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A New Stable and Accurate Algorithm of Concrete Crack Image Mosaic

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Abstract

Due to the concrete crack images are self-similarity in the contents, it makes the matching procedure more difficult and unstable than the others. For the purpose of finding out the stable and accurate matching algorithm of concrete crack images, we give an analysis of different kinds of characters, such as, scale invariant feature transform (SIFT), local maximum gradient descriptor, Harris corners, and the maximum curvature points of the image edges, etc. Based on the experiments of different concrete crack images, a new stable matching algorithm is proposed in this paper. In our model, the edge information is combined with the local maximum gradient of the input matching images. After the extraction of the local maximum gradient character points, we use the edge information to divide these points into different classes. Then, the searching of the stable and accurate matching problem becomes to find out the best matching results which agree to the edge constraints. The experimental results show that the proposed algorithm is more consistence and stable than the other kinds of matching algorithms especially in the proposing of sequential concrete crack images.

Keywords: *Image mosaic; Concrete crack; Harris corner; Image matching; Gradient information; Edge detector*

1. Introduction

A crack is one of the earliest signs of the structural failure in the concrete constructions. Conventional methods for crack detection are implemented by experienced inspectors who mark the cracks manually and read the width is the cracks with their naked eyes. However, such detection methods [1] are very expensive, time-consuming, dangerous, labor-intensive and subjective. Therefore, crack detection methods based on the image processing are desired for acquiring objective and accurate data.

Many researchers have paid attention to concrete crack inspection methods based on image processing. A crack is the sensitive area of a concrete image and it provides the most important information for image segmentation. Because of the non-uniform illumination, contaminated concrete surface, and variations of crack types, image processing becomes a stubborn step during crack extraction. For the purpose of improving the image resolution, we exchange the image acquiring ways by using the focal lens camera to take the local information along the concrete crack line. On this condition, the concrete crack information is taken as a sequential of images. After the sequential images have been acquired, the mosaicking of each pairs of the images becomes the main task in the following procedure because of the accurate and stability of the mosaicked image pairs influenced the total detection of the concrete crack.

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Image mosaicking [2-6] is a very effective method for solving the contradiction between field of view and resolution in remote sensing field. Its principle is to utilize registration and blending techniques to stitch two or more image which have overlapped areas into one large image, which is always of wide field and high resolution. Unfortunately, because of the complicated imaging condition, we will inevitably get the final image with alignment error. Focus on the stability, time consuming, and accurate of the concrete image mosaicking, we will give a comparison study of different character based matching algorithms. Figure 1 shows the global and local images of the concrete crack.

Figure 1. The Global and Local Concrete Images

Commonly, the mosaic of image pairs consist three steps: the extraction of the image character points, the matching of the character points, and the alignment of the image pixels. In the first step, the character points are often considered as the Harris corners, SIFT points, and high-gradient points. From Figure 1, we may found the concrete images are self-similarity in much of the contents, any of the above mentioned detectors may cause the wrongly dividing the detected points in correlation matching procedure. At the same time, the threshold setting is also another problem. In the image matching procedure, the main purpose is to find out the character points those both existed in the left and right image. It is very difficult to find out a standard to make this step stable, because of the 3-dimension perspective transform is often obey the 2-dimension geometric characters. For the purpose of improving the stability of this step, some constrains, such as line, edge, geometric relation, and region character are often added to the character descriptions. On this condition, the matching of the character points becomes to the matching under the inner constrains of each image.

Inspired by [3-4] and [7], in this paper, we proposed a new concrete crack detect algorithm based on the local area sequential image mosaicking detection. Under this condition, we deeply give the study of the different character points detection algorithms and the matching stability of the sequential images. Comparing to the other concrete crack detecting algorithms, the main advantages of our method can be highlighted as:

(1) Due to the concrete crack scene information is acquired as the local image sequence, the resolution ratio has been improved to a large extent. At the same time, the local image acquiring way can avoid the influencing of the contaminated scene where the crack does not existed.

(2) For the purpose of avoiding the problem of unpredicted character point number under the threshold condition, we give a comparable study of the different character detection algorithms, and proposed a new fixed character point number detecting algorithm.

