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## FINAL REPORTS

# PAVEMENT DISTRESS EVALUATION USING 3D DEPTH INFORMATION FROM STEREO VISION



### PROJECT TEAM

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# DEVELOPMENT of a COMPUTER INTERFACE and DATABASE for the EVALUATION of PAVEMENT by the PASER METHOD

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FINAL REPORT

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# **PAVEMENT DISTRESS EVALUATION USING 3D DEPTH INFORMATION FROM STEREO VISION**

**Dr. Ezzatollah Salari, Principal Investigator  
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## **ABSTRACT**

The focus of the current project funded by MIOH-UTC for the period 9/1/2010-8/31/2011 is to enhance our earlier effort in providing a more robust image processing based pavement distress detection and classification system. During the last few decades, many efforts have been made to produce automatic inspection systems to meet the specific requirements in assessing distress on the road surfaces using video cameras and image processing algorithms. However, due to the noisy images from pavement surfaces, limited success was accomplished. One major issue with pure video based systems is their inability to discriminate dark areas not caused by pavement distress such as tire marks, oil spills, shadows, and recent fillings. To overcome the limitation of the conventional imaging based methods, a probabilistic relaxation technique based on 3-dimensional (3D) information is proposed in this report. The primary goal of this technique is to integrate conventional image processing techniques with stereovision technology to obtain an accurate topological structure of the road defects. In addition, a road scene often contains other objects such as grass, trees, buildings which should be separated from the pavement. Therefore we have enhanced our earlier algorithm to extract the pavement region from a road scene using a Support Vector Machine (SVM). Various types of cracks are then obtained from the pavement surface images and classified using a feed-forward neural network. The proposed algorithms are implemented in MATLAB and the results are presented.

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## I. BACKGROUND INFORMATION

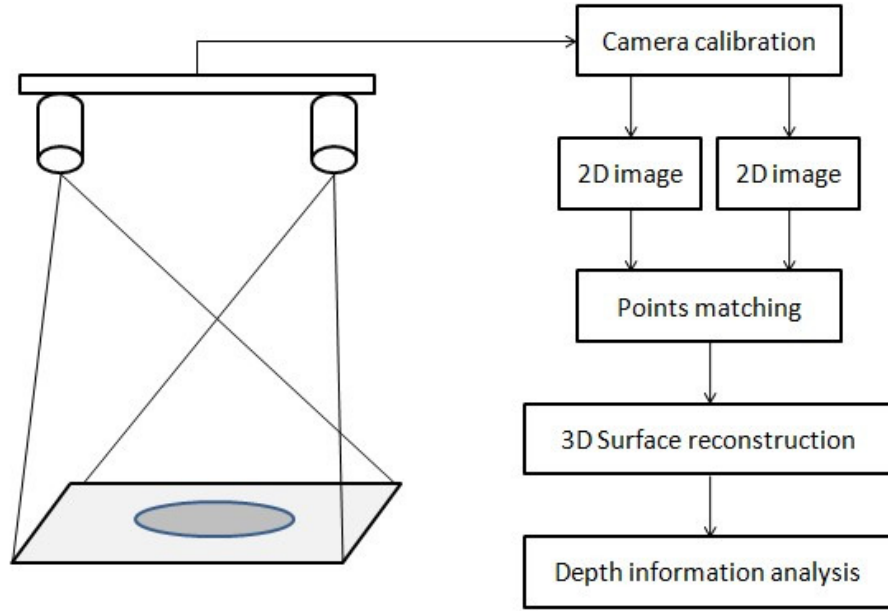
A pavement distress inspection system is essential to maintaining optimal service and keeping the pavement condition safe in economical ways. Automated pavement distress evaluation research based on 2-dimensional (2D) pavement surface images has been conducted extensively in the past two decades. However, the use of 3-dimensional (3D) road surface information in surface distress detection and evaluation is considerably new and has not been fully exploited. Since all the existing 2D methods are based on assumptions that the distress pixels are darker than their surroundings, the major issue with pure video based systems is their inability to discriminate the dark areas that are not caused by pavement distress but rather caused by tire marks, oil spills, shadows, or recent fillings. Recently many studies have been conducted to produce road information by using various advanced equipment. Bursanescu et al. employed a 3D vision system to obtain road surface profiles [1, 2]. Laurent et al. adopted an auto-synchronized laser scanning system to detect road rutting and cracking [3]. More recently, Wang et al. employed stereovision to acquire pavement 3D characteristics for a comprehensive pavement survey [4, 5].

This work aims to integrate 2D and 3D information together to further enhance the automatic pavement inspection systems. Our main focus is the recovery of the 3D depth information as an important feature from a road surface using a stereovision technique. Using the depth information, a relaxation process is carried out to adjust the intensity value of the 2D pavement images. The distress patterns are then detected and reformatted into tile images from which statistical measurements are obtained. A feed forward neural network is used as a tool to classify the various types of distress information. In addition, an enhancement of our earlier work using a Support Vector Machine (SVM) was employed to extract the pavement region from a complicated background. The proposed method is implemented in MATLAB and the results of simulation are presented.

## II. 3D PAVEMENT SURFACE RECONSTRUCTION

The area of obtaining 3D information from 2D images is considered to be well established and has been around for a long time. However, reconstructing detailed and accurate 3D models of the road surface to detect pavement distress has only appeared in recent years. Stereovision is seen as a promising approach in providing accurate, robust data for pavement distress studies. Its basic principle is to extract the depth information of the road surface from a pair of images of the same scene with slight relative displacement.

This section introduces a photogrammetric based pavement evaluation approach by utilizing stereo-images and image processing techniques. The detailed procedure is illustrated in Figure 1. In the first step, two digital cameras are set up for calibration to provide the important parameters needed for 3D reconstruction. We adopted a calibration approach developed by Tsai [6]. After the spatial relationship between two cameras is established by the corresponding points, a pair of 2D images is taken from the same pavement surface (as shown in Figure 2) to reconstruct a 3D surface model. Deficiencies, particularly those exhibiting certain depths, can be found from the 3D model, which are later used in this report as a guide in the relaxation process to refine the 2D segmentations.



**Figure 1. Procedures for 3D Reconstruction Using Stereovision**



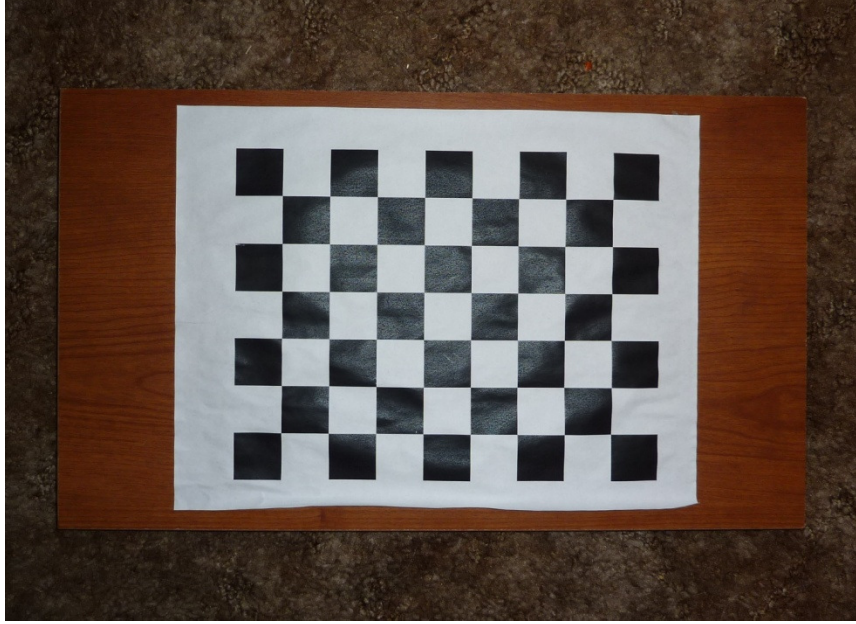
**Figure 2. Stereo Images of the Pavement Surface**

### **A. Camera Calibration**

Camera calibration is a necessary step in the 3D reconstruction. The purpose of calibration is to provide an accurate relationship between 2D image planes and 3D world coordinates. In this section, a popular calibration method proposed by Tsai [6] is tested to provide the parameters needed for the 3D reconstruction.

Figure 3 shows a calibration object, which is a printed checker board page on a flat wooden board, lying on the ground. The corners of each block are extracted by corner detection techniques and used as distinguishing points to define the real world coordinates. The result of the corner detection techniques will give the correspondences between known points in the 3D world coordinates and their positions in the 2D images.

At least 5 points are required to recover the parameters of the camera. We refer to them as  $\{([x_i, y_i, z_i], [u_i, v_i]) \mid i = 1, 2 \dots n\}$ . More feature points distributed evenly across the field of view can greatly improve the precision of the system [7].



**Figure 3. A Calibration Object with Known Coordinates in 3D Space**

## B. Point Matching

From the epipolar geometry we know that knowing a point in the left image, the matching point on the right image must lie on the epipolar line of the right image. This fact is very important to the points matching process since it suggests that there is no need to search the entire 2D images for matching, but only needed is a search on the epipolar line.

