AUTOMATED PAVEMENT IMAGING PROGRAM (APIP) FOR PAVEMENT CRACKS CLASSIFICATION AND QUANTIFICATION – A PHOTOGRAMMETRIC APPROACH

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ABSTRACT:

The evaluation of pavement conditions is an important part of pavement management. Traditionally, pavement condition data are gathered by human inspectors who walk or drive along the road to assess the distresses and subsequently produce report sheets. This visual survey method is not only time consuming and costly but more importantly it compromises the safety of the field personnel. With an automated digital image processing technique, however, pavement distress analysis can be conducted in a swifter and safer manner. Pavement distresses are captured on images which are later automatically analysed. Furthermore, the automated method can improve the objectivity, accuracy, and consistency of the distress survey data. This research is aimed at the development of an Automated Pavement Imaging Program (APIP) for evaluating pavement distress condition. The digital image processing program enables longitudinal, transverse, and alligator cracking to be classified. Subsequently, the program will automatically estimate the crack intensity which can be used for rating pavement distress severity. Advancement in digital photogrammetric technology creates an opportunity to overcome some problems associated with the manual methods. It can provide a low-cost, near real time geometrical imaging through digital photogrammetry without physically touching the surface being measured. Moreover, digital photogrammetry workstation (DPW) is user-friendly, less tedious and enables surface conditions to be represented as ortho-image, overlay contour with ortho-image, as well as digital elevation model.-The algorithms developed in this study are found to be capable of identifying type of cracking and its severity level with an accuracy of about 90% when compared to the traditional method. This is to show that the combination of the photogrammetric approach and APIP is a viable system to be used in pavement evaluations.

1. INTRODUCTION

Pavement distresses are visible imperfections on the surface of the pavements. Therefore, the evaluation of pavement condition is an important part to provide information to keep pavements in good condition. Accurate evaluations would result in a better chance that resources will be distributed normally. Thus, yielding a better service condition (Kim, 1998). Pavement can be evaluated through the different types of distress experienced, such as cracking, disintegration and surface deformation. At present, there are various methods of conducting distress surveys, recording and analysing distress survey data (Cheng and Miyojim, 1998). Pavement engineers have long recognized the importance of distress information in quantifying the quality of pavements. This information has been used to document present pavement condition, chart past performance history, and predict future pavement performance.

2. PROBLEM STATEMENT

Manual visual inspection of pavement surface condition is costly and time consuming. In many cases, work has to be done along fast moving traffic. Such condition would endanger the safety of the personnel involved. In the wake of tedious manual measurements and safety issues, various types of automated equipments have been developed for the purpose of pavement monitoring and evaluation.

Visual observation of pavement distress is the most common method for monitoring pavement surface condition. This has been traditionally performed by trained engineers who work or drive along the road and counts the distresses (Oh, 1998). However this method of field inspection poses several drawbacks, such as:

(i)   Slow, labour intensive and expensive.
(ii)   Subjective approach generating inconsistencies and inaccuracies in the determination of pavement condition.
(iii)   Inflexible and does not provide an absolute measure of the surface.
(iv)   Has poor repeatability since the assessment of given pavement section may be differ from one survey to the next.
(v)   Could expose a serious safety hazard to the surveyors due to high speed and high volume traffic.

Numerous system users believe that there is a need to minimise the drawbacks listed above, replacing manual data collection system with automated systems. In response to these demands, various studies have been conducted to apply new technologies in pavement monitoring. Among these technologies, close-range digital photogrammetry is seen as a possible approach in providing accurate, consistent data and easy visualisation for pavement distress studies. Furthermore, a combination of a close-range digital photogrammetry data collection system with a suitable image processing analysis would result in a system that is reliable and dependable. Therefore, this study looks at developing a photogrammetric based pavement evaluation approach by utilising ortho-images and image processing techniques.

3. RESEARCH APPROACH

An overview of the research procedure developed for pavement distress evaluation is presented. A combination of close-range photogrammetric and image processing metrology were developed in various stages and is illustrated in Figure 1 and 6, respectively.

