Scientific Research and Essays Vol. 7(10), pp. 1175-1184, 16 March, 2012
Available online at http://www.academicjournals.org/SRE
DOI: 10.5897/SRE12.028
ISSN 1992-2248 ©2012 Academic Journals

Full Length Research Paper

An improved beamlet tree-structured algorithm and its application in pavement crack detection

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Accepted 21 February, 2012

In order to overcome the high computational complexity of beamlet tree-structure algorithm, the paper proposes an improved algorithm and applies it to pavement crack detection, thereby; solving the problem of pavement crack detection which has the disadvantages of poor noise immunity and inaccurate test results. First, the pavement crack image is rectified by multiplicative factors to eliminate the influence of non-uniform background illumination. Then, the image is transferred to the binary image by Otsu's threshold segmentation algorithm. At last, based on discrete Beamlet transform and integrating multi-scale tree structure of beamlet itself, extract pavement crack from the binary image by using the beamlet tree-structured algorithm, which change a "bottom to top" strategy to look for the optimal value of objective function into a "top to bottom" searching process. Therefore, the proposed method reduces calculation complexity and time. Experimental results show that the proposed method can quickly extract crack from the complex pavement background and noises. Moreover, it keeps the continuity of the crack as well.

Key words: Beamlet transform, tree-structured algorithm, Otsu algorithm, crack detection.

INTRODUCTION

The beamlet transform (Donoho et al., 2001) is a recently emerged tool for multi-scale geometric analysis, and it has been successfully applied to image edge detection (Li et al., 2009), line feature extraction from remote sensing image (Mei et al., 2008), weld image detection (Deng et al., 2009), extraction from core fissures images and so on (Gao et al., 2010). According to computational complexity, beamlet algorithm is divided into four different levels of the algorithm, namely; structureless algorithm, tree-structured algorithm, local chaining of line segments, and global chaining of line segments. Among them, structureless algorithm is simply for computation, but it extracts line feature at single scale.Tree-structured algorithm uses "bottom to top" strategy to look for the optimal value of objective function and extract line feature at different scales, and then the superiority of Beamlet algorithm in multi-scale analysis is fully reflected. Besides, it is with excellent capability of reducing noise. However, it is with high computation complexity.

With the rapid development of the highway construction, it is more and more important to maintain and monitor large-scale and complex transportation network. However, the traditional manual detection method of pavement disease is costly, time-consuming and needs a large amount of labor while it cannot get objective and accurate detection results (Siwaporn, 2008).

With the development and progress of video technology and image processing, they are also getting more and more widely applied in transportation. Therefore, they make automatic pavement disease detection possible (Chi et al., 2009). Pavement crack detection has been a research hot spot. Cheng et al. (1999) trained a neural network to select a threshold for pavement image segmentation. Chu et al. (2003) proposed a method

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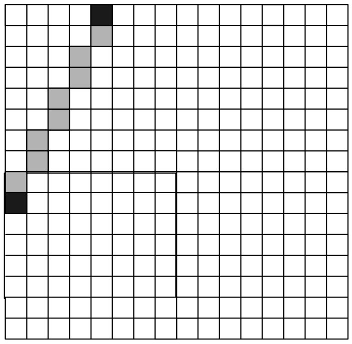


Figure 1. A discrete beamlet.

based on moment invariant feature for pavement distress image recognition. It has a relatively higher recognition rate for lumpy and mesh pavement distress image, but the recognition rate is lower for single crack image which is vulnerable to the noise. Wang et al. (2004) proposed a method based on the ridgelet transform for pavement crack detection. This method has good effect in linear crack extraction and noise suppression, but not in extracting curve crack. Wei et al. (2010) proposed a method which segment the pavement image into unit image, and then transformed to binary image, at last used beamlet structureless algorithm to detect crack. But structureless algorithm is short of scale inhibition. Hu et al. (2010) proposed a novel LBP based operator for pavement crack detection, but the method showed its limimation which canot detect crack under the shaow. In Tsai et al. (2010), six different segmentation algorithms such as canny operator, multi-scale wavelets, region growing method, iterative method, dynamic optimization-based method and so on are assessed. The experimental results show that no proposed algorithm can meet both the requirements of accurate crack extraction and relatively higher computational speed.

Therefore, we propose a pavement crack detection method based on improved Beamlet tree-structured algorithm.

Firstly, the image is preprocessed to revise the gray level of pavement distress images by calculating the multiplicative factors to reduce the image non-uniformity. Secondly, the image is transferred to the binary image using Otsu's threshold segmentation algorithm. And then, the image is decomposed by discrete Beamlet transformation to calculate Beamlet coefficients within dyadic squares on all scales. Next, we use the improved Beamlet multi-scale tree-structured algorithm looking for optimal value, which transforms a "bottom to top" strategy to look for the optimal value of objective function to a "top to bottom" search process. Therefore, the calculation complexity and time are reduced. At last, draw a line to depict those discrete beamlets corresponding to the optimal value of objective function. Experimental results show that the proposed method can quickly extract different types of crack from the complex pavement background and noises. Moreover, it keeps the continuity of the crack as well.

