Real-time Distress Screening in Automatic Pavement Condition Data Collection

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Pavement condition data collection is one important part for best cost-benefit pavement management and maintenance in all transportation agencies. Large amount of pavement distress data of crack, rutting, potholes, etc. are surveyed to better manage and maintain the pavement asset. However, most of the data collected have no distress inside at all. It is a waste of resource to sample and process it for on-line data acquisition and off-line post-processing. The quick screening of being crack or not could adaptively improve the imaging interval and exposure of acquisition, and relieve the amount of data for quality review. This paper proposes the real-time screening of pavement crack to demonstrate the feasibility of avoiding the irrelevant data during pavement condition survey. The proposed algorithm takes advantage of and integrates the accuracy of multi-scale crack integral profiling (M-CIP) and high speed of crack progressive screening (CPS). Based on the Gaussian-smoothed profile, crack integral profiles (CIPs) are formulated to characterize the transverse continuity of crack pixels. CIP value at a pixel reflects the degree of being crack of a certain width. It is calculated quickly using the innovative integral profile. M-CIP is then conducted to get the optimal crack characterization among different scale widths using the running mean. A fast crack progressive screening strategy is finally proposed to mimic the manual drawing of significant crack indications by the connected M-CIP analysis and crack connectivity check on a profile-by-profile basis. The proposed algorithm is tested on a diverse set of actual pavement images taken on interstate highway G-4 near Beijing provided by the National Center of Measurement for Equipment of Roads and Bridges, Research Institute of Highway of China under varying lighting conditions. Experimental results show the proposed algorithm runs 62 nanoseconds per pixel and 97ms for a 1023*1528 image on a normal personal computer with zero false negative (FNs). It is fast and accurate enough for real-time and reliable crack screening at an acquisition speed of 100 Km/h. The proposed algorithm is promising for practically implementing distress screening of various types in pavement condition data collection.
1. INTRODUCTION
Pavement condition data collection is one important part for best cost-benefit pavement management and maintenance in all transportation agencies. Pavement distress data of crack, rutting, potholes, etc. are surveyed due to the overloading, environmental impacts, and aging of pavement materials. With time, the amount of pavement condition data could be very large, which brings big challenge to data storage and processing. For the latest laser profiling of pavement distress using Laser Crack Measure System (LCMS), the transverse profile has 4096 pixels for full-lane coverage [1, 8]. During its continuous scanning along the road, the amount of LCMS data is prohibitively large. However, most of the data collected have no distress inside at all. It is a waste of resource to sample and process it for on-line data acquisition and off-line post-processing. Moreover, the quick screening of being distressed or not could adaptively improve the imaging interval and exposure of acquisition, focus more on the segments of distress with better sampling rate and lighting contrast, and relieve the amount of data for quality review. This paper proposes the real-time screening of pavement crack to demonstrate the feasibility of avoiding the irrelevant data during pavement condition survey.

With the advances in sensing and information technology, many transportation agencies, including the Georgia Department of Transportation (GDOT), the Texas Department of Transportation (TxDOT), the Ministry of Communication of China (MoC, China), etc. have invested resources to collect their pavement condition data for the decision making of the best treatment. Due to the lower cost and ever-improving resolution of digital cameras and laser profiling, both intensity and range images are now widely adopted in transportation agencies for automatic pavement distress evaluation.

The most common type of pavement distress is crack. Pavement crack weakens the pavement and allows water to penetrate, which possibly causes accelerated deterioration of pavement performance. A timely and appropriate treatment of pavement crack at a certain pavement segment is necessary for an optimal pavement management system (PMS) [6]. Therefore, this paper will first focus on the real-time crack screening in automatic pavement condition data collection.