3.1 Photogrammetric System

In the first stage, a stereovision measurement technique is developed to evaluate and monitor the pavement conditions. To achieve this, several processes were conducted. These processes were categorized as, camera calibration, ground control, image acquisition and digital photogrammetry workstation (VirtuoZo) processing. The following sections describe these processes.

3.1.1 Ground Control

Ground control is currently provided by means of a frame that was calibrated in the laboratory. This arrangement was chosen because it is convenient to be used in the field.
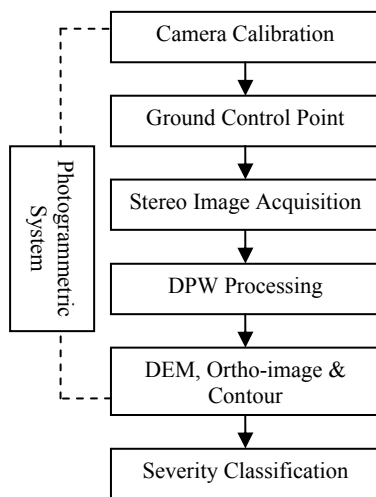
Figure 1. Schematic diagram of the photogrammetric system

3.1.2 Image Acquisition

Ten pairs of stereo images were captured using the same digital camera with its axis perpendicular to the road surface. Stereo vision technique showed great potential for metrology application in pavement condition monitoring.

3.1.3 PW (VirtuoZo) Processing

DPW processing was carried out using the VirtuoZo NT system (version 3.2) running on a workstation. The process has two key steps (1) Requirement and parameter setup for VirtuoZo and (2) Running VirtuoZo software. VirtuoZo, which is low user interaction software, had proved highly flexible and is easy to use in terms of preparation modules (for example, creating image overviews and automatic image orientation) for ortho-image and digital elevation model generation.

3.1.4 Ortho-image and Contour

After performing the steps in VirtuoZo digital photogrammetry workstation, ortho-image and contour overlay as well as 3D DEM data was generated. Figures 3 and 4 show the ortho-image and contour overlay of pothole (disintegration) distress respectively.
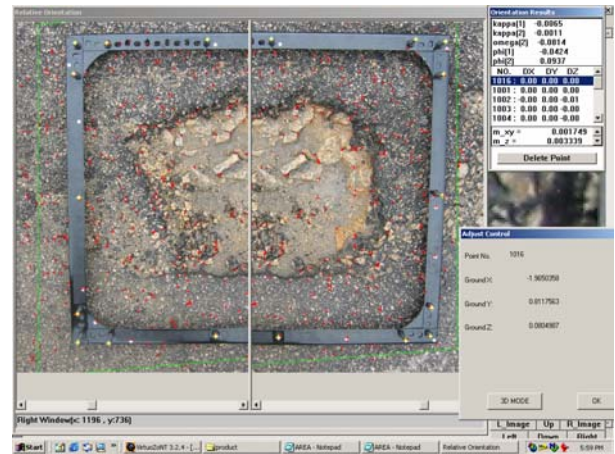
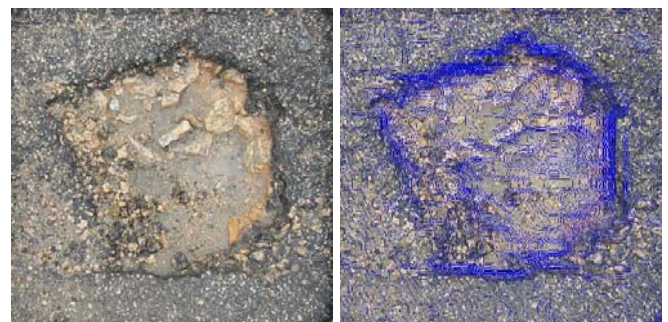Figure 3. Relative orientation of stereo image