(3) Because of the total detecting accurate is influenced by the matching accurate of each image pairs, and the total crack detecting time is influenced by the stability of the matching processing, by adding the edge constraint and pre-matching procedure, our algorithm improved the total crack detecting efficient and accurate to a large extents.

The remainder of this paper is organized as follows. In Section 2, we give the briefly introduction of the related concrete detect studies. The proposed matching algorithm and detailed introduction of each step, such as the character point detection and edge extraction, are introduced in Section 3. In Section 4, we mainly give the detailed introduction of matching procedure. Section 5 is the experimental comparison of our model with other image matching results. We go on analyzing the results different kinds of character detecting and matching algorithms. Finally, the conclusion and limitations of our model have been discussed in Section 6.

2. Related Work

There are many papers aimed at the detection of the concrete crack detection. In recent years, the image detecting algorithms have been got more and more attention. The crack analysis is necessary for automatic repair and maintenance of concrete surfaces. Hass *et. al,*. [8] developed an automated field prototype crack sealing system which required fully automated crack detection, surface mapping, and control systems. In digital imaging process, crack pixels need to be separated from their background. For segmentation of a crack from its background, a threshold is used for extracting the crack boundary pixels. The threshold can be estimated from mean and standard deviation of gray-level images. However, this method does not ensure proper crack connectivity because of the complicated background.

The purpose of crack image processing is to extract area of interest from a given image gram. For example, the extraction of length and width of crack is necessary for crack analysis of concrete members. So, proper definition of crack length and width needs to be stated explicitly. This could be possible by dividing a long crack into small crack segments and retrieving average length and width for each segment. In current literature, crack segmentation has been proposed by searching of crack connectivity and matching with pixel orientations [9-12]. These approach need input of at least one crack skeleton pixel to start searching of crack connectivity. Image stitching algorithm has been discussed in some papers. Aimed at acquired the large area of the concrete surface, Li, Gang *etc.*, [3] using the image mosaic algorithm to evaluate the reconstruction of the concrete pavement surface. In [4], Chia-Han Lee *etc.*, give a study of the validation of simple image-mosaic technology for interpreting cracks on tunnel lining. According to their study, on the laboratory-scale tunnel condition, the mosaicked layout from vertical images is about 1.6° with sufficient image resolution for detecting lining cracks with widths exceeding 0.45mm.

Although the image mosaic algorithm has been used in the concrete crack surface detection, the efficient and stability of the segmented crack image matching have not yet been deeply discussed in the proposed papers. For the purpose of improving the efficient, Jun-Wei Hsieh [13] use the edge pixel as the pre-matching procedure, and then use the character pixel to optimize the total matching of the input pair of images. In [14], the author use the SVM to estimate the matching and mosaic results, but for the SVM classification, the input training images and the evaluation of the parameters is very difficult. For the purpose of improving the traditional method that based on characteristic, Gang Xu *et. al.*, [15] use the granular computing algorithm to detect the image character points. Aimed at obtain the topology information, Armagan Elibol *et. al.*, [16] use the information to improve the robust of their matching procedure. For the purpose of measure the different descriptors of shape, color, and size in image mosaic, Zoe Falomir [5] give a comparative analysis of different descriptors. All the above mentioned papers are aimed at improving the stability and accurate of image mosaic algorithm.

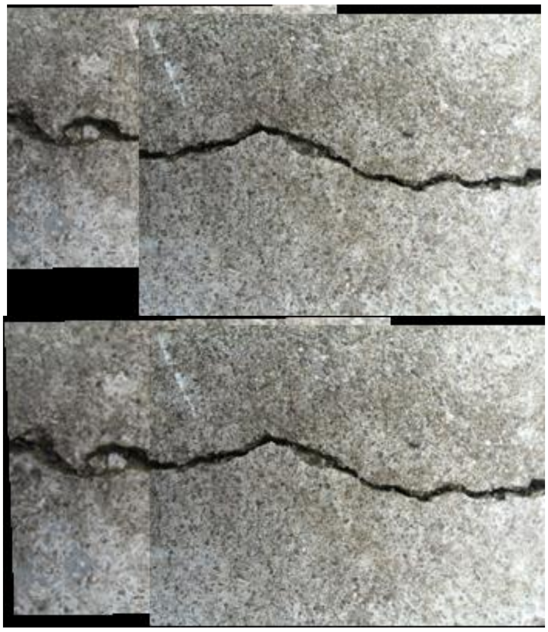


Figure 2. The Mosaic Result of Wrong (Left) and Correct (Right) Estimated Homograph Matrix