Many researchers have made lots of efforts to automate pavement crack detection in the past decade. Huang and Xu [4] present a high-speed, real-time detection of pavement crack by crack seed analysis, verification and clustering of grid cells in pavement images. The grid cell based crack seed analysis reduces the computation cost in clustering. This method is quite fast but it is hard to find universal verification methods that will work for images with different contrast, lighting, and shadow effects. Zhang et al [5] proposed the matched filtering algorithm to detect cracks by matching pre-designed filters with crack features in terms of shape, orientation or intensity. Though the matched filtering algorithm shows its distinctive advantages of extracting a single crack, and recording the crack’s orientation, under different conditions, such as changing road conditions and noisy objects, the design of matched filters need to be improved, which need more time and limits its practical use, especially for the online crack screening. To improve the computation time, Huang and Tsai [6] proposed the algorithm which is based on the distinctive, multi-scale line shape elements of cracks in small connected components, and establishes the fundamental crack elements, which opens the door to comprehensive characterization of various
types of crack on multi-scale levels. Though this proposed algorithm is faster with satisfying accuracy, it is still far below the real-time requirement of crack screening due to the Dynamic Programming (DP) based global optimization. A fuzzy set theory based pavement crack detection algorithm is proposed in [2] by the crack membership function and 8-directional connectivity. The connectivity checking algorithm evaluates the extensibility for each crack pixel along eight directions. The direction that has the maximum extensibility is chosen into its connectivity list until the maximum list length is attained or no crack pixel is found. It is a pixel-by-pixel depth first neighborhood searching, which is time-consuming especially for the combinational optimization of parameters in membership function in case of high resolution images [6]. Among other methods [3, 7, 9-10], though they can detect the crack curve from the complex pavement background and noises, the algorithms are too complex to suit real-time crack screening.

To tell whether there is crack in the collected data online and reliably during pavement condition survey, this paper proposes a real-time distress screening algorithm using multi-scale crack integral profiling (M-CIP) and crack progressive screening (CPS). Unlike the traditional crack detection, the proposed algorithm quickly explores the local intensity and continuity property of crack, which opens the door to real-time distress screening of different types in the pavement condition data collection.

This paper is organized as follows: section 1 describes the need and challenge for a real-time distress screening in pavement condition data collection. Section 2 introduces the multi-scale crack integral profiling, followed by the fast screening of significant crack indications by progressive drawing over profiles in section 3. The experimental results are presented in section 4, with the conclusions and recommendations in the last section 5.

2. CRACK INTEGRAL PROFILING

In this section, the crack integral profiling strategy is elaborated to quickly locate the crack-like pixels on a profile-by-profile basis.

The proposed profiling strategy for fast crack location consists of the following steps:

1. Denoise the crack image using Gaussian filtering;
2. Calculate each crack integral profiler using cumulative summation;
3. Multi-scale crack integral profiling using running mean;
4. Determination of significant crack indications.

2.1 Denoise the crack image

Due to the CCD noise in camera or laser sensor devices, stains or dark dirt interference on the pavement surface, digitization error, etc, it is inevitable that pavement images contain lots of random noise. The intensity value of a pixel in an image reflects the ambient illumination and reflectance of the objects. Crack pixel tends to be darker than its surrounding because of its lack of lighting during the image acquisition. Fig. 1(c) shows the 87th profile in the original image of Fig. 1(a). It can be seen that the profile is full of noise and that the crack indication at 120th
column can be hardly differentiated among the noise. To eliminate the high-frequency noise in the profile, a Gaussian filtering with the default standard deviation of 3 is employed. From Fig. 1(b), we can see that most of the white-point noise in the pavement surface of Fig. 1(a) is eliminated after the denoising, and that the profile becomes much clearer at each profile, especially for the crack indication at 120th column, as shown in Fig. 1(d).

2.2 Calculate integral profilers

The primary cue for a pixel being crack is that 1) crack pixels are continuous and locally connected to each other; 2) crack pixels can be distinguished from their surroundings by their sharp changes of intensity; 3) any small segments on the crack curves have the pattern of a thin and connected strip. As shown in Fig. 1(d), the crack pixels around 120th column are continuous horizontally and darker than their neighborhood. While the pavement surface is regarded as flat level in a local area, crack pixels of a profile are then connected drop-offs from the level. To characterize the sharp drop-off of crack in a profile, the cumulative summation along the profile is calculated to quickly get the local mean of any continuous pixels along the profile. We will explore the inter-profile connection of crack indications in the later section.

Fig. 2 shows the integral profile with crack. It can be seen that the crack segment CD is far below the neighboring pavement segment AB and EF on both sides. The crack segment is W-pixel wide due to its continuity, and is differentiated from the pavement surface by the drop-off of D1 and D2 on both sides. Therefore, we define the degree of being crack at location C as follows
\[ CIP = \frac{D_1 + D_2}{2} = \frac{(\sum AB - \sum CD) + (\sum EF - \sum CD)}{2} \]  
where \( \sum AB, \sum CD, \) and \( \sum EF \) is the intensity mean of left pavement segment AB, crack segment CD, and right pavement segment EF respectively; CIP is the crack integral profile (CIP) value at the transition point of B or C. CIP becomes larger when the crack is more significant, as compared with its neighboring pavement surface.