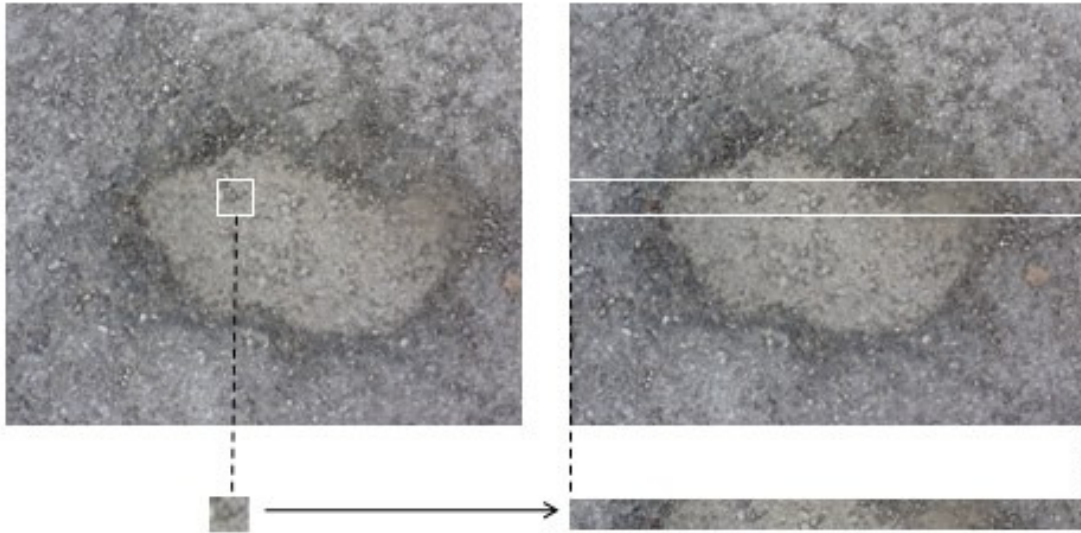
Matching one single point in two images can be very difficult due to the noisy surfaces of pavements because there are often many potential matches for a single point. To reduce the ambiguity, a set of points within a small square window along with the epipolar line are considered instead of matching only a single point. As illustrated in Figure 4, given a point of interest on the left image, to find the corresponding point, we measure the intensity variation by shifting a small square window along the epipolar line on the right image. The intensity variation is calculated by taking the average sum of squares of intensity differences of corresponding pixels within the square neighborhood using Equation (1).

$$D(r, c) = Ave \left( \sum_{\text{square window}} \left( I_{left}(i, j) - I_{right}(i, j) \right)^2 \right) \quad (1)$$

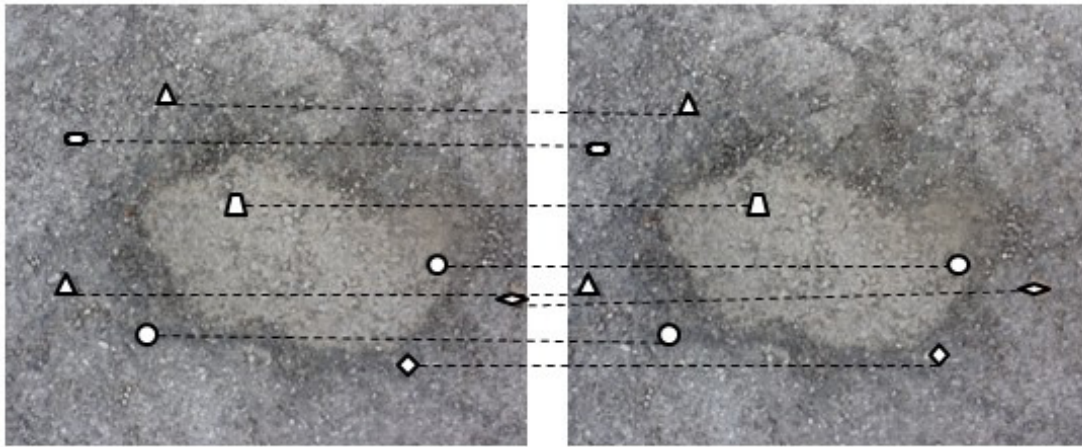


where  $I(i, j)$  denotes the corresponding intensity value within a square neighborhood of point  $(r, c)$  on the right image.

For each point on the epipolar line, a different value  $D$  is obtained. A small value for  $D$  determines a higher probability for a matching point. Therefore, the intensity difference  $D$  is used as a criterion to determine the match. The search range can be adjusted by changing the size of the square window. The point matching process is shown in Figure 5.



**Figure 4. Point Matching along the Epipolar Line**



**Figure 5. Matching Feature Points**



### C. 3D Surface Reconstruction

Let  $[x, y, z]$  be the coordinates of a 3D point, and let  $[r_1, c_1]$  and  $[r_2, c_2]$  be the coordinates of the two image planes, respectively. The following imaging equations with 3 unknown variables  $x, y, z$  can be obtained using projection geometry.

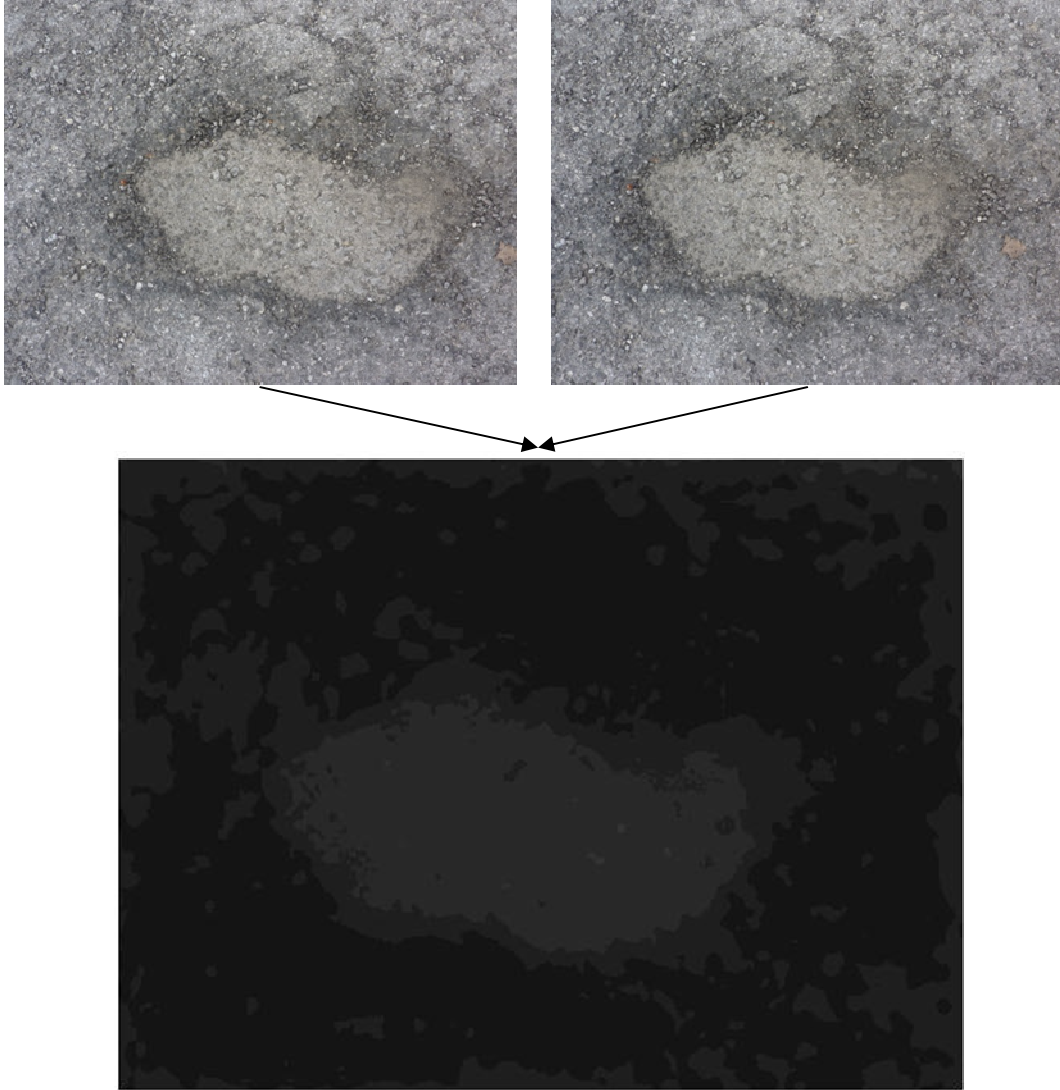
$$\begin{bmatrix} s & r_1 \\ s & c_1 \\ s & s \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & b_{13} & b_{14} \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \quad (2)$$

$$\begin{bmatrix} t & r_2 \\ t & c_2 \\ t & t \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} & c_{13} & c_{14} \\ c_{21} & c_{22} & c_{23} & c_{24} \\ c_{31} & c_{32} & c_{33} & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \quad (3)$$

After eliminating the homogeneous coordinates  $s$  and  $t$  from Equations (2) and (3), we obtain the following four linear equations:

$$\begin{aligned} r_1 &= (b_{11} - b_{31}r_1)x + (b_{12} - b_{32}r_1)y + (b_{13} - b_{33}r_1)z + b_{14} \\ c_1 &= (b_{21} - b_{31}c_1)x + (b_{22} - b_{32}c_1)y + (b_{23} - b_{33}r_1)z + b_{24} \\ r_2 &= (c_{11} - c_{31}r_2)x + (c_{12} - c_{32}r_2)y + (c_{13} - c_{33}r_2)z + c_{14} \\ c_2 &= (c_{21} - c_{31}c_2)x + (c_{22} - c_{32}c_2)y + (c_{23} - c_{33}c_2)z + c_{24} \end{aligned} \quad (4)$$

Any three of these four equations could be solved to obtain the coordinates of the point  $[x, y, z]$ . Figure 6 shows the depth information obtained from the two stereo images.



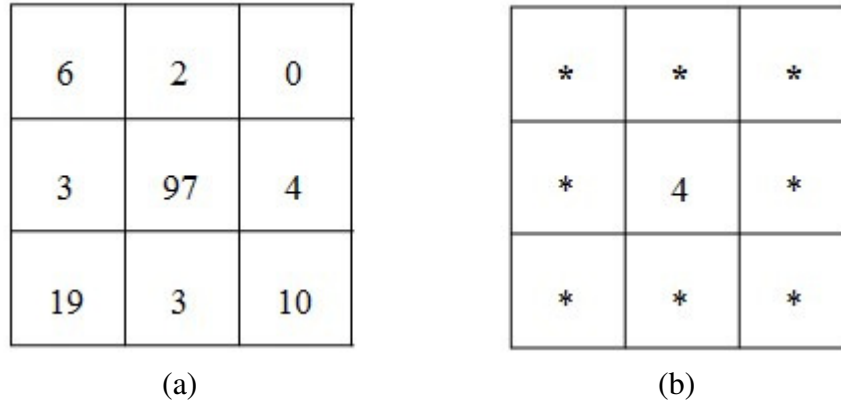
**Figure 6. Recovered Depth Information of a Pothole**

### III. PRE-PROCESSING

The result from the 3D reconstruction is sparse and irregular since only scattered points are reconstructed considering the computation time. To obtain more detailed road surface data, an interpolation method is applied to fill in the unknown points with the average value of its neighborhood. Following the interpolation, a  $3 \times 3$  median filter is applied to both 2D and 3D images to remove impulse noises.

