify for deformation are stored in the new matrix. The output matrix would be an estimated shape of the pothole. The process is shown in Figure 5.



(a) A typical road surface scan image

(b) Deformation tiles detected from the scan. The row with the maximum deformation is stored in a new matrix

(c) Deformation rows are accumulated frame by frame and the estimated shape of the pothole is generated

Figure 5 Template matching method for pothole shape estimation

3.1.2 Depth index

Depth information is defined based on the extent of the deformation that affects rows in each frame. For example, in Figure 5 (a), deformation could be detected in 2 rows, so the depth information of this frame would be 2. All depth information is stored frame by frame until no further deformation is detected. The average of this information is computed as the depth index for the detected pothole and stored for further analysis.

III. CRACK TYPE & POTHOLE SEVERITY CLASSIFICATION

Distress extracted through the process as explained in the previous section can be classified into different types of cracks (transversal, longitudinal) or potholes with various severity levels (low, moderate, or high). In our research, a three-layer feed-forward neural network is used for distress classification [6].

The distress measure in an image is calculated by accumulating the differences between adjacent histogram values. The neural network distinguishes the distress type by finding the unique pattern of uniformity in these distress values. Histograms are used to measure the statistical information by counting the number of distress tiles (zeros) in each column, row and the whole matrix.

The vertical distress measure is determined by accumulating the differences between the numbers of deformed tiles in adjacent columns using Equation (3),

$$VD[i] = \sum_{i=1}^{Nc-1} |Hv[i+1] - Hv[i]| \quad i = 1 \ldots Nc \quad (3)$$

where VD is the vertical distress measure, Hv is the vertical histogram, and Nc is the number of columns, respectively.

Similarly, the horizontal distress measure is computed by accumulating the differences between the number of deformation tiles for adjacent image rows using Equation (4),

$$HD[i] = \sum_{i=1}^{Nr-1} |Hh[i+1] - Hh[i]| \quad i = 1 \ldots Nr \quad (4)$$

where HD is the horizontal distress measure, Hh is the horizontal histogram, and Nr is the number of rows, respectively. For example, in Figure 6, the vertical distress is 18. The horizontal distress is 30 and the total number of distress tiles is represented by the total number of zero tiles in the image, which is 86.

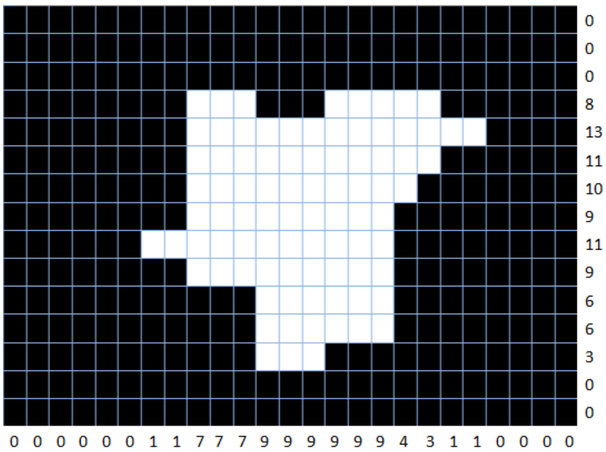


Figure 6 Distress tiles distribution

If the distress is of a transversal crack type, the vertical distress measure should have a low value, which indicates that there is little deviation between any of the columns for this image. If the distress is of the longitudinal type crack, the horizontal distress measure should have a low value, which indicates that there is little deviation between any of the rows for this image. If both distresses measures have a large value, the distress is classified as a pothole, which indicates the deviation is significant in both directions. Following this step, based on the total number of distress tiles computed from the segmented image matrix and the depth index from the previous steps, we are able to classify the distress into different types of cracks or potholes with different degree of severity levels.

Four parameters (the vertical distress measure, the horizontal distress measure, the total number of distress tiles and the depth index) are used to provide the inputs to a feed-forward neural network. The architecture of the neural network which has a total of 4 input nodes, 8 hidden nodes and 5 output nodes is shown in Figure 7.

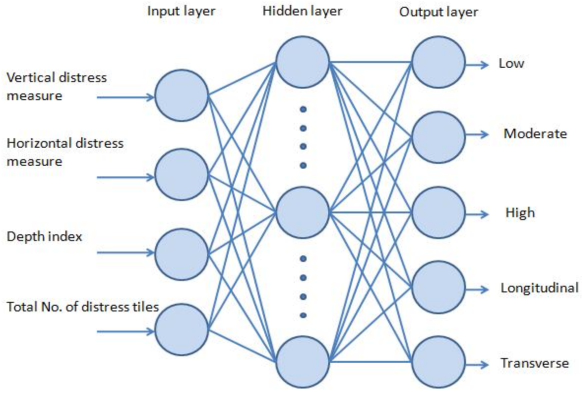


Figure 7 The architecture of the neural network

The crack type and severity level of the pothole is classified according to the data shown in Table 1. Using this table, the distress in Figure 6 is classified as a pothole with a moderate level.