To speed up the calculation of CIP at each location of the profile, cumulative summation of the profile is adopted

\[ \sum AB = \frac{\sum B - \sum A}{m} \]  
where \( m \) is the number of pixels of segment AB, \( \sum B \) is the cumulative summation of the intensity value of pixels from the left-most starting point to point B of the profile. It can be seen that \( \sum B \) is similar to the integral image although it operates on a profile-by-profile basis. Therefore, we name \( \sum B \) of all points of the profile as integral profile, and CIP of all points as crack integral profile with respect to a width of W respectively. Combining (1) and (2), CIP can be reformulated as

\[ CIP_{\text{W}} = \frac{\sum B - \sum A}{2m} + \frac{\sum F - \sum E}{2n} - \frac{\sum D - \sum C}{W} \]  
where \( m, n, \) and \( W \) are the number of pixels of segment AB, CD, and EF respectively. Usually we can choose \( m = n = W \) to capture the local drop-off of crack. It can be seen from Equ. (3) that CIP can be quickly obtained from integral profiles of an image. Since integral profiles can be calculated once in advance, CIP cost less than 62 nanoseconds per pixel based on our experiments.
CIP is dependent on the width of $W$. However, it is hard to know the exact crack width at a certain point of the profile. To address this issue, a multi-scale crack integral profiling (M-CIP) is adopted. As shown in Fig. 3(b), M-CIP is the collection of CIPs at different widths of $W > 1$. CIP with the width of $W$ can be gotten from the CIP with the width of $W - 1$ using the running mean, because most pixels are the same for the width of both $W$ and $W - 1$, i.e.,

$$CIP^w_c = CIP^{w-1}_c + G_{c+w+n} - G_{c+w} \quad (4)$$

where $G_p$ denotes the intensity value at location $p$. It can be seen that M-CIP introduces little extra computation effort.

Fig. 3(b), as an example, shows the CIP of $W$ from 2 to 6 around the red rectangle area in Fig. 3(a). For a certain column index in Fig. 3(b), the maximal CIP value of different $W$ is set to be the value of M-CIP of that column index, i.e.,

$$M - CIP_c = \arg \max_w \left( CIP^w_c \mid W \geq 2 \right) \quad (5)$$

Therefore, the M-CIP value of the 115th column is the CIP value of $W = 5$, as shown by the small circle in Fig. 3(b).
2.4 Determination of significant crack indications

Based on the M-CIP, we get the optimal degree of being crack for each pixel, as well as the horizontal continuity of crack along the profile. As shown in Fig. 4, at 115\textsuperscript{th} column of 87\textsuperscript{th} profile of Fig. 1(a), there is a significant crack of width $W = 5$.

Crack indication is significant in terms of not only different scale width but also its neighborhood. M-CIP represents the strongest response of being crack with respect to different scales. The local maxima of M-CIP of a profile is the starting point for drawing significant crack segments vertically. It can be seen from Fig. 4 that there exists a local maxima (115\textsuperscript{th} column with $w=5$) around the crack area, which reflects the exact drop-off of crack pixels from the local pavement surface. Fig. 3(a) shows 115\textsuperscript{th} column is the beginning of the local crack of the profile. The crack width at 115\textsuperscript{th} column is exactly 5. Therefore, significant crack indications are significant horizontally and with different scales.
3. CRACK PROGRESSIVE SCREENING

Based on the significant crack indications obtained in the previous section, a fast crack progressive screening strategy is presented in this section to locate the significant segments of crack curves using the M-CIP based crack drawing.

3.1 Connected M-CIP Analysis

Starting with the significant crack indications, connected M-CIP analysis is conducted, as shown in Fig. 5. The crack indication of $w=3$ at location (2, 7) suggests that three-pixel wide crack is located from coordinate (2, 7) to coordinate (2, 9). Meanwhile, it also contributes to the possible crack occurrence from location (1, 1) to (1, 10) at the upper row, assuming the maximal crack width is set to 6. Therefore, both the green and red pixels in Fig. 5 are theoretically connected to the yellow significant crack indication. Unlike the traditional 4- or 8- neighborhood connected component analysis, we will do the connected M-CIP analysis in the neighborhood shown in Fig. 5. It should be noted that M-CIP analysis could be adopted for processing images which contain crack pixels with varied widths and different orientations.
3.2 M-CIP Based Crack Drawing

Inspired by the manual ground truth establishment of pavement engineers, an efficient crack drawing method is proposed to explore the vertical connection of crack pixels. As shown in Fig. 6, starting with the significant crack indication at location (1, 10), where there exists a 5-pixel wide crack with a CIP value of 92, the proposed crack drawing finds the local maxima around the connected M-CIP neighborhood of the crack indication profile-by-profile. The connected M-CIP neighborhood is marked out by the arrows to the next profile locations. The next significant crack indication is then found at next local maxima location (2, 10). This process is repeatedly conducted until there is no significant crack indication or the border of the image is met, as shown in the Appendix.