In practical concrete surface images, there can be many problems such as shading, stains, and cracks, to complicate the crack detection process. For accurate and automatic crack detection, it is necessary to overcome these problems. In our previous work, we proposed two non-uniform background removal methods: background subtraction by median filtering and background subtraction by morphological operations to ensure the same background lighting condition for all the pavement images.

The median filter is often used to remove "shot" noise and other spurious features of single pixel extent while preserving overall image quality. The median filter is a sliding-window spatial filter which replaces the center value in the window with the median of all the pixel values within the window. The window, or the kernel, is usually square but it can also be any shape. An example of median filtering of a single  $3 \times 3$  window of values is shown in Figure 7. When applying the median filter, all the values within the window are sorted in an increasing order, which is 0, 2, 3, 3, 4, 6, 10, 19, and 97. It can be seen that the median value of this array is 4. Thus, after filtering, the center value (previously 97) is replaced by the median of all nine values, i.e. 4, as shown in Figure 7 (b).

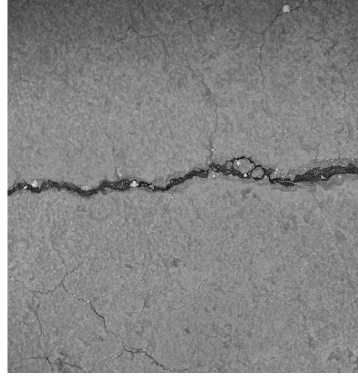


**Figure 7. An Example of Median Filtering**

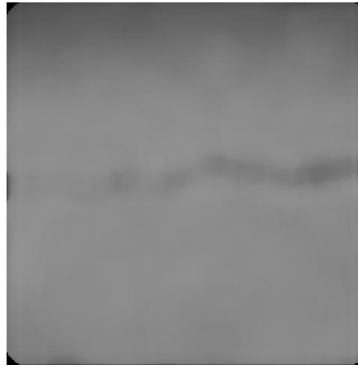
Figure 8 illustrates the process of removing light variation like shadings by using a median filter. First, we use a  $15 \times 15$  window size median filter to smooth the original image to remove cracks. Then the original image is subtracted from the smoothed image to obtain a subtracted image as the output of the non-uniform illumination removal process. The subtracted image is obtained by

$$I'(x, y) = \max (M - I(x, y), 0) \quad (5)$$

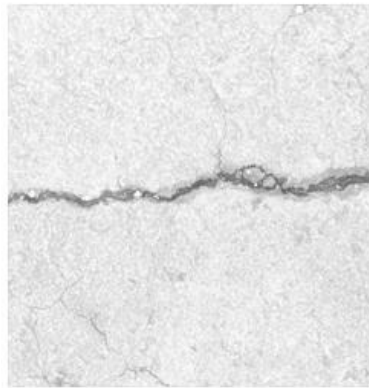
where  $I(x, y)$  denotes the intensity value of the pixel with index  $(x, y)$ , and  $M$  denotes the median intensity value of the pixel's neighborhood.



(a)



(b)



(c)

**Figure 8. Non-Uniform Illumination Removal by Median Filtering**  
**(a) Original Image (b) Smoothed Image with the Median Filter (c) Subtracted Image**

#### IV. PROBABILISTIC RELAXATION BASED ON 3D INFORMATION

The next step for automatic distress detection involves binary segmentation. Thresholding creates a binary image from the grey-level image by assigning all pixels with intensity values below a certain threshold to zero and the others to one. Most 2D thresholding techniques are based on the assumptions that the distress pixels are darker than their surroundings. However, in practice, due to the non-uniform illumination and the presence of undesired objects on the pavement surface such as shadows and oil spills, misclassifications of distresses can easily occur. To overcome this limitation, a probabilistic relaxation labeling technique is developed to enhance the accuracy of the distress detection.

Probabilistic relaxation [8] is a process mainly used for solving labeling problems in various image processing applications. For each pixel in the image, the initial probability  $P_d(i, j)$  corresponding to a distress is assigned according to the intensity value  $I(i, j)$  and the corresponding depth information  $z(i, j)$  recovered from 3D reconstruction is as follows:

$$P_d(i, j) = \frac{(\frac{I_{min}}{I(i, j)} + \frac{z(i, j)}{Z_L})}{2} \quad (6)$$

where  $I_{min}$  represents the minimum intensity value in the 2D image and  $Z_L$  represents the depth of the lowest point on the 3D surface model. Note that the (x, y) plane of the imaging system is located on the surface of the pavement, therefore, the depth value of  $z(i, j)$  including  $Z_L$  assume a negative value. In addition, the probability of a pixel to be labeled as background would be  $P_b(i, j) = 1 - P_d(i, j)$ .

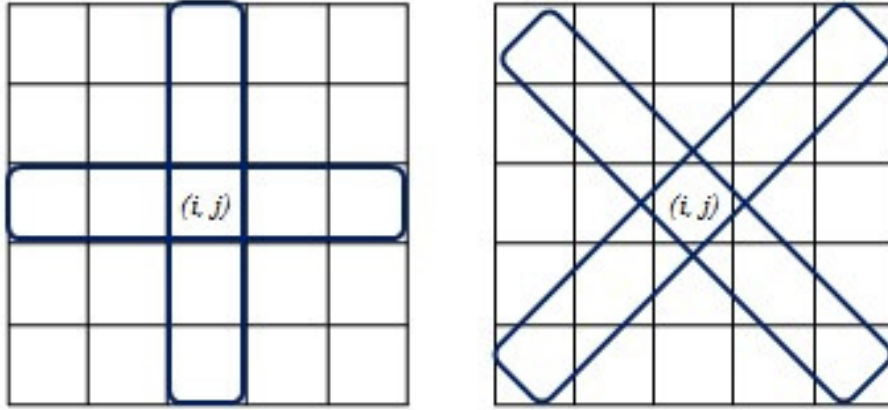
Using the relaxation technique, the probability of a pixel to be part of a distress is updated by considering the label probabilities of its neighborhood. Since most of the cracks share a linear structure, we consider four types of linear sub-regions in each neighborhood according to direction and the estimate of the probability of each sub-region. This means that four estimates of each pixel are calculated along with four angular directions  $0, 1/4\pi, 1/2\pi$  and  $3/4\pi$  passing through the pixel under consideration. Only the maximum value of the four estimates is used to update the probability. In this way, the influence of isolated noisy points and the weakness effect of using square neighborhood can be minimized. The new probability  $P'_d(i, j)$  is updated by:

$$P'_d(i, j) = \text{Max}_k \left( \frac{P_d(i, j)Q_d^k(i, j)}{P_d(i, j)Q_d^k(i, j) + P_b(i, j)Q_b^k(i, j)} \right) \quad (7)$$

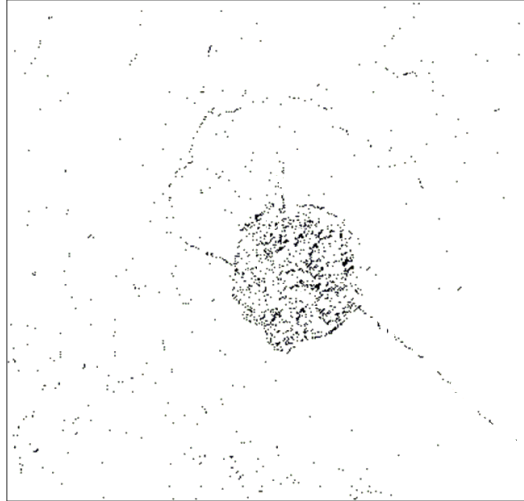
where,

$$Q_l^k(i, j) = \frac{1}{N(R^k)} \sum_{x \in R^k} P_l(x) \quad k = 0, 1/4\pi \dots, 3/4\pi \quad (8)$$

Note that  $R^k$  is one of the four sub-regions illustrated in Figure 9 and  $l$  denotes the label  $d$  (distress) or  $b$  (background), respectively. The updating process for all pixels is repeated until a convergence is reached. At this point, a common thresholding, e.g. Otsu's method based on the obtained probability rather than the original intensity values, is applied to the image. This thresholding technique is able to remove undesired disconnected pieces of cracks. Figure 10 shows the results of segmentation of the pothole image presented in Figure 2.



**Figure 9. Four Sub-Regions used for Updating the Probability**



**Figure 10. Segmentation Result using Probabilistic Relaxation Technique**

## V. DISTRESS CLASSIFICATION AND EVALUATION

This section aims to develop a pavement distress classification and evaluation system using an artificial neural network. To represent the distress in a computationally economical way, the binary image is first partitioned into square blocks called “tiles” [9]. Whether a tile is considered to be a distress tile or not is determined by the percentage of crack pixels in a tile. If the percentage of crack pixels within a tile exceeds a predefined threshold value, the tile is assigned to be a distress tile, otherwise, the tile will be called a background tile. The major benefit of this method is that the tile-based technique could significantly reduce the computational complexity over pixel-based approaches. Further, it is now possible to train the neural network in a more reasonable amount of time with a better convergence. Another benefit of the tile-based approach is that it is less affected by the background noise since a few noise pixels would not be sufficient for a tile to be considered as a distress tile. Thus, the robustness of the system is also enhanced.

### A. Tile-based Histograms

For each tile-based image, two types of histograms, a vertical and a horizontal histogram are calculated to represent the distribution of distress tiles in each column and row as follows:

$$H[i] = \sum_{j=1}^M \text{distress\_tiles}[i, j], i = 1, 2 \dots N \quad (9)$$

$$V[j] = \sum_{i=1}^N \text{distress\_tiles}[i, j], j = 1, 2 \dots M \quad (10)$$

where V and H represent vertical and horizontal histograms, M and N denote the number of rows and columns, respectively. If the distress is a longitudinal crack, there is a clear peak in the vertical histogram. Similarly, if the distress is a transversal crack, there is a clear peak in the horizontal histogram. Otherwise, if the distress is a pothole, peaks can be found in both histograms.