Basically, the mosaic procedure may be divided into three steps: the extraction of the image character points, the estimating of the affine model, and the alignment of the each pair of image pixels. Given two images I_m and I_n, let $p = (x, y)^T$ be a pixel location in I_m, and $q = (x', y')^T$ be the transformed location in I_n. The affine model is mathematically expressed as:

$$\begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = M * \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \tag{1}$$

where $M = \begin{pmatrix} m_0 & m_1 & m_2 \\ m_3 & m_4 & m_5 \\ m_6 & m_7 & m_8 \end{pmatrix}$. The technique used to estimate M is random sample consensus (RANSAC) [17]. RANSAC is used to select a set of inliers that are compatible with a homograph between the images and apply a probabilistic model to verify the match.

RANSAC is a robust estimation procedure that uses a minimal set of randomly sampled correspondences to estimate image transformation parameters, and finds a solution that has the best consensus with the data. In the case, we may choose the matched feature points pairs to evaluate M using the direct linear transformation (DLT) method. Unfortunately, when the input pairs of character points of the first step extracted are redundancy, this algorithm may leads to local minimum. Figure 2 shows the wrong and correct estimated results of the homograph matrix.

3. The Proposed Algorithm

In this section, we aimed at improving the stability and accurate of the mosaic result of concrete crack sequential images. To improve the accurate and stability of image mosaic, the accurate of the extracted character points is very important. SIFT [18] descriptors can accurately extract invariant image characteristics around key points. But when this descriptor is used in crack images, it may lose its role because of self-similarity in much of the content.

The Harris detector [19] measures the local variation by shifting in various orientations, which is convoluting the original image with a Gaussian kernel. Given the input image I , the convolution of the input image is defined as:

$$S(x, y) = G(x, y) * I(x, y) \tag{2}$$

$$\begin{aligned} G_x(x, y) &= \frac{-x}{2\pi} \exp\left(-\frac{x^2 + y^2}{2}\right) \\ G_y(x, y) &= \frac{-y}{2\pi} \exp\left(-\frac{x^2 + y^2}{2}\right) \end{aligned} \tag{3}$$

where $G(x, y)$ is the Gaussian kernel function, $G_x(x, y)$ and $G_y(x, y)$ are the two directions, horizontal and vertical ones. In our paper, we use the smoothing window of 7×7 in Equation (2) and (3) represent the positions of every pixel in the window. Therefore, two kernels G_x and G_y focusing on two orientations are formed. Then, $I_x(x, y)$ and $I_y(x, y)$ of the directional kernels convolution may be calculated.

After every convolution, we have a T calculated as follows:

$$T(A) = Det(A) - \varepsilon Tr^2(A) \tag{4}$$

where A is matrix composed of four elements

$$A = \begin{pmatrix} a_{xx} & a_{xy} \\ a_{xy} & a_{yy} \end{pmatrix} \tag{5}$$

and a_{xx} is the summary of all the $I_x^2(x_i, y_i)$, belonging to the smoothing window. Here a_{xy} is the total value of all the $I_x(x, y) I_y(x, y)$, and accordingly, a_{yy} is the sum of $I_y^2(x, y)$.

Harris and Stephens [19] believed that the corner points are selected by examining the maximum T of every 7×7 window after generating all T in the image. And a sample image based on Harris corner detector is shown in Figure 3 (a).

Because of the Harris corner use the 7×7 window to calculate the maximum value of the character points, it makes the edge information lost to a large extent. For the purpose of comparing different kinds of character points, we use the magnitude of image gradient, directional gradient of each pixels, and local maximum difference as the main characters. The magnitude of the image gradient $M_g(x, y)$ is defined as:

$$M_g(x, y) = \sqrt{G_x^2(x, y) + G_y^2(x, y)} \tag{6}$$

$$M_d(x, y) = \max\left\{\left|G_x(x, y)\right|, \left|G_y(x, y)\right|\right\} \tag{7}$$

where $G_x(x, y)$ and $G_y(x, y)$ is the directional gradient of the image pixel in x-direction and y-direction. Figure 3 (b) shows the extracted character point based on magnitude of the image, and Figure 3 (c), is the extracted points of the directional gradient. For the purpose of extracting the local maximum difference points, we use the local minimum template of 3×3 or 5×5 filter T_L to processing the image, and then using the rough image to deduce it. The extraction of the local maximum point is based on the deduced result. Given an input image I, the local maximum difference is defined as Equation 7. Figure 3 (d) is the extracted result of this kind of character points.