Figure 4. Ortho-image and contour overlap of pothole

3.1.6 Severity Classification

3D DEM coordinates output from VirtuoZo became the input data for SURFER software and MATLAB to produce contour plotting and cross section plotting respectively. SURFER consisted of three programs: QGRID, TOPO and SURF. QGRID takes irregular data from ASCII file and created a regularly spaced 'grid'. The reformatted file was then entered into a graphics programs, TOPO or SURF. TOPO created topographic maps and SURF created three dimensional terrain surfaces. The 3D surface as shown in Figure 5 shows that the Y-axis coordinates were positive in the direction of traffic movement; the X-axis coordinates represented the measurements crossing the road; and the Z-axis coordinates area were positively upward.
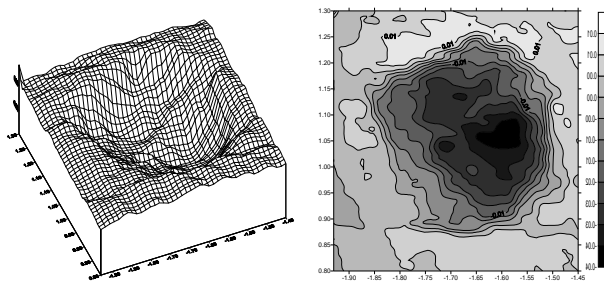
Figure 5. 3D model and contour plots generated by SURFER

The SURFER menu offered a variety of options for manipulating data. The options ranged from minor editing of graphics such as smoothing relief to the choice of mathematical procedures for determining volume, area and elevation.

Negative surface area of 3D model shown in figure was assumed as the bowl shaped cavity in the pavement surface (area of pothole). Volume and area of pothole was then calculated at about 0.00354 m^3 and 0.1182 m^2 respectively, with the help of the program SURFER. Consequently, depth of the distress of about 29.95 mm could be easily determined by dividing the volume with the area. The severity of pothole was classified according to the DEM data based on guidelines set by the Public Works Department (JKR) of Malaysia. Based on Table 1, the pothole was classified as a moderate level.

	AREA (m^2)		
DEPTH (mm)	< 0.1	0.1 - 0.3	> 0.3
< 25	Low	Low	Moderate
25 - 50	Moderate	Moderate	High
> 50	Moderate	High	High

Table 1. Severity level of pothole (JKR, 1992)

3.2 Matlab Environment

The second stage is to develop an Automated Pavement Imaging Program (APIP). The APIP for pavement crack analysis involved six major steps: image enhancement, image thresholding, morphology closing, thinning, distress classification and distress quantification.

3.2.1 Image Acquisition

The first step involved in the automated image processing is the acquisition and digitization of the image. The height from digital camera (5.4mm) lens to the pavement was about 1.00 meter. The digitized array size was 640 by 480 pixels, which resulted in 480 lines vertically and 640 elements horizontally. The original image was a mathematical representation of a colour image in a 24-bit per pixel size format. This colour image consisted of a combination of three 8-bit arrays, and 8 bit arrays contained brightness value for red, green and blue, respectively. To facilitates image processing and manipulation of the image, a brightness level of each pixel, assigned at a value between 0 (black) and white (255) is needed to convert the colour image to gray scale image. Thus, the 24-bit per pixel

format was converted to a 8-bit per pixel format, and this reduced the file space required for storage by two-thirds.
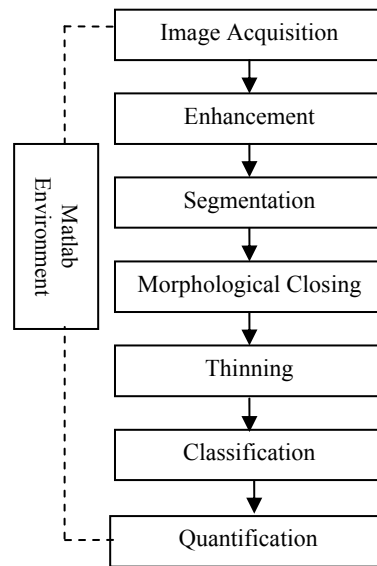

Figure 6. Schematic diagram of the Matlab environment

3.2.2 Image Enhancement Algorithm

Image enhancement was applied in an attempt to remove noise in pavement images. Median filtering was therefore applied as pavement image enhancement technique in this research. It is similar to using an averaging filter, in that each output pixel is set to an average of the pixel values in the neighborhood of the corresponding input pixel. The size of the neighborhood used for filtering is 3-by-3. However, with median filtering, the value of an output pixel is determined by the median of the neighborhood pixels, rather than the mean. The median is much less sensitive than the mean to extreme values. Median filtering is therefore better able to remove these outliers without reducing the sharpness of the image.