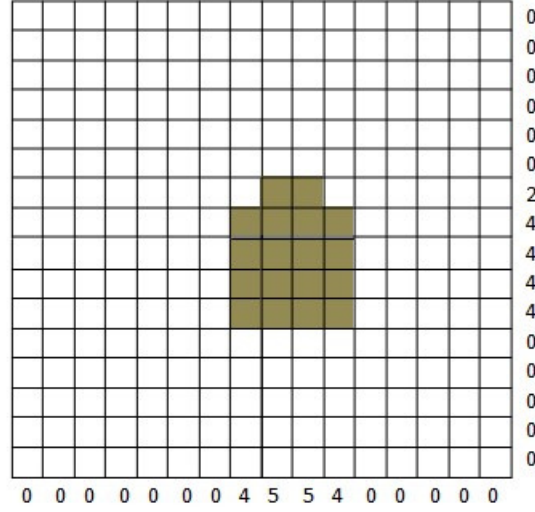
To represent the above observations in the form of a scalar, standard deviations of both histograms are calculated using Equations (11) and (12).

$$\sigma_H = \text{stdev}(H[i]), i = 1, 2 \dots N \quad (11)$$

$$\sigma_V = \text{stdev}(V[j]), j = 1, 2 \dots M \quad (12)$$

In the example shown in Figure 11, standard deviations of two histograms,  $\sigma_H$  and  $\sigma_V$ , are calculated to be 2.02 and 1.67, respectively, showing peaks in both histograms. Thus, in this case the distress is more likely to be a pothole.





**Figure 11. A Tile-Based Image Generated from Binary Image shown in Figure 10**

### B. Shape Complexity Estimation

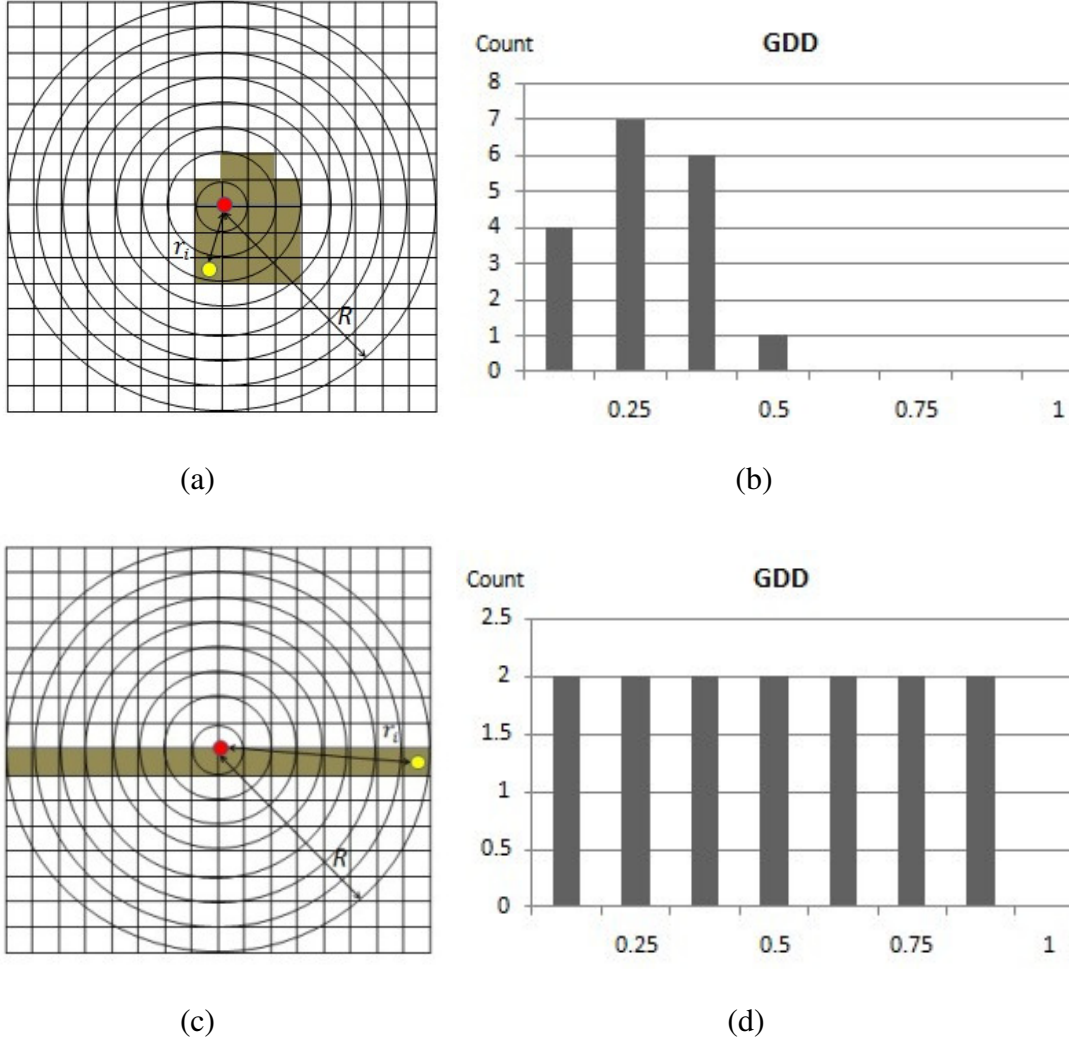
The shape complexity is estimated using the entropy of the distress tiles distribution [10]. For each distress tile, the distance between the distress tile and the centroid point of the image is calculated. If the distances fall into a small range, then the shape of the distress should be a simple circle or circle-like shape (see Figure 12 (a)), whose complexity is low. Otherwise, if the distances are more widespread, the shape should be either linear or scattered (see Figure 12 (c) whose complexity is high).

To represent the shape complexity, we first normalize the actual distance values into an interval  $[0, 1]$  by dividing them by the maximum distance value  $R_{\max}$ , which is the radius of the largest circle enclosed in the image. The normalized distance  $r_i$  is then uniformly quantized into 8 levels to create the normalized distance histogram as follows (see Figure 12 (b) and (d)):

$$n(k) = \{\text{number of } r_i \mid r_i \in \left[\frac{k-1}{8}, \frac{k}{8}\right]\}, k = 1, 2 \dots 8 \quad (8)$$

With a distance histogram, we can easily estimate the pdf of distance distribution  $P(k)$  by dividing  $n(k)$  by  $N$ . Thus, we can define the distance entropy as:

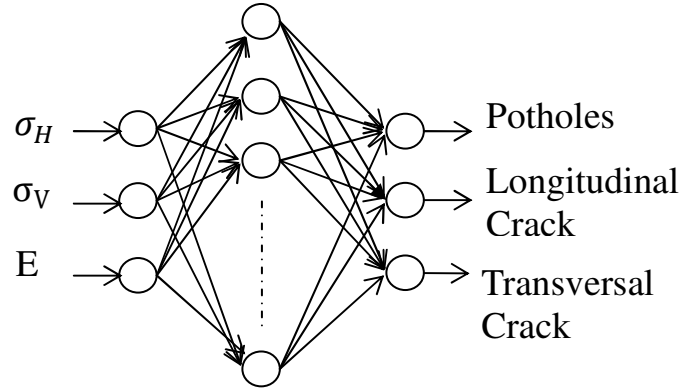
$$E = - \sum_{k=1}^8 P(k) \cdot \log_2 (P(k)) \quad (9)$$



**Figure 12 (a) A pothole shape in normalized distance space. (b) Corresponding normalized distance histogram of (a). (c) A transversal crack shape in the normalized distance space. (d) Corresponding normalized distance histogram of (c).**

### C. Neural Network Training

The two deviation parameters  $\sigma_H$  and  $\sigma_V$  together with the entropy of the distance distribution  $E$  are able to show a clear pattern of a distress. Therefore, they are used as inputs to a specially designed artificial neural network as shown in Figure 13 for the distress classification. The network is a 3 layer feed-forward neural network whose weights were obtained from the training process by using artificially generated tile images.



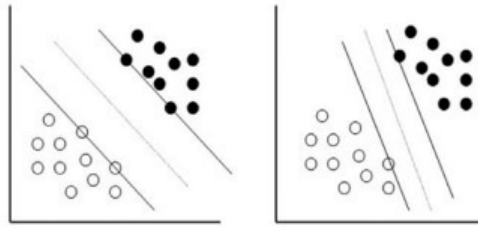
**Figure 13. Architecture of the Neural Network**

## **VI. PAVEMENT SEGMENTATION USING A SUPPORT VECTOR MACHINE (SVM)**

In this section, we explore the Support Vector Machine (SVM) which was proposed by Vapnik and his group at AT&T BELL Laboratories to segment the road scene into the pavement region and the background. Generally speaking, the SVM is a supervised learning method that can analyze data and recognize patterns. It has been widely used in human face recognition, handwriting recognition, and vehicle license plate recognition and can outperform other competing methods in most cases [12, 13].

The main concept of the SVM is to construct a hyper-plane or a set of hyper-planes in a high or infinite dimensional space, and use them to classify the data. Among the possible hyper-planes, SVMs select the one where the distance of the hyper-plane from the closest data point is as large as possible. The distance between this data point and the hyper-plane is known as the margin.

Figure 14 shows the geometric interpretation of the SVM, the figure on the left presents a large margin whereas the image on the right displays a small margin. As a result, the hyper-plane on the left is more desirable than the one on the right for the purposes of classification.



**Figure 14. Geometric Interpretation of SVM**

The challenge in SVM classification is to find a hyper-plane with a maximal margin. Let's define a training sample  $D_i = (x_i, y_i)$ , with the input data  $x_i \in \mathbb{R}^N$  and the corresponding target  $y_i \in \{-1, +1\}$ , and construct a hyper-plane classifier,

$$g(x) = w \cdot x - b \quad (10)$$

where  $w$  is the weight vector and  $b$  is the bias. Note,  $g(x_i) \geq 1$  if input vector  $x_i$  is in class 1, otherwise,  $g(x_i) \leq -1$  if  $x_i$  is in class -1. If the training data are linearly separable, we can select two hyper-planes in a way that there are no points between them and then try to maximize their distance. The distance between these two hyper-planes can easily be obtained as  $2/\|w\|$ . As a result, minimizing the value of  $\|w\|$  becomes the primary goal. Hence, the problem becomes a quadratic programming optimization problem as follows:

$$\min \frac{1}{2} \|w\|^2 \quad (11)$$

$$s. t. y_i(w \cdot x_i - b) \geq 1$$

The solution to this problem is given by the saddle point of the Lagrange function:

$$L(w, b, \alpha) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^n \alpha_i \{y_i [w \cdot x_i - b] - 1\} \quad (12)$$

where  $\alpha_i$  are the Lagrange multipliers. Classical Lagrangian duality enables the primal problem to be transformed to its dual form, which is easier to solve. The dual form is given by

$$\max_{\alpha} \tilde{L}(\alpha) = \max \{ \min_{w, b} L(w, b, \alpha) \} \quad (13)$$

The solution to the dual problem is given by

$$\tilde{L}(\alpha) = \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j x_i^T x_j \quad (14)$$

$$= \sum_{i=1}^n \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j y_i y_j (x_i, x_j)$$

$$s. t. \alpha_i \geq 0, \sum_{i=1}^n \alpha_i y_i = 0$$

where a linear kernel is used, i.e.,  $K(x_i, x_j) = x_i^T x_j$  and the optimal weight vector is obtained as,

$$w = \sum_{i=1}^n \alpha_i y_i x_i \quad (15)$$

Therefore, the decision function will be

$$g(x) = \text{sign}(\sum \alpha_i y_i x_i \cdot x + b) \quad (16)$$

To implement the SVM for pavement segmentation, both the color as well as the textural information is used. The color information is specified by RGB values and the texture is obtained by the application of the Gabor filter. The use of SVM for pavement segmentation requires an initial training phase for the estimation of the optimal parameters.