It should be noted that the proposed crack drawing takes full advantage of the M-CIP and the vertical continuity property of crack. It can perform very quickly as the determination of significant crack indication was completed in the last step. Also the geometric property of M-CIP connected crack segments can be obtained simultaneously while drawing the crack curves. Only crack segments of thin strip shape are kept. Most False Positives are greatly suppressed using this geometric constraint.
4. EXPERIMENTAL RESULTS

In this section, the proposed algorithm is tested in terms of its accuracy and computation time for crack screening using the dataset from National Center of Measurement for Equipment of Roads and Bridges, Research Institute of Highway of China. The dataset was collected by the Laser Road Imaging System (LRIS). It includes a diverse set of actual pavement images taken on interstate highway G-4 near Beijing, China under varying lighting conditions and shadows.

1) Accuracy

Fig. 7 shows the result of the proposed fast distress screening algorithm, where Fig. 7(a) is the original crack image, Fig. 7(b) is the multi-scale crack integral profiling (M-CIP) image, Fig. 7(c) is the drawing result of significant crack indications over profiles using the proposed crack progressive screening strategy. The red segments in Fig. 7(c) have a thin strip shape of length-width ratio greater 2, as demonstrated by the two green rectangles in Fig. 7(c). If the number of red crack segments is more than 3, the image is regarded as being crack and stored during the pavement condition survey; otherwise, it is discarded for not being crack. It can be seen from Fig. 7(c) that most significant crack segments are accurately located by the proposed algorithm.

![Fig. 7 Accuracy of the fast distress screening algorithm](image-url)
Fig. 8 Result of M-CIP and crack drawing

Fig. 8 shows the details of multi-scale crack integral profiling and crack drawing. For the wide crack in Fig. 8(a), CIP becomes more significant with the increase of W. Based on our experiments, a crack width of W = 2 to W=6 works for all crack types. From Fig. 8(c) and 8(d), we can see that some crack segments are not well connected due to the missing of significant crack indications. But the result of Fig. 8(d) is enough to tell whether there is crack or not in the image because of the accurate screening of significant crack segments.

To measure the accuracy of the proposed algorithm, the False Negative (FN) is also adopted. FN means that the proposed algorithm mistakenly tells no occurrence of crack in images of crack curves. The purpose of the proposed crack screening algorithm is to minimize FN cases as low as zero. From the first and second column of Table 1, we can also see that FN rate of the proposed algorithm is zero in our experiments, i.e., the proposed algorithm is reliable for crack screening. FN rate is calculated as follows

\[
FN = \frac{\# N_{alg}}{\# Y_{ground-truth}} \times 100\% \tag{6}
\]
where $N_{\text{alg}}$ denotes the number of images of which crack is missed by the proposed algorithm, and $Y_{\text{ground-truth}}$ is the total number of images that have crack. The ground-truth crack indication was identified visually by the pavement engineers in transportation agencies, including those of various crack types.

### Table 1 Performance of the real-time crack screening algorithm

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Average $FN = 0$  
8.0552 84.5954 3.9200 96.5706

#### 2) Computation Time

Another measure for the performance of the proposed crack screening algorithm is the computation time. As shown in the last four columns of Table 1, the average time of
Preprocessing (PP), Multi-scale Crack Integral Profiling (M-CIP), Crack Progressive Screening (CPS), and Total processing for a 1023*1528 image on an Intel Core 2 Duo 2.4GHz, 4G RAM machine is 8ms, 85ms, 4ms, and 97 ms respectively. While the pavement condition survey vehicle is running at a speed of 100 Km/h, the maximal time cost for a real-time, full-lane crack screening of 5-meter pavement segment along the driving direction is 180ms. Therefore, the proposed algorithm is fast enough for real-time crack screening during the pavement distress condition survey.