3.2.3 Image Thresholding Algorithm

The spatial and light intensity information on the image is usually combined with a thresholding technique for the improved image segmentation. The segmentation relates the threshold for a given image to the mean and standard deviation value of the corresponding gray scale histogram through an equation.

Once the optimal threshold value was determined, the pixels with gray level below the threshold were referred to as distress pixels and pixels whose gray level value exceeded the threshold were referred to as background. The selection of an appropriate value played a very important role in the entire process since it was the value that ultimately defined the mapping of the distress features in the binary image. It is found that the simple image enhancement algorithm worked well in predicting the presence or absence of distress features on the image as shown in Figure 7. Figure 8 show the binary image obtained from proposed segmentation algorithm
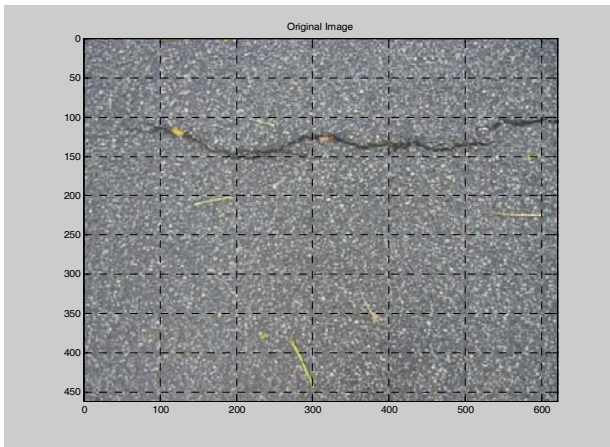
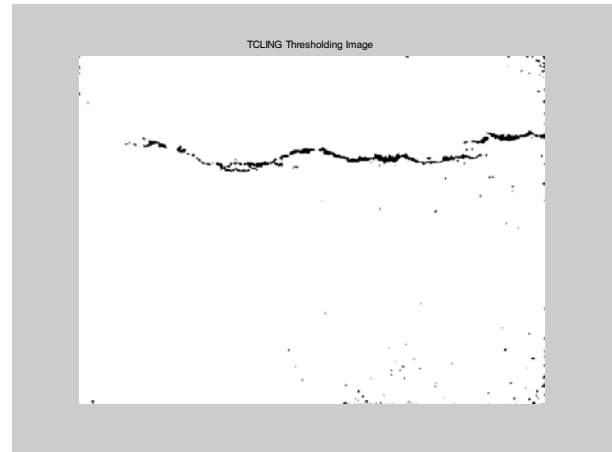Figure 7. Original image of pavement cracks

Figure 9. Image segmented of Figure 3 before closing
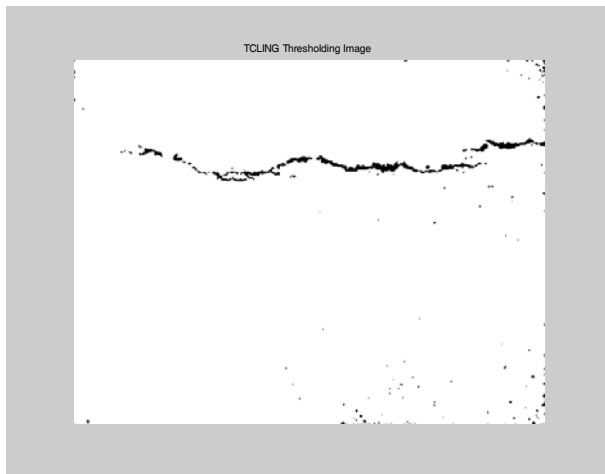and noise removal