The training phase involves the extraction of the features both from the background and the pavement. For the proposed approach, we have chosen two kinds of features: the color feature and the texture feature.

The RGB value is one of the dominant factors in pavement segmentation. Each point has a set of values called the RGB value which is a number between 0 and 255. As a result, the RGB value has been used as the color feature. The texture feature is another crucial factor in the pavement image segmentation. For texture feature extraction, we apply a Gabor filter to the image [14]. In the spatial domain, a 2D Gabor filter is defined as follows:

$$\begin{aligned} g(x, y) &= h(x, y) \exp(2\pi j W x) \\ &= \frac{1}{2\pi\sigma_x\sigma_y} \exp\left(0.5\left(\frac{x^2}{\sigma_x^2} + \frac{y^2}{\sigma_y^2}\right)\right) \exp(2\pi j W x) \end{aligned} \quad (17)$$

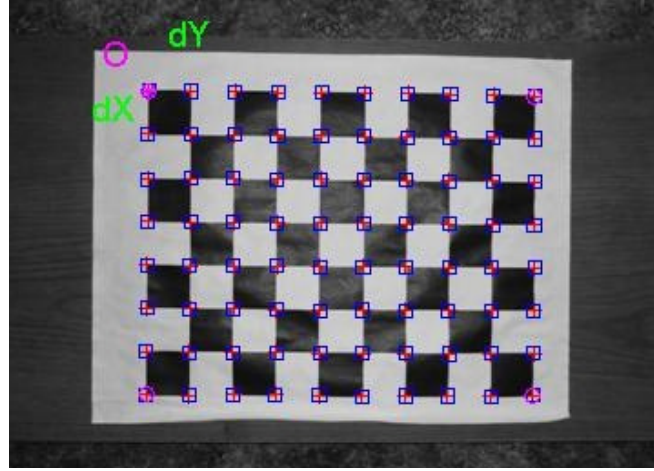
where  $\sigma_x^2$  and  $\sigma_y^2$  are the variances in the x and y directions, and W is the modulation frequency.

To extract the texture feature, the image is first transformed from the RGB color space to the Ycbr color space. In this specific color space, the Y value represents the luminance component and the Cb, Cr are the chrominance components of the image. The Gabor filter is applied to the Y component in four dominant orientation values, 30, 60, 90, 120 degrees, and its mean value is used as a measure of the texture.

To train the SVM classifier, we have taken 20 sample points from the background and 20 sample points from the pavement, a total of 40 points to form the training sample. Each feature vector is organized with four components: the RGB values along with output of the Gabor filter representing the texture. As a result, the dataset is a 4x40 matrix. The trained support vector machine is then used to classify the original color image into two groups: the background group and the pavement group.

## VII. SIMULATION RESULTS

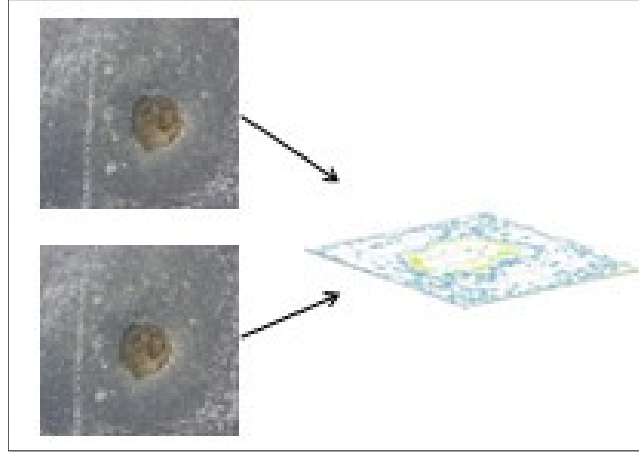
The proposed algorithm has been implemented in MATLAB, and its performance and simulation results are presented in this section. To obtain the depth information from the stereo system, the two camera sets are calibrated using Tsai's [6] method. Figure 15 shows the calibration module used in the calibration process. The model plane is a checker board pattern containing 9x7 blocks, the corners of which define the real world coordinates. The size of each block is 25mm x 25mm. The easiest way to find the corresponding corners in an image is by first segmenting the image in some way to find the shape of an object and then using an edge detector to find the edge chains. Searching the edges for turnings in the boundary will result in a corner [11].



**Figure 15. Calibration Plane**

After the correspondence between the image plane and the world space has been established, the Tsai's method is applied to provide 3D calibration. A successful calibration provides the accurate parameters needed for transforming a 3D coordinate system into an image coordinate system. The obtained parameters for each camera are given in Table 1, where  $f$  is the focal length,  $k$  is a scale factor,  $(u, v)$  is the relative displacement and  $(\mathbf{R}, \mathbf{t})$  are rotation and translation parameters.

The image data set is collected from the pavement surface using the calibrated cameras. The scene contains prominent depth information in the form of pothole or large scaled cracks. The result of the reconstructed 3D pavement surface is shown in Figure 16. Using the depth information recovered from 3D reconstruction, the probability of each pixel in the 2D image that is considered to be a distress can be updated following the method described in section IV. Experimental results suggest that probabilistic relaxation can effectively separate the distresses from a noisy background and the method is not sensitive to the non-uniform illumination. A subjective evaluation and comparison of the proposed method and the traditional global thresholding technique is shown in Figure 17. These results show that the proposed method can detect cracks and potholes with high accuracy, compared with conventional thresholding approaches.

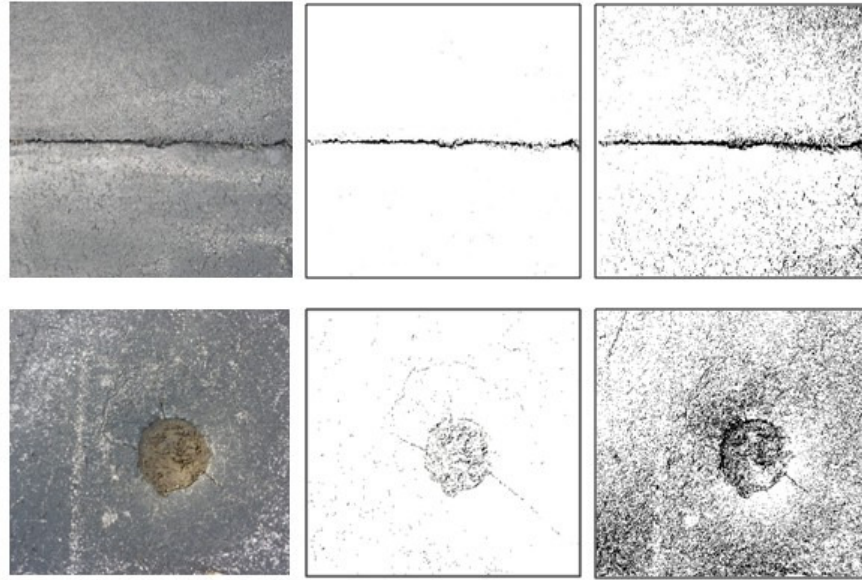


**Figure 16. Pavement Surface Reconstruction**

**Table 1. Calibration Results for the Right Camera**

	Intrinsic parameters		Extrinsic parameters	
Left camera	$f$	15.67435	$t_x$	-1409.87468
	$k_1$	$1.24102e^{-3}$	$t_y$	1100.27368
	$u_0$	259.20988	$t_z$	2487.09676
	$v_0$	487.18364	$R_x$	179.29476
			$R_y$	-1.38475
			$R_z$	-0.34658
Right camera	$f$	15.79975	$t_x$	-1599.80918
	$k_1$	$1.14252e^{-3}$	$t_y$	1210.72452
	$u_0$	254.89820	$t_z$	2427.06254
	$v_0$	489.16924	$R_x$	178.52760
			$R_y$	-0.98446
			$R_z$	-0.64952





**Figure 17. Implementation Results**

(the left column: original images; the middle column: segmentation results using the proposed relaxation method; the right column: segmentation results using global thresholding based on intensity value alone)

Table 2 shows the detailed training parameters for the distress classification neural network. Thirty actual pavement images are utilized to train the network under manual supervision. With a learning coefficient equal to 0.01, the neural networks can achieve a high training accuracy of 97% and higher.

**Table 2. Training Process for the Distress Classification Neural Network**

Learning coefficient	Nodes for each layer	Epochs	Accuracy
0.01	3-20-3	1500	97%

Figure 18. (a) represents an original image in which 20 background samples and 20 pavement sample points are selected to train the SVM. Figure 18 (b) shows the result of the segmentation.



(a) (b)  
**Figure 18. (a, b) A Pavement Image and Segmentation Result**

## **VII. CONCLUSION**

This report presents a pavement inspection system using 3D information from the stereo images of the pavement surface. A stereovision technique is applied to guide the probabilistic relaxation process which can provide accurate segmentation results for pavement image analysis. Since this method does not rely on the assumption that defects and pavement do not share the same color and texture features, it works very well in cases where the road has a noisy surface with shading and oil spills. In addition, a Support Vector Machine (SVM) is used to extract the pavement segment from a road scene containing other objects, such as, trees, grass, and buildings. Future work will focus on the measurement of the severity of the detected distresses.