$$I_{LM} = I - I * T_L \tag{8}$$

where T_L is the minimum filter, when the template size is 3×3, the calculated value of the template is $z_{i,j} = \min\left\{I_{k,l}, k = i-1, i, i+1; l = j-1, j, j+1\right\}$.

In this paper, our processing image size is about 3264×2448. The calculating of image convolution is also very time-consuming. So, before the calculation of character points and edge of the input image, we resize the image to 192×256. After the detection of the small size image, we pre-matching the two image and evaluate the homograph matrix M'. Then we evaluate the pre-calculated homograph matrix M' using the edge information. If the homograph matrix M' was agree with the edge constraint, we choose the correct matching points as the seed pixel to search the rough image character pixel, otherwise, recalculating the homograph matrix M'. The pre-evaluated homograph matrix M' is used as the constraining of the refining character point detection. At this step, we use the matched points to calculate the rough image local region character points. On this condition, we can avoid the calculating of the large total image. Generally, the edge constrained concrete crack image mosaic can be summarized in the following steps:

Step 1: Calculating and extracting the character points of the resized input image pair.

Step 2: Extracting the resized image edge and extracting the edge covered character points.

Step 3: Calculating the pre-matching homograph matrix M'.

Step 4: Checking the edge constrain condition of the rough matched character points. If the condition is matched, go to Step 5, else, recalculating homograph matrix M' until the constrain condition matched.

Step 5: Calculating the accurate character points of the rough image.

Step 6: Calculating the accurate homograph matrix M.

Step 7: Transform original image and achieve built-up image in.

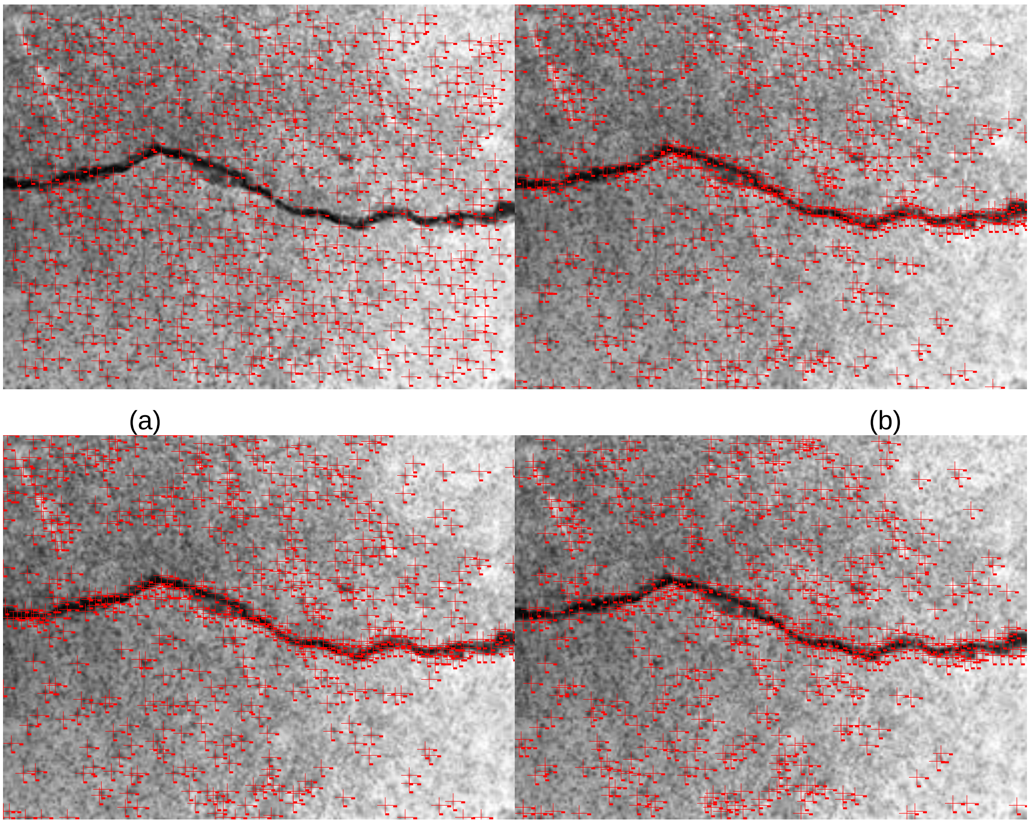
Step 8: Blending the input pair of images.