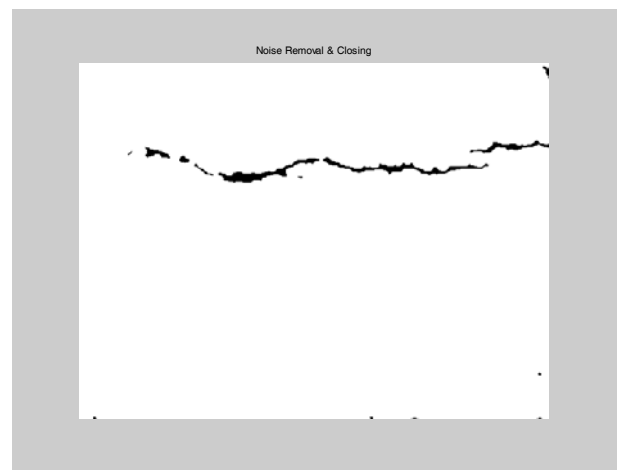Figure 8. Binary image (proposed algorithm)
of pavement cracks

Figure 10. Image segmented of Figure 7 after closing
and noise removal

Figure 11. Image of Figure 6 after thinning

3.2.4   Morphological Closing

Figure 9, which is a segmented image of Figure 7, shows how some noise cluster occupies open space corresponding to the background. Noise removal at the threshold of 10 pixels was applied, followed by performing morphological closing with structural element of size 5, than producing another binary image. The resulting aspect is shown in the sample of Figure 10, where it can be noticed that some of the noises have been removed and some holes being filled with object pixels.

3.2.5   Thinning Algorithm

The binary image with clusters was not useful enough and had to be further processed by thinning. After thinning, a generic source image had the appearance as shown in Figure 11. Crack length was determined using the thinning algorithm based on the central lines with one pixel wide. Then, the average width of crack was obtained by dividing the area and the length. These parameters were found to be very beneficial for cracking quantification.
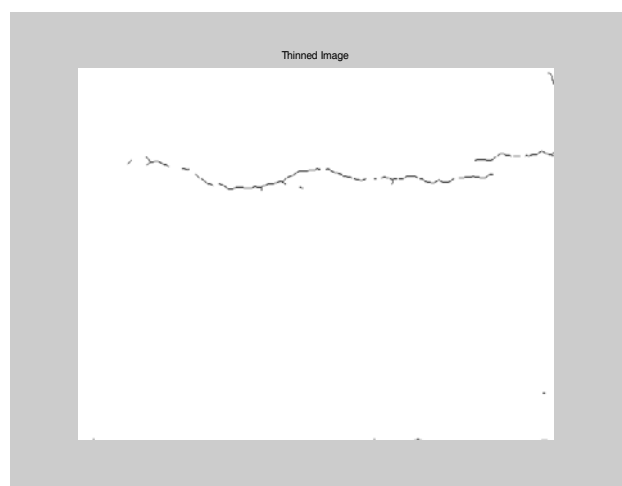
3.2.6   Classification

A simple rule-based classification approach was developed, taking into account four distress types: longitudinal cracking, transverse cracking, alligator cracking and non-cracking. Subroutines were implemented with decision rules that compare the several parameter in x and y-array extracted from the binary image.

From the characteristics of summed gray level graphs for a number of pavement images with the different types of distresses, the following was found to be true.   Different distresses will give distinctly different summed array profiles. For alligator crack, the distress zones in two arrays are relatively wide. For a longitudinal and transverse crack, the narrow and sharp peak of summed gray level is always found in the x-array and y-array respectively, whereas the summed gray level in the other array should not show noticeable peaks

3.2.7   Quantification

Another deterministic approach in APIP is to classify distress severity level based on "A Guide to Visual Assessment of Flexible Pavement Surface Condition" (JKR, 1992).   The manual explains how to measure and give the unit of measurement for each type of crack.   Alligator cracking is measured in square meters.   Longitudinal cracking and transverse cracking are measured in linear meters. The severity levels of each type of crack are classified as low, moderate, or high.   For example, a moderate severity of longitudinal cracking is described as "cracks with moderately severe spalling; meaning unsealed crack width greater than 3 mm; sealant material in bad condition" (JKR, 1992).