## VIII. REFERENCES

- [1] L. Bursanescu, M. Bursanescu, M. Hamdi, A. Lardigue and D. Paiement. “Three-dimensional Infrared Laser Vision System for Road Surface Features Analysis”. Proc. SPIE, ROMOPTO 2000: 6th Conf. on Optics, Vol. 4430 pp. 801–808, Bucharest, Romania, 2001.
- [2] L. Bursanescu and F. Blais. “Automated Pavement Distress Data Collection and Analysis: a 3-D Approach”. IEEE, 3-D Digital Imaging and Modeling, Int. Conf. on Recent Advances, pp. 311–317, Ottawa, Ontario, Canada, 1997.
- [3] J. Laurent, M. Talbot and M. Doucet. “Road Surface Inspection using Laser Scanners adapted for the High Precision 3D Measurements of Large Flat Surfaces”. IEEE, 3-D Digital Imaging and Modeling, Int. Conf. on Recent Advances, pp. 303–310, Ottawa, Ontario, Canada, 1997.
- [4] K. C. P. Wang and W. Gong. “Automated Pavement Distress Survey: A Review and A New Direction”. Pavement Evaluation Conf., pp. 21–25, Roanoke, VA, USA, 2002.
- [5] Z. Hou, K. C. P. Wang and W. Gong. “Experimentation of 3D Pavement Imaging through Stereovision”. ASCE, Int. Conf. on Transportation Engineering, Vol. 246 pp. 376–381, 2007.
- [6] R. Tsai. “A Versatile Camera Calibration Technique for High-accuracy 3D Machine Vision Metrology using off-the-shelf TV Cameras and Lenses”. IEEE J. Robot. Autom. Vol.3, pp.323–44, 1987.
- [7] Q. Li, M. Yao, X. Yao and B. Xu. “A Real-time 3D Scanning System for Pavement Distortion Inspection”. Measurement Science and Technology, Vol.21, pp. 015702 1-8, 2010.
- [8] Y. Fujita and Y. Hamamoto. “A Robust Automatic Crack Detection Method from Noisy Concrete Surfaces. Machine Vision and Applications, Vol. 22, pp. 245-254, 2011.
- [9] B. J. Lee. “Position-invariant Neural Network for Digital Pavement Crack Analysis”. Computer-aided Civil and Infrastructure Engineering, Vol.19, pp. 105-118, 2004.
- [10] Y. Chen and H. Sundaram, “Estimating Complexity of 2D Shapes”, IEEE 7th Workshop on Multimedia Signal Processing, pp.1-4, Shanghai, China, 2006.
- [11] A. Henrichsen. “3D Reconstruction and Camera Calibration from 2D Images”. MS. Thesis, *University of Cape Town*, 2000.
- [12] Christianini, Nello and John Shawe-Taylor, *An Introduction to Support Vector Machines*, Cambridge University Press, Cambridge, 2000.
- [13] Vapnik, Vladimir N, *The Nature of Statistical Learning*, Springer-Verlag, New York, 1999.
- [14] Thomas P. Weldon, William E. Higgins, and Dennis F. Dunn, "Efficient Gabor Filter Design for Texture Segmentation", *Pattern Recognition*, Vol. 29, No 12, pp. 2005-2015, 1996.

# **Development of a Computer Interface and Database for the Evaluation of Pavement by the PASER Method**

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## ABSTRACT

The PI has started on the development of a software package that would allow the user to review digital photographs of pavement, evaluate that pavement by the PASER method, store the results in a database, and then make decisions based on the results of that analysis.

The computer interface and analysis portion of the software was written in Microsoft Visual BASIC 2008. The software allows the user to enter basic information on a road to be evaluated, and then evaluate individual segments within that road. The segments are evaluated by identifying defects in the pavement and then using controls on the Visual BASIC form to select the type of defect and severity of the defect. The code analyzes the selected defects and corresponding severities to determine the PASER rating. Once the segment has been evaluated, the user saves the results and advances to the next segment.

The long-term goals of this project include linking the evaluation results to a geographical information system database and developing various reporting strategies. The reporting strategies, once developed, would be coded.

Thus far, the computer interface and analysis portion of the software has been developed and tested. The testing was performed by selecting roads for which evaluation data were available, evaluating the roads using the software developed as part of this research, and comparing those results. The results of the testing indicated that the PASER ratings determined with the software developed for this research were within 1 of the published values, and that is considered to be acceptable.

## 1. INTRODUCTION

The state of the nation's infrastructure is generally poor and the cost of upgrading it to acceptable levels is high. The American Society of Civil Engineers (ASCE) periodically prepares a *Report Card of America's Infrastructure*, in which they collect and analyze data in a variety of categories. The results are presented as letter grades in which *A* is excellent and *F* is failing, and as a cost of upgrading deficient areas to passing. As of 2009, the overall condition warranted a letter grade of *D* and the cost of upgrading the infrastructure to acceptable levels was estimated at \$2.2 trillion (ASCE, 2009). Given the size of the nation's infrastructure, its current condition, and the resources available to address the condition issues, upgrading the nation's infrastructure to acceptable levels would require many projects over many years. A conclusion one could draw from ASCE's assessment is that policy makers need to make informed decisions regarding the allocation of resources for the upgrading of the nation's infrastructure.

Engineers are obviously involved in the design and construction of various infrastructure projects, as well as the management and assessment of this infrastructure in service. Engineers also need to be involved in the policy-making decisions related to infrastructure spending. When engineers work with the public and law makers in these policy-making decisions, they need to present their information completely, but in a clear and concise way that is not overly-technical. Additionally, engineers need to be concerned about the cost of their professional services such as inspections, design, and construction supervision.

As computer technology has grown in power and decreased in cost, it has become an indispensable part of the practice of engineering. Furthermore, computer technology allows engineers to solve problems in a cost-effective manner. In many cases, this technology can allow engineers to solve problems that cannot be solved by hand.

This paper presents the development to date of an integrated pavement evaluation software package. Roads are an area of the nation's infrastructure that are in poor condition, require significant investment if they are to be upgraded to acceptable condition, and can benefit greatly from the use of computer technology. The interface allows the user to review digital photographs of pavement sections, identify defects in those photographs, and store the data in a database and generate reports.

To date, the interface has been tested. The working interface was used to evaluate the condition of several roads. Where possible, the results of the pavement evaluation conducted with this software package were compared against published condition data for the subject roads. Long-term development of this software package includes linking the database to geographical information systems (GIS) software, and developing modules for life-cycle analysis.

## 2. PAVEMENT MANAGEMENT

The goal of pavement management is to properly allocate resources related to the construction and maintenance of pavement structures. A pavement management program would consider factors such as current and anticipated traffic counts, and pavement condition. Decisions would be made to optimize a selected measure of effectiveness (MOE). Figure 1 shows one proposed method of collecting and managing data, making decisions based on that data, and implementing the decisions.

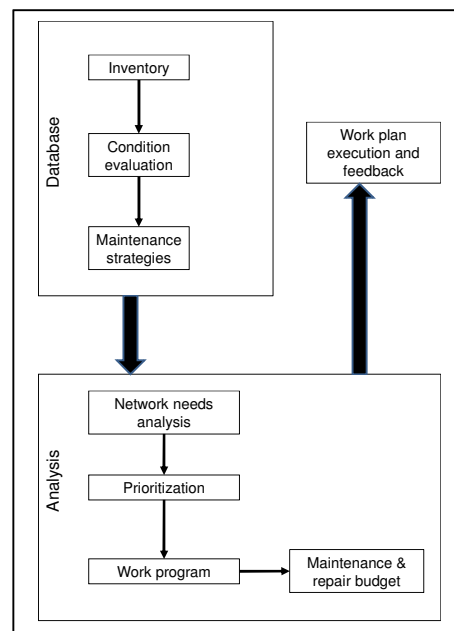


Figure 1: Pavement management structure (After Medina et al., 1994)



## 2.1 Database Component of a Pavement Management System

The database component of a pavement management system, which includes the *Inventory*, *Condition Evaluation*, and *Maintenance Strategies*, is the first part of managing a pavement network.

The *Inventory* is the set of roads for which an owner is responsible. Within the boundaries of a particular agency, different roads may be owned by different agencies. For example, a city may own side roads and some major roads, the county may own some of the major roads, and the state may own some of the major roads.

The *Condition Evaluation* portion is used to identify the types, extent, and severity of defects in the pavement or deterioration of the pavement. In Michigan, where this research was conducted, the Pavement Surface Evaluation and Rating (PASER) method is used. The PASER method uses visual inspection to identify the type and severity of defects, and these defects are used to determine the condition of the road (Walker et al., 2002). The data collection is typically performed via a windshield survey, i.e, from a moving vehicle. The evaluation is typically performed by a team of evaluators, each of whom completes this assessment, and then they compare results. If the results are acceptably close to each other, the evaluation is complete. If not, further work must be performed, which could extend to re-evaluating the pavement.

The limitation of visual methods is that they do not necessarily indicate the cause of an observed condition. For example, alligator cracking is a structural problem that can be caused by excessive load or weak subgrade (Walker et al., 2002). Visual inspection of the pavement surface is not adequate for identifying the cause of alligator cracking. Nondestructive test methods, such as the Falling Weight Deflectometer (FWD) can be used to determine the elastic properties and layer thicknesses of pavement, aggregate base, and subgrade soils (Huang, 1993). In the case of alligator cracking caused by a weak subgrade, FWD results would identify that weak subgrade. Destructive testing, including pavement cores and soil borings, can be used to determine the layer thickness of the pavement, aggregate base, and subgrade soils. Pavement cores and split spoon samples from soil borings can also be used as laboratory specimens for further testing. Pavement cores can also be used to determine whether a crack in the pavement is top-down or bottom-up.

The *Maintenance Strategies* portion of the database can be broadly categorized as maintenance, rehabilitation, and reconstruction (Roberts et al., 1991). Some examples of maintenance strategies are identified in Table 1.

Table 1: Maintenance strategies for pavement

Maintenance strategy	Details of this strategy
Preventive maintenance	Conducted to extend the life of the pavement Examples include surface seals and crack seals
Corrective maintenance	Conducted to extend the life of the pavement Examples include patching and thin overlays
Rehabilitation	Conducted to repair isolated areas or to correct deficiencies Examples include recycling and structural overlays
Reconstruction	Conducted to replace unserviceable pavement Involves removing and replacing pavement and may include aggregate base replacement, subgrade improvement, and drainage improvement

The selection of a maintenance strategy depends on factors such as the condition of the road and the budget for maintenance.

## 2.2 Analysis Component of a Pavement Management System

After each road in the network has been evaluated and possible maintenance strategies have been assigned, the owner needs to allocate resources. It is unlikely that the owner would have the money to implement the recommended maintenance strategy on every road in the network; therefore, the owner needs to decide what to do.