4. Optimization

In this section, for the purpose of making our proposed algorithm more stable and accurate, we give the analysis of the character point extraction and the constraint condition. For more accurate mosaicking purpose, the extraction of the rough image matching points will be analyzed here too.

4. 1. The Extraction of the Feature Points

In the procedure of character point extraction, the number and distribution of character points are the main problems. Basically, the character points should match the following three conditions before the matching procedure.



(a) (b) (c) (d)

Figure 3. The Different Kinds of Extracted Character Points: (a) is the Harris Corner, (b) is the Magnitude of the Gradient, (c) is the Directional Gradient, and (d) is the Local Maximum Character Points of 5×5 Template

(1) The character points should be uniformly distributed in the image, when there is any overlapped information of the two images.

(2) The feature of the extracted points should consistence to the global condition, instead of the local condition.

(3) The number N of the character points should be fixed or within a range.

Along with the above mentioned standards, we adjust the character point extraction algorithm. Firstly, we calculate the value of the size adjusted image points according to Equation (6-8). The second step is to decide the character number. Commonly, the choosing of the character points is use a pre-decided threshold, when the threshold is higher, the detected number may be less, otherwise, the detected points may become much more. Both of the two conditions may leads to the matching procedure unstably. Considering of the strength and distribution of the image character points, we choose the maximum points of the image step by step, and after the extraction of the current maximum points, we eliminate the current points and its local region adjacent points. The local region size may be chosen according to the input image size. Under this condition, we may set the number of character points previously, for example 400. The Figure 3(b-d) is the extracted character points when the number set as 400.

Comparing to the other kinds of character point extraction algorithm, the proposed algorithm may avoid the concentration of the strong response image pixels of the measurement. And at the same time, it may also keep the extracted points uniformly or nearly uniformly distributed.

4. 2. The Classification of the Extracted Points

There are many kinds of edge detection algorithms, such as, the simple Gradient vector function, the normal Gradient Modulus function, and the Wavelet Modulus function [20], and some kinds of edge detecting templates. Finding out the enclosed region of the image is very difficult, and it is always the problem of image segmentation. Here, we need only to find out the strong line of the image regions. Based on this condition, we choose the Sobel edge detector as the edge extraction operator. After the extraction of the main edges, we choose the extracted character points which cover the edge lines as the constraint condition. Figure 4, shows the result of edge covered character points.