The standard crack density concept can be readily and logically implemented in pavement image processing (Lee and Oshima, 1994). The standard crack density is determined by multiplying the extent with the average crack width. The standard crack density concept is at an advantage for use in image processing analysis since it takes into consideration both extent and width of cracks simultaneously.

A simple concept of determining length, area, average width and extent of crack is developed. Area (A) of distress can be calculated from the total number of pixels from distress area and multiplied by the pixel size. Length (l) will be determined based on the polylines of one pixel width. Then, the average crack width (CW) can be derived from area by dividing the length. To illustrate the computation of cracking quantification in APIP, rule-based classification of severity level was programmed and severities of each type of crack are mainly referred to crack density and average width.

4   RESULTS AND ANALAYSIS

The accuracy of the system performance was determined by using t-test. This is required in order to determine how close an observation matches the accepted reference value or the assumed true value.   For comparison purposes, visual field surveys were adopted as the true values or reference values. Therefore, the observed data from the photogrammetric system and Automated Pavement Imaging Program (APIP) were compared with the data from the visual field inspection.

4.1 Photogrammertric System

Ten pavement distresses, including five potholes and five delaminations were randomly selected at fields and processed through the photogrammetric system. The final estimations of volume, area and depth resulted from manual inspection along with the values from the photogrammetric system were calculated.

The t-test was performed to determine whether the mean of photogrammetric system was different from the mean of manual method. At a significance level of 0.20, the computed t_α value was found to be 1.332 with 18 degrees of freedom. To examine the relationship between the evaluations, t statistic values were determined using the calculated data. As indicated in Table 2, we do not reject the null hypothesis since the computed t statistic (volume), t statistic (area) and t statistic (depth) were not greater than the t_α value.   Therefore, the mean of the volumes, areas and depths obtained from the photogrammetric system are not significantly different from those of the visual field surveys.

(a) Analysis of Volume				
Technique	Mean (m^3)	S.D	t	t_α
Manual	0.001341	0.001243		
Photogrammetry	0.001246	0.001196	0.175	1.332
(b) Analysis of Area				
Technique	Mean (m^2)	S.D	t	t_α
Manual	0.0642	0.0398		
Photogrammetry	0.066	0.0387	0.104	1.332
(c) Analysis of Depth				
Technique	Mean (mm)	S.D	t	t_α
Manual	17.28	8.26		
Photogrammetry	15.4	8.3	0.509	1.332

Table 2. Paired t-test for manual and photogrammetric system

Sam. No.	Distress Type	Severity Level		Accuracy
		Manual	Photogram.	
1	Pothole	Low	Low	100
2	Pothole	Low	Low	100
3	Pothole	Low	Low	100
4	Pothole	Moderate	Moderate	100
5	Pothole	Moderate	Moderate	100
6	Delamination	Moderate	Moderate	100
7	Delamination	Low	Low	100
8	Delamination	Low	Low	100
9	Delamination	Low	Low	100
10	Delamination	Low	Low	100
Total Accuracy				100

Table 3. Severity level comparison (Manual vs. Photogram.) using ten samples

Table 3 summarizes the severity rating results from the photogrammetry and manual approaches. It can be clearly seen that, in all the samples testes, the severity level detected by the photogrammteric method is in total agreement with the level obtained from manual method.

4.2 Automated Pavement Imaging Program

The validation of the Automated Pavement Imaging Program (APIP) algorithms is discussed in this section. Firstly, proper

constant values of A (1.8 and 2.0) were selected for the image segmentation (thresholding) algorithm. This is followed by comparing the crack width (CWs) and cracking density (CDs) obtained from the automated rating against those from the manual rating. Twenty-eight image samples collected from various road segments were used for the analysis.