Table 1 shows the computation time for preprocessing crack image (column 4), the time for the subsequent multi-scale crack integral profiling (column 5) and crack progressive screening (column 6). It can be seen that the preprocessing of Gaussian filtering and calculation of integral profiles accounts for less than 10% of the total time of crack screening while the M-CIP is the most time-consuming computation although running mean is adopted. The time spent on crack drawing is as least as 4ms (5% of the total) due to the progressive screening of significant crack indications profile by profile. The processing time varies with different lighting, noise, and pavement texture. From the last column of Table 1, we can see the maximal time cost of the proposed crack screening algorithm is 105ms and minimal is 89ms, with an average time cost of 97ms/(1023*1528) = 62 nanoseconds per pixel. This average time cost can be further enhanced by parallel processing and the advancement of computation capability.

5. CONCLUSION AND RECOMMENDATIONS

Pavement condition data collection is one important part for best cost-benefit pavement management and maintenance in all transportation agencies. Large amount of pavement distress data of crack, rutting, potholes, etc. are surveyed to better manage and maintain the pavement asset. However, most of the data collected have no distress inside at all. It is a waste of resource to sample and process it for on-line data acquisition and off-line post-processing. A quick crack screening procedure could adaptively improve the imaging interval and exposure of acquisition, and relieve the amount of data for quality review. This paper proposes the real-time screening of pavement crack to demonstrate the feasibility of avoiding the irrelevant data during pavement condition survey.

The proposed algorithm takes advantage of and integrates the accuracy of multi-scale crack integral profiling (M-CIP) and high speed of crack progressive screening (CPS). Based on the Gaussian-smoothed profile, crack integral profiles (CIPs) are formulated to characterize the transverse continuity of crack pixels. CIP value at a pixel reflects the degree of being crack of a certain width. It is calculated quickly using the innovative integral profile. M-CIP is then conducted to get the optimal crack characterization among different scale widths using the running mean. A fast crack progressive screening strategy is finally proposed to mimic the manual drawing of significant crack indications by the connected M-CIP analysis and crack connectivity check on a profile-by-profile basis. Unlike the traditional crack detection, the proposed algorithm quickly explores the local intensity and continuity property of crack, which opens the door to real-time distress screening of different types in the pavement condition data collection.
The proposed algorithm is tested on a diverse set of actual pavement images taken on interstate highway G-4 near Beijing provided by the National Center of Measurement for Equipment of Roads and Bridges, Research Institute of Highway of China under varying lighting conditions. Experimental results show the proposed algorithm runs 62 nanoseconds per pixel and 97ms for a 1023*1528 image on a machine of an Intel Core 2 Duo 2.4GHz, 4G RAM machine with zero false negative (FNs). It is fast and accurate enough for real-time and reliable crack screening at an acquisition speed of 100 Km/h. The proposed algorithm is promising for practically implementing distress screening of various types in pavement condition data collection.

Although the proposed algorithm demonstrates its capability for real-time crack screening, we recommend that:
1) Parallel computing could be incorporated for the inherently parallel multi-scale crack integral profiling analysis to speed up the bottleneck part of the proposed crack screening algorithm;
2) More comprehensive tests with the proposed M-CIP analysis be conducted for different types, severity levels and extents of crack;
3) Innovative and consistent protocols for the distress-aware pavement condition survey in the upcoming era of big data.

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REFERENCES
Appendix - The proposed crack drawing algorithm

1. Given the M-CIP image with the optimal scale (W) and CIP (M) for each pixel
2. for every m lines i
3.   for j=1 to the width of photo do
4.     # compare M(i, j) with M(i, j-1) and M(i, j+1)
5.     if M(i, j) is the maximum, then M(i, j) is a seed
6.     Save M(i, j) as a seed S(x, y)
7.  for each seed S(x, y) do
8.    Let MaxX = x, MinX = x
9.    # go up
10.   # find the index of the maximum value of M
11.    Let MaxM = 0, index = 0;
12.    for j=x-6 to x-2
13.      if MaxM < M(j, y-1) and j+W(j, y-1) >= x-1
14.        MaxM = M(j, y-1), index = j
15.    for j=x-1 to x+W(j, y-1)
16.      if MaxM < M(j, y-1) and j+W(j, y-1) >= x-1
17.        MaxM = M(j, y-1), index = j
18.    if M(index, y-1) is not 0 and the pixel is not Crack
19.      the length of crack add 1
20.      if index < MinX, then MinX = index
21.    else
22.      the width of crack is MaxX-MinX
23.      stop going up
24.  # go down...