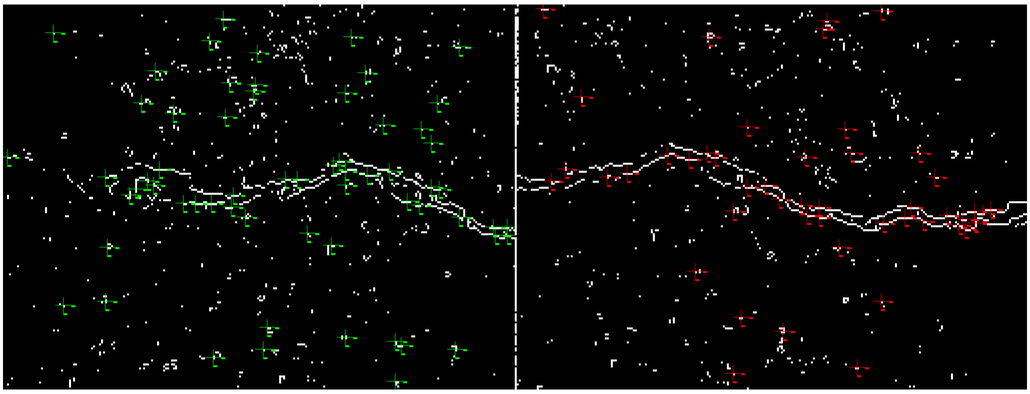
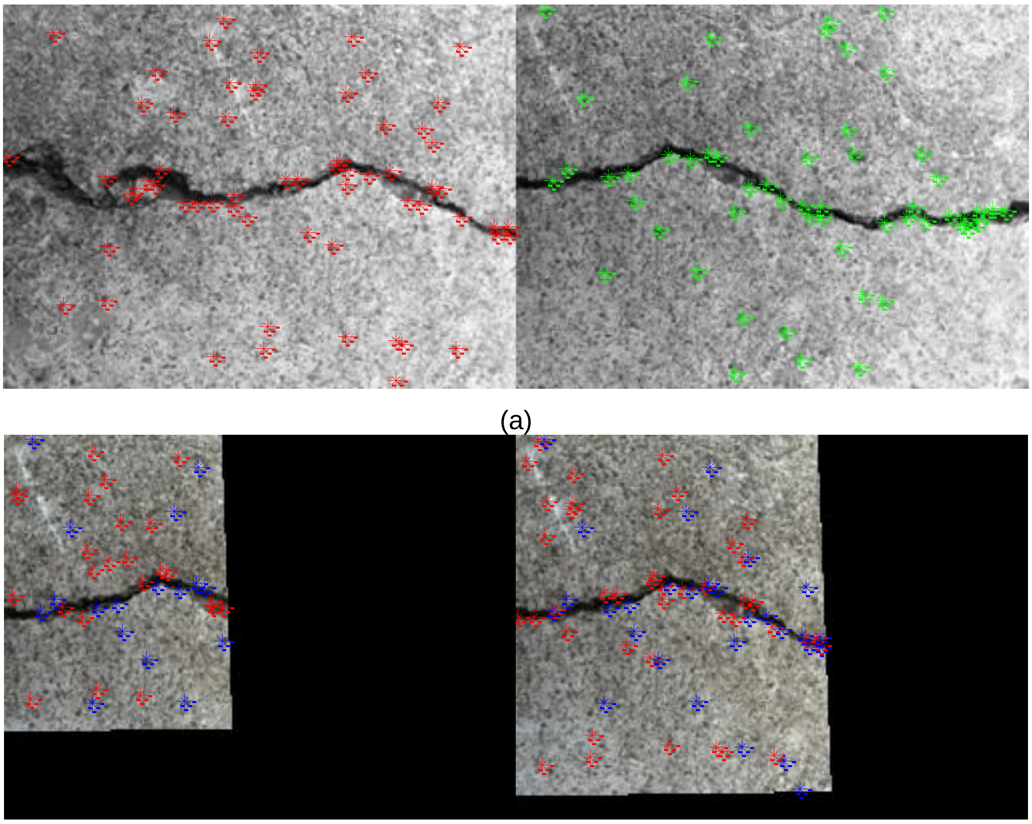


Figure 4. The Extracted Edge Covered Character Points of One Pair of Images

Many papers have been give the study of matching based on different constraints, such as, the Delaunay triangulation and affine invariant geometric constraint [21], the template matching with arctangent Hausdorff distance measure [22], the coloring based approach for matching [23], the fast and scalable approximate spectral graph matching [24], the optimized hierarchical block matching [25], and improved robust algorithm for feature point matching [26] *etc.*, In this paper, considering of the time-consuming and stability of the total algorithm, we choose the edge cover condition as the constraint of the matching result. On this condition, the edge covered points in one image should cover the edge exactly on the matched image edge. From Figure 2(a), the wrong matched result figure, we may found when the matching result is wrong, the edge cover points are not fit the constraint condition to some extent.

To measure the proposed constraint, we need to find out the accurately matching of the detected edge covered points. But, the single image based edge covered character points detector may not keep the consistence of the matching image, because of the common contents of the images are unknown before the matching procedure. The searching of the matching point in another image is the only way we can acquire them. Fortunately, the pre-matched homograph matrix M' has provided us the information of the roughly searching region in the matched image.