4.2.1   Crack Width and Cracking Density

To evaluate the APIP performance using the on-field measurement approach, the results had to be analysed by using statistical approaches. The results of the paired t-test are summarized in Tables 4 and 5. The statistic t-values from the t-test are listed in two categories, i.e., CWs and CDs.

(A) Analysis of Average Crack Width				
Technique	Mean (mm)	S.D	t	t_α
Manual	6.077	2.271		
APIP	6.08	2.503	0.363	2.004
(B) Analysis of Average Cracking Density				
Technique	Mean (cm/cm^2)	S.D	t	t_α
Manual	0.0422	0.428		
APIP	0.0516	0.0415	0.841	2.004

Table 4: Statistic test for Manual and APIP (A=1.8) inspection

As shown in Table 4, all statistic t-values were lower than the t_α at the significance level $\alpha = 0.20$. Thus, t-distribution indicated that there were no significant differences between the overall crack width and cracking density for the 1.8_APIP and the field inspections. In Table 4, test for 2.0_APIP also showed higher t_α-values than the statistic t-values at the 0.20 significance level. This indicates that the mean difference between each data was not significantly different.

(A) Analysis of Average Crack Width				
Technique	Mean (mm)	S.D	t	t_α
Manual	6.077	2.271		
APIP	5.735	2.41	0.222	2.004
(B) Analysis of Average Cracking Density				
Technique	Mean (cm/cm^2)	S.D	t	t_α
Manual	0.0422	0.428		
APIP	0.0444	0.0373	0.206	2.004

Table 5. Statistic test for Manual and APIP (A=2.0) inspections

4.2.2   Cracking Type Prediction

The APIP was then tested to determine whether it could distinguish between several types of crack and images without crack. Using additional three actual pavement images without crack, the automated imaging algorithms correctly identified most of them.

From the results, APIP worked very well in predicting the presence or absence of distress features on the image. Of the 25 images with distress features, the 1.8_APIP correctly predicted 23 images that had distress features while 2.0_APIP correctly predicted 24 images. Only 2 images out of 25 images with distress features were incorrectly categorized by using 1.8_APIP. However, 2.0_APIP had only wrongly categorised 1 image. Of the 3 distress-free images, both 1.8_APIP and 2.0_APIP correctly categorised them all as non-crack distress.

Therefore, the overall predictions were found to be 92.86 % accurate for 1.8_APIP and 96.43% accurate for 2.0_APIP.

4.2.3   Severity Level Classification

Severity comparisons indicated that the APIP algorithms were mainly in the range of 88%. However, in a few cases, severity appeared to be lower by using the automated system. The lower classifications of the severity indicated similar concerns that were present during any of the survey at fields, which resulted from interpretations of the severity level from person to person.

5   CONCLUSIONS

It has been shown that the combination of a digital photogrammetric system and APIP allows complete automation with near real-time measurement of pavement distresses. More importantly however, the accuracy of this system in identifying pavement distress meets the standards of set out by the road authority for pavement evaluation. From the ten tested samples, the photogrammetric system produced very reliable and objective results. The output from APIP will be in a form of a report detailing the type, extent and severity of the various types recognized. To date, the overall system has been found to be about 90 percent accurate.

Even though there were some limitations, the system is expected to provide a user-friendly approach to local transportation agencies as well as the government sector. An integration of several image processing algorithm in one Automated Pavement Imaging program has the capability of a) processing the image to isolate the distress features, b) displaying the binary image, c) reporting the type and severity of that image in an output report. It is anticipated that the distress quantification will be effectively and conveniently done without physically touching the pavement area, thus reducing the risk of traffic movement interference.

Whilst the application developed in this research was focused towards pavement evaluation, the concept derived from non-contact, close-range digital metrology and the image processing algorithms are clearly independent of the specific application. The methods utilized in this study could be applied to many other civil engineering fields.

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