The *Network Needs Analysis* portion of the Analysis involves matching each road with the appropriate *Maintenance Strategy* or a set of reasonable strategies.

The *Prioritization* portion of the Analysis involves identifying the order in which roads will be addressed. The prioritization criteria could include items such lowest cost, worst road, and traffic counts. Lowest cost would likely consist of roads that need the least amount of work; however, the largest number of roads could be addressed. Worst road would likely be the most expensive but would result in a fully-serviceable road. However, this strategy would allow the maintenance of the fewest roads. Traffic counts would result in maintenance on the roads that have the largest amount of traffic; therefore, this would provide benefits to the greatest number of users.

The *Work Program* uses those roads identified during *Prioritization* to recommend the roads that will receive corrective action to address deficiencies or deterioration.

Finally, the actual roads that will receive corrective action are selected based on the available *Budget*. Of course, owners frequently lack the funds required to perform the corrective action on all roads identified in the *Work Plan*.

## 2.3 Work Plan and Execution Component of a Pavement Management System

The visual inspection portion of the *Condition Evaluation* provides an overview of the entire road but cannot directly identify below-grade causes of the observed surface distress. On the other hand, nondestructive testing and destructive testing provides data on the surface and subsurface conditions, but only at discrete locations. The observed surface conditions and the subsurface conditions will almost certainly change across any sufficiently large road. The uncertainty of the evaluation techniques and expected variations of the pavement and subgrade lead to a set of concerns during the *Work Plan and Execution* of the pavement maintenance

- Inspection and testing during construction are necessary to ensure quality
- Record keeping is necessary for proper payment
- All of the results should be entered into appropriate databases for better analysis and prioritization in the future and for developing better cost estimates and schedules in the future

## 3. GEOGRAPHICAL INFORMATION SYSTEMS

Geographical information systems (GIS) are software packages that include computer aided drafting (CAD) features and relational database features, which makes them well-suited for events that are distributed in both space and time.

Accidents at different intersections are an example of a good application for GIS. Traffic engineers could quantify the number and type of accidents at various intersections in an area, and analyze the results to look for trends. Some trends could include time of day, direction of travel, turning or not, and the presence of traffic control devices. These results could then be used to decide whether the traffic control measures should be changed. For example, if the most common accident includes a vehicle turning left, the remedy could be adding a left-turn light or not allowing left turns.

In pavement evaluation, the condition of the road is a spatially-varying property: the condition of an individual road will likely vary across the portion under consideration and different roads in a network will have different conditions. In pavement management, the owner must consider road condition in selecting a remediation method. If the owner lacks the funds required to address all pavement condition issues in a network, the remediation work must be prioritized. GIS can be used to analyze pavement condition data across a network such that the owner can prioritize remediation work and optimize the allocation of resources.

The condition of a particular pavement segment is expected to vary over time. When remediation work is conducted, its condition will improve; as the road is subjected to traffic loads and environmental factors, its condition will deteriorate. Sometimes, however, the deterioration may occur more frequently than expected or in unexpected ways. Owners may have anecdotal knowledge or institutional memory but no formal assessment of the premature pavement failures. The database functions of GIS can help identify unusual conditions and may also allow the evaluator to identify other factors that contribute to the pavement condition.

For example, suppose the number of trucks driving over a road increased dramatically over a short time. The pavement evaluators may not have traffic counts and the traffic planners may not have pavement data, but all of this data could be included in a GIS database. If the evaluators wanted to determine the cause of the pavement failure, they could generate a report in GIS that includes pavement condition and a variety of other factors. Eventually, they would consider truck traffic as one of the “other factors” and identify the increase in truck traffic. This would, therefore, solve the mystery.

#### **4. DESIGN OF THE PAVEMENT EVALUATION AND MANAGEMENT SYSTEM**

The software developed in this research project is intended to allow the user to review digital photographs for the purpose of rating the pavement according to the PASER method and then store that information in a database. The PASER rating would be added as a field into a GIS database. The system contains an interface and code that allows the interface to operate, along with code that allows the user to collect and analyze the data.

The code for the interface was written in Visual BASIC, and includes a number of Forms and Classes. In Microsoft Visual Studio, the user creates a project and then typically starts with a form. The form includes two files: the interface and the code (Boehm, 2008). The form is the graphical object that the user sees when running the program. In Microsoft Visual Studio, the developer uses the “Design” mode to create the form and place controls on that form. The code file associated with the form contains functions corresponding to various actions performed on the controls and the developer enters code into these functions to make the controls operate. The user can also create additional functions and enter code into those functions. Classes are strictly code and are designed to process data. Data can be transferred back and forth between forms in several ways:

- The user enters a set of data on a form and that data is sent to the class
- The class manipulates the data and generates a set of output data
- The form uses this output data and displays the results

In this program, the forms are

1. Main Form
2. Asphalt PASER Form
3. Portland Cement Concrete PASER Form
4. Cost Estimate Form
5. Road Information Form

When the user runs the program, the main form, which is shown in Figure 2, opens.

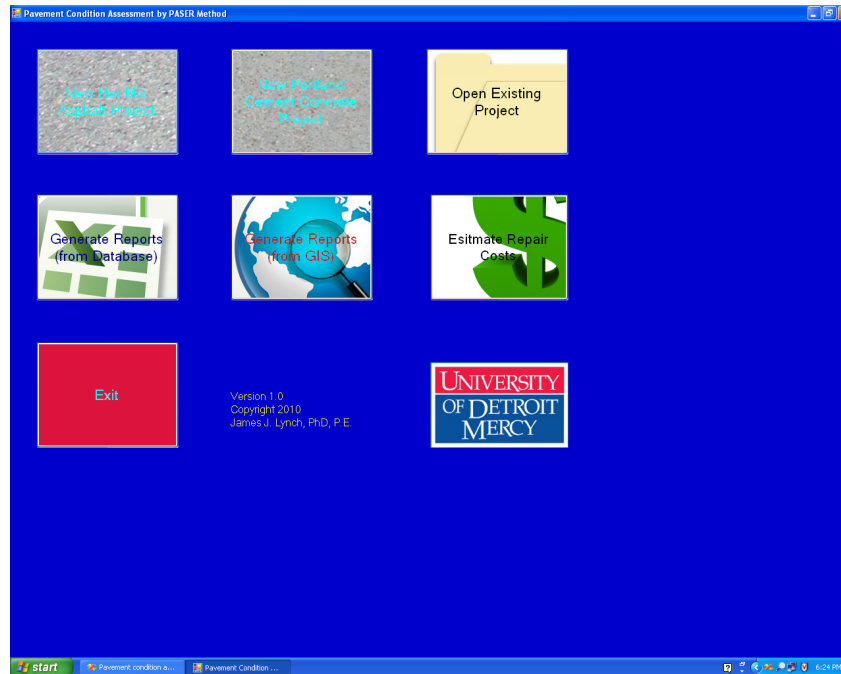


Figure 2: Main form used in the pavement evaluation program

The objects on the form are either text boxes or controls. The text boxes provide copyright information and credits. The controls allow the user to take action. Each control includes text defining the control and graphics that indicate the purpose of the control.

Suppose the user were to create a “New Hot Mix Asphalt Project” for example. The first form that would open is the “Road Information Form” which is shown in Figure 3.

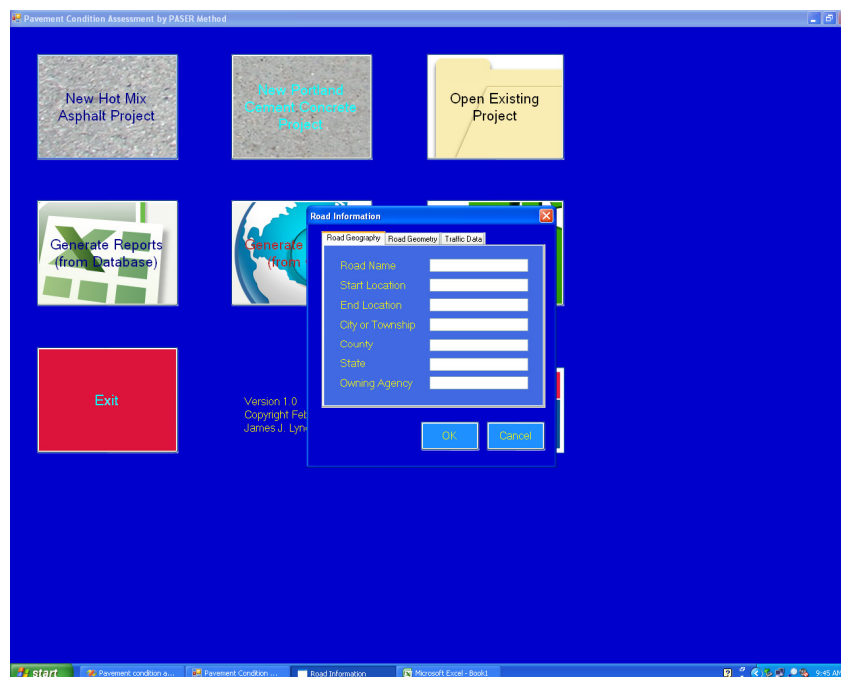


Figure 3: Road information form in pavement evaluation software

This allows the user to enter basic information on the road to be evaluated. Once the user has completed the information in that form and pressed the “Update” button, the form closes and the “Hot Mix Asphalt Form” opens. The Hot mix asphalt form is shown in Figure 4.

Figure 4: Asphalt PASER form used in pavement evaluation program

The user would open the photograph in the Road Object and then use the Edit Boxes to select which defects are present and the severity of those defects. The user would select the ‘Update’ button once the section has been evaluated. Once the entire session has been completed, the user would select ‘Save’.

The basic approach for the data analysis is to assume the PASER Rating is 10, and then to reduce that rating based on the types and severity of the defects. The types of defects, their severity, and corresponding PASER Rating are defined in the “Rating system” table of the *Asphalt Roads PASER Manual* (Walker et al., 2002). The print-out of the code that determines the PASER Rating is included in the Appendix.

As an example, consider the segment in Figure 4. The defects observed in the photograph, along with their severity, and PASER Rating are listed in Table 1.