(a)

(b) (c)

Figure 5. The Searching Region of the Constraining Point Based on the Roughly Matched Result, (a) is the Detected Constraint Points of the Image Pair, (b) is the Wrong Matching Result, and (c) is the Correct Matching Result

All the above mentioned [21-26] pre-matching algorithm are using the self-character of the image contents to find out the best match condition. Although, these pre-defined characters may improve the matching efficient and stability of the matching procedure, for the accurate matching in the crack detecting condition, we need to compare the characters of the each control pixels of the overlapped region. Figure 5(b-c), shows the overlapped region of the two matching results M_1' and M_2'. Comparing with the two results, we may found, when the matching result was correct, the difference of the local characters such as gradient and the gradient direction is small, and vice versa. For the purpose of avoiding the influence of lighting, we use the normalized directional difference of all the overlapped constrain points as the evaluating of the matching result.

4. 3. The Matching and Blending

After each pairs of the resized images have been matched, we save all the homograph matrixes M_i' in the computer. Figure 6, shows the total matching result of 5 sequential images. When the pre-matching results have been calculated, we use each homograph matrix M_i' to segment the rough images into overlapped and un-overlapped regions. The extraction of the character points will be done only in the overlapped regions.

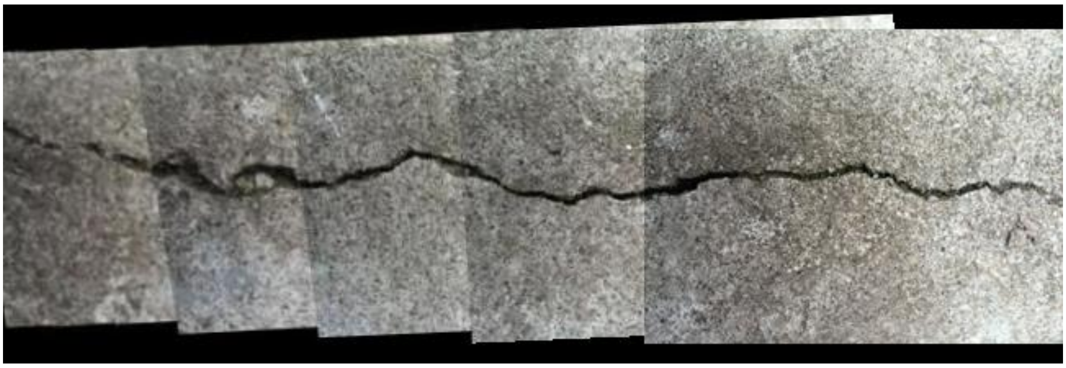


Figure 6. The Matching Result of 5 Sequential Resized Images

5. Experimental Results

To demonstrate the accurate of the matching results, we choose a sequential crack images, and calculate these images on Matlab 2010. Three pairs of images of Figure 6, have been experimented in the following experiments. The motivation of our current development is to provide the high accurate matching solution to the rough images of local concrete crack.

Figure 7. The Blending Result of the Sequential Images

For the rough concrete crack images (3264×2448), we use the above mentioned algorithm to pre-match the resized images of the sequential. Then, we use the calculated matching result, the matching points and homograph matrix M_i', to realize the accurate matching of the rough image sequence. Figure 7 shows the matching result of the first image pair in Figure 6.

Figure 8. The Local Image of the Matched Sequential Image Results

To improve the efficient of the rough sequential image matching procedure we use the matching points of the resized matching result as the basic searching region. In the following experiments, we choose the 5×5 region centered at the mapped matching pixels as the searching region of the character points. On this condition, the searching region and calculating procedure would be decreased to a large extent. To illustrate the mosaic accurate, we use the partial of the mosaic result centered at the crack as the result images. Figure 8 shows the results of three pair images.

6. Conclusion

Comparing to the other algorithms which aimed at finding out the relative characters of the mosaicking images, our method is more stable, accurate, and adaptable to different kinds of images. On the other hand, all the self-constraint conditions are unstable when it meets the perspective transform. In our algorithm, the constraint condition was adopted after the pre-matching procedure. It improved the stability and made the constraint condition more simply.

In the character point extracting procedure, the distribution and number of character points is the main influence of image matching accurate and stability. In this paper, we extract the character points from strong to weak response and at the same time limit the maximum point number. This algorithm may also improve the stability of the matching processing.

For the purpose of making the concrete crack detection procedure more automatic, in the following works, we will give the deep study of the stability and accurate of the mosaicking algorithm. The segmentation of the local detail concrete crack images is also the main study of the future work.

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