Table 1 Distress classification guideline

	Vertical distress measure	Horizontal distress measure	Total No. of distress tiles	Depth index
Low	> 5	> 5	< 40	1
Moderate	> 5	> 5	40-120	2
High	> 5	> 5	> 120	3
Transverse	< 2	> 5	< 40	1-3
Longitudinal	> 5	< 2	< 40	1-3

IV. EXPERIMENTAL RESULTS

The proposed algorithm has been implemented in MATLAB R2008b on a set of over 100 images (10 images for each distress) taken from the road surface and its performance results are presented in this section. Figure 8 shows sample distress classification results extracted from the image database.

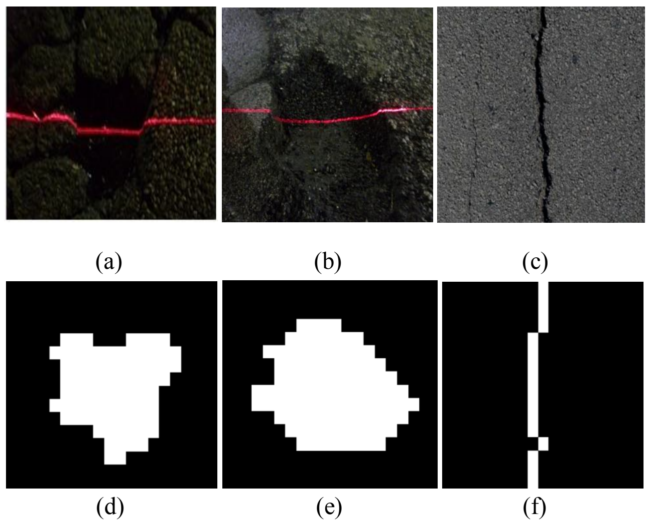


Figure 8 (a) & (b) Two typical road surface scans of pothole images. (c) Original pavement image with a longitude crack. (d) & (e) Pothole image represented by tiles. (f) Longitude crack represented by tiles.

Table 2 summarizes the rating results from manual and proposed laser-based approaches. It can be clearly seen that, in all tested samples, the severity level and the crack type detected by the proposed method is in agreement with the level obtained from the manual method.

Table 2 Severity level and crack type comparison (Manual vs. Proposed methods)

Sam. No.	Distress Type	Severity Level or Crack Type	
		Manual	Proposed
1	Pothole	Moderate	Moderate
2	Pothole	Moderate	Moderate
3	Crack	Longitudinal	Longitudinal

In comparison with other existing 2-D pavement distress detection and classification methods, the proposed method has a better ability to discriminate the dark areas that are caused by lane marks, oil spills, or shadows. The experimental results indicate that our proposed system provides reliable and accurate results from the above tested samples.

V. CONCLUSION

This paper presents an economical, accurate and efficient laser based pavement distress detection and classification method using advanced image processing techniques. It has been shown that the proposed pavement analysis system allows complete automation with the evaluation of pavement potholes and cracks. More importantly, the proposed method has the ability to discriminate the dark areas that are caused by lane marks, oil spills, or other effects. The experimental results indicate that our proposed system provides reliable and accurate results from the tested samples.

The application developed in this research, was mainly focused towards pothole detection and classification by analyzing the deformation of a laser line. Future developments will target the analysis of different laser patterns, such as parallel lines, grid and dot-matrix. In addition, since the pavement surface is uneven and randomly bumped, cameras would capture shaky, tilted, rotated image of the laser pattern as it moves along the road. The laser pattern shifting due to inherent vibrations must be handled. Thus, in order to be able to estimate the pattern shift, robust and efficient algorithms need to be developed to keep track of pattern between consecutive frames. The output from the algorithm can then be used as a more accurate description of the laser pattern's deformation.

REFERENCES

[1] McGhee, K. H. (2004). Automated Pavement Distress Collection Techniques. NCHRP Synthesis 334. National Cooperative Highway Research Program, Transportation Research Board, Washington D.C.

[2] Acosta, J. A., J. L. Figueroa, and R.L. Mullen (1992). "Low-Cost Video Image Processing System for Evaluating Pavement Surface Distress". Transportation Research Record 1348, pp. 63-72.

[3] Mraz, Alexander, S. Amarasiri, M. Gunaratne, and A. Nazef. (2007). "Innovative Method for Enhancing Pavement Crack Images". Presented at 86th Annual Meeting of Transportation Research Board, Washington, D.C.

[4] Kim, Jung Yong, "Development of new automated crack measurement algorithm using laser images of pavement surface", Phd Thesis, The University of Iowa. Jan 2009

[5] P.S. Liao, T.S. Chen and P.C. Chung, 2001. "A Fast Algorithm for Multilevel Thresholding". Journal of Information Science and Engineering. Vol.17, pp713-727.

[6] B.J. Lee and H.D. Lee. "Position-Invariant Neural Network for Digital Pavement Crack Analysis". Computer-Aided Civil and Infrastructure Engineering 19 (2004) 105-118.

[7] B.J. Lee and H.D. Lee. "A Robust Position Invariant Artificial Neural Network for Digital Pavement Crack Analysis". Technical Report TRB2003-000996. 2003. http://www.ltrc.lsu.edu

[8] Canute Mascarenhas. "Active Light for a small Planetary Rover". Master's Thesis, University of Wuerzburg. 2008