Table 2: Pavement condition assessment for example segment

Defect	Description	PASER Rating
Longitudinal cracks	Width is between ½-inch and ¾-inch No secondary cracks are identified The cracks are not in the wheelpath	7
Transverse cracks	Width is between ½-inch and ¾-inch Spacing is between 10 and 40 feet No secondary cracks are identified	6
Polishing	Slight to moderate	6
Raveling	Very slight	7

Of the defect observed and the severity of these defects, the lowest PASER Rating is 6; therefore, the rating of the overall segment is 6.

When the user presses the “Calculate Rating” button, a dialog box with the current rating appears, as shown in Figure 5.

Figure 5: Asphalt PASER form of pavement evaluation program, with rating displayed

The computer-determined PASER Rating is the same as the one determined by manual analysis. If the user is satisfied with the PASER Rating of the segment, the “Update Record” button is pressed to save the data in the spreadsheet.

The form includes sample photographs of the nine conditions that must be considered in the evaluation of HMA pavement. These photographs are actually the graphics on controls which,



when double-clicked, open a form with more detailed information on the condition. An example for the transverse cracking condition is shown in Figure 6.

Figure 6: Asphalt PASER form of pavement evaluation program with example photographs of transverse cracks

Transverse cracking is identified based on the crack width and crack spacing, and whether secondary defects present (Walker et al., 2003). The example photographs show spacing greater than 40 feet, 40 feet to 10 feet, and less than 10 feet, which correspond to PASER Ratings of 8, 7, and 6, respectively. Secondary defects could include cracking or raveling. If raveling were present at the transverse cracks, the PASER Rating would be 4, regardless of spacing. In the interest of storage requirements and speed of operation, the example photographs do not include every combination of crack size, spacing, and secondary defects. If the user wanted more information on raveling, similar photographs are available for that condition.

The operation of the Portland cement concrete form is conceptually the same as the operation of the hot mix asphalt form, except that the types of defects are different. When the user creates a new Portland Cement Concrete Project, the “Road Information Form” opens and the user populates the fields in that form – this is exactly the same procedure and form used in hot mix asphalt projects. Once the user has entered the information in the “Road Information Form” and pressed the “Save” button, that form closes and the “Portland Cement Concrete” form opens, allowing the user to evaluate roads.

As a test of the interface and the validity of using digital photographs for the evaluation of hot mix asphalt pavements, the PI employed an undergraduate student to find a local agency for which pavement evaluation data were available, select roads within that jurisdiction, evaluate the roads using the pavement evaluation program developed herein, and compare the results against

published values. The results were that all roads selected were within 1 PASER value of the published values (Lynch and Dutta, 2010). These results were considered to be acceptable given that any two evaluations are likely to have some differences. Some explanations for the differences between the published values and the values obtained for this research include different ages of the same pavement in different photographs and limitations of the methods.

## 5. FUTURE WORK

Future work includes further development of the software, calibration of the method, and cost studies of different techniques for data collection and analysis.

Further development of the software includes

- Improving the ability to search records
- Improving the ability to modify records
- Linking the spreadsheet created during the pavement evaluation process to a GIS database
- Developing the report functions
- Improving the cost estimating functions

Once the computer programs are fully working, in-depth studies on the effectiveness of pavement evaluation from digital photographs can be performed. These studies would include the cost of collecting data, the time (and therefore cost) of analyzing the data, and the reliability of the data.

## 6. REFERENCES

- ASCE "Report Card of America's Infrastructure," <http://www.infrastructurereportcard.org>
- Boehm, A. (2008). *Murach's Visual BASIC 2008*, Mike Murach and Associates, Inc.
- Huang, Y. H. (1993). *Pavement Analysis and Design 2<sup>nd</sup> Edition*, Prentice Hall, Upper Saddle River, NJ.
- Lynch, J. J. and Dutta, U. (2010). "Transportation Informatics: Advanced Image Processing Techniques for Automated Pavement Distress Evaluation," final report to MIOH UTC of project TS18p2.
- Medina, A., Flintsch, G. W., Zaniewski, J. P., (1994). "Geographic Information Systems-based Pavement Management System: a Case Study," *Transportation Research Record 1652*,
- Roberts, F. L., Kandhal, P. S., Brown, E. R., Lee, D.-Y., Kennedy, T. W. (1991). *Hot Mix Asphalt Materials, Mixture Design, and Construction*, NAPA Educational Foundation, Lanham, MD
- Walker, D., Entine, L., and Kummer, S. (1993). *PASER Manual: Asphalt Roads*, Transportation Information Center, University of Wisconsin – Madison.

## 7. ACRONYMS

ASCE	American Society of Civil Engineers
BASIC	Beginners All-purpose Symbolic Instruction Code
CAD	Computer-aided Drafting
FWD	Falling Weight Deflectometer
GIS	Geographic Information System
HMA	Hot mix asphalt
PASER	Pavement Surface Evaluation and Rating

## APPENDIX: Code for the Determination of PASER Rating

```
Public Class Condition_Values
    Public Shared intPASER As Integer

    Public Function Identify_Defects(ByVal A_C As Integer, ByVal B_C As
Integer, _
                                ByVal L_C_Si As Integer, ByVal L_C_L As
Integer, _
                                ByVal L_C_Se As Integer, _
                                ByVal T_C_Si As Integer, ByVal T_C_Sp As
Integer, _
                                ByVal T_C_Se As Integer, _
                                ByVal Pa As Integer, ByVal Po As
Integer, _
                                ByVal P_H As Integer, _
                                ByVal Ra As Integer, ByVal Ru As
Integer, _
                                ByVal Ov As Integer, ByVal Fa As
Integer)
        'Determine values
        'Determine if it is a 10
        intPASER = 10

        'Determine if it is a 9
        If Ov = 1 Then
            intPASER = 9
        End If

        'Determine if it is an 8
        If L_C_Si = 1 And L_C_L = 0 And L_C_Se = 0 Then
            'Longitudinal cracks with widths of 1/4" or less
            'Longitudinal cracks due only to reflection
            'No raveling or secondary cracking
            intPASER = 8
        ElseIf T_C_Si = 1 And T_C_Sp = 0 And T_C_Se = 0 Then
```

```

        'Transverse cracks with widths of 1/4" or less
        'Spacing is greater than 40 feet
        'No raveling or secondary cracking
        intPASER = 8
    End If

    'Determine if it is a 7
    If L_C_Si = 1 And L_C_L = 3 And L_C_Se = 0 Then
        'Longitudinal cracks with widths of 1/4" or less
        'Longitudinal cracks are not at the pavement edge or in the
wheelpath
        'Slight raveling or secondary cracking
        intPASER = 7
    ElseIf T_C_Si = 1 And T_C_Sp = 1 And T_C_Se = 0 Then
        'Transverse cracks with widths of 1/4" or less
        'Spacing is 10 feet to 40 feet
        'No raveling or secondary cracking
        intPASER = 7
    ElseIf Pa = 1 Then
        'Very few patches and in excellent condition
        intPASER = 7
    ElseIf Ra = 1 Then
        'Very slight ravelling
        intPASER = 7
    End If

    'Determine if it is a 6
    If L_C_Si = 2 Then
        'Longitudinal cracks with widths of 1/4" to 1/2"
        intPASER = 6
    ElseIf T_C_Si = 2 Or T_C_Sp = 2 Then
        'Transverse cracks with widths of 1/4" to 1/2"
        'Spacing may be less than 10 feet
        intPASER = 6
    ElseIf Pa = 2 Then
        'Occasional patches and in excellent condition
        intPASER = 6
    ElseIf Po = 1 Then
        'Slight to moderate polishing
        intPASER = 6
    ElseIf Ra = 2 Then
        'Slight ravelling
        intPASER = 6
    End If

    'Determine if it is a 5
    If B_C = 1 Then
        'Block cracking less than 50%
        intPASER = 5
    ElseIf L_C_Si = 3 Or L_C_L = 1 Or L_C_Se = 1 Then
        'Longitudinal cracks with widths of 1/2" or more
        'Longitudinal cracks near pavement edge
        'First signs of ravelling or secondary cracks
        intPASER = 5
    ElseIf T_C_Si = 3 Or T_C_Se = 1 Then
        'Transverse cracks with widths of 1/2" or more
        'First signs of ravelling or secondary cracks

```

```

        intPASER = 5
    ElseIf Pa = 3 Then
        'Some patches and in good condition
        intPASER = 5
    ElseIf Po = 2 Then
        'Extensive to severe polishing
        intPASER = 5
    ElseIf Ra = 3 Then
        'Moderate to severe raveling
        intPASER = 5
    End If

    'Determine if it is a 4
    If B_C = 2 Then
        'Block cracking greater than 50%
        intPASER = 4
    ElseIf L_C_L = 2 Or L_C_Se = 2 Then
        'Longitudinal cracks in wheelpath or multiple longitudinal cracks
        'Slight ravelling or secondary cracks
        intPASER = 4
    ElseIf T_C_Se = 2 Then
        'Slight ravelling or secondary cracks
        intPASER = 4
    ElseIf Pa = 4 Then
        'Some patches and in fair condition
        intPASER = 4
    ElseIf Ra = 4 Then
        'Severe raveling
        intPASER = 4
    ElseIf Ru = 1 Then
        'Slight rutting
        intPASER = 4
    End If

    'Determine if it is a 3
    If A_C = 1 Then
        'Alligator cracking less than 25% of surface
        intPASER = 3
    ElseIf B_C = 3 Then
        'Severe block cracking
        intPASER = 3
    ElseIf L_C_Se = 3 Then
        'Moderate ravelling associated with longitudinal cracks
        intPASER = 3
    ElseIf T_C_Se = 3 Then
        'Moderate ravelling associated with transverse cracks
        intPASER = 3
    ElseIf P_H = 1 Then
        'Occasional potholes
        intPASER = 3
    ElseIf Pa = 5 Then
        'Some patches and in fair to poor condition
        intPASER = 3
    ElseIf Ru = 2 Then
        'Moderate rutting
        intPASER = 3
    End If

```

```

'Determine if it is a 2
If A_C = 2 Then
    'Alligator cracking greater than 25% of surface
    intPASER = 2
ElseIf Pa = 6 Then
    'Extensive patches and in poor condition
    intPASER = 2
ElseIf P_H = 2 Then
    'Moderate to severe potholes
    intPASER = 2
ElseIf Ru = 3 Then
    'Severe rutting
    intPASER = 2
End If

'Determine if it is a 1
If Fa = 1 Then
    intPASER = 1
End If
Return intPASER
End Function

End Class

```