BEAMLET TREE-STRUCTURED ALGORITHM AND ITS IMPROVEMENT

Discrete beamlet transform

David L. Donoho and Xiaoming Huo introduced a new multi-scale image analysis tool-Beamlet transform in literature (Donoho et al., 2001).They proposed continuous Beamlet transform and its application in multi-scale analysis. In order to reduce computation complexity and be more suitable for computer processing, Xiaoming Huo et al introduced discrete beamlet transform in literature (Huo et al., 2005).

Discrete Beamlet: A discrete image ($n \times n, n = 2^j$, j is the scale of the dyadic square) is decomposed by recursive dyadic partition. Within each dyadic square, any pair of vertices on its boundaries determines a line segment. This line segment is called a beamlet. We can locate all pixels in the line segment by interpolation method. Now we locate all pixels of each beamlet by the method applied in Shi et al. (2004). A discrete beamlet in 16×16 dyadic square is shown in Figure 1 (black pixels mean two endpoints of a beamlet while gray pixels refer to its other pixels).

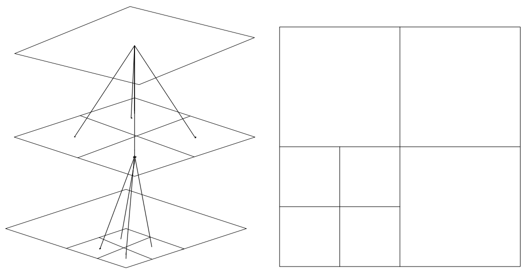
Discrete Beamlet Transform: Discrete Beamlet transform of a beamlet is weighted sums of gray values of all pixels in the beamlet. The discrete Beamlet transform of the whole image could be expressed by the sum of pixel gray value *G(x, y)* on b, that is

$$T(b) = \sum_{(x,y) \in b} G(x,y), \; b \in B \qquad (1)$$

Where *B* is the sets of all discrete beamlets, *b* is a sub-beamlet of *B*, *G(x, y)* is the gray value of the point *(x, y)*, and *T (b)* is the beamlet coefficient associated to beamlet *b*.

Beamlet tree-structured algorithm and its shortcomings

Tree-structure is an algorithm which can give fully play to advantages of multi-scale Beamlet transform. The basic idea as follows: firstly, all dyadic squares of original image on every scale is decomposed by Beamlet transform to find the optimal discrete beamlet, then use these beamlets to build discrete Beamlet tree-structure and traverse to search for the optimal BD-RDP at last. Figure 2A shows a common tree structure, and parent-child relationships are expressed by line segment which connects the center of the parent square to the center of the child square. Besides, the tree structure corresponds



A B

Figure 2. The tree structure and corresponding recursive dyadic partition.(A)Tree structure; (B) Recursive dyadic partition (RDP).

to a recursive dyadic partition (RDP) (as shown in Figure 2B). Donoho et al. (2001) shows a well-defined notion of RDP. From the perspective of an RDP, if there is an associated beamlet within all sub-blocks or parts of sub-blocks, then the RDP will be called beamlet-decorated RDP or BD-RDP for short. A key property of BD-RDP lies in the inter-scale inhibition among different scales of beamlets. That is to say, if the line feature of a dyadic square can be expressed by beamlet of large scale, then the square won't be decomposed into small scale any more to avoid the overlap of line features.

In fact, Multi-scale line feature extraction is to find the optimal objective function. The objective function given by Donoho et al. (2001) is:

$$J(p) = \sum_{S \sim P} C_S^{\,2} - \lambda \ \# P \qquad (2)$$

where $C_S = \max_{b \sim S} T(b)/l(b)$, and S is a dyadic square of this RDP, b is a beamlet of S, $T(b)$ is the coefficient of discrete Beamlet transform and $l(b)$ is the Euclidean length of beamlet b. λ is the penalty parameter while $\# p$ means the number of dyadic squares of RDP.

The optimal objective function of BD-RDP is the maximization of $J(p)$ in all possible RDP and at first the objective function $J(p)$ is shown in Donoho et al. (2001) in the form of an additive function:

$$J(p) = \sum_{S \sim P} \Gamma_S \qquad (3)$$

Where $\Gamma_S = C_S^{\,2} - \lambda$ while other parameters are the same as those of equation (2). Secondly, use a gradual "bottom-up" tree pruning process, that is to say, starting from the smallest scale, to recursively determine whether it is better to leave a dyadic square unsub-divided or to divide it into four subblocks by comparing the value of Γ_S.

In this process, we record all beamlets corresponding to the dyadic square when $\Gamma_S > 0$. At last, draw a line segment to depict those beamlets that have met the requirements to be detected as line features. However, finding the optimal value by using "bottom to top" method is with high computational complexity. Concrete analysis is as follows: Firstly, starting from each dyadic square S of 2-by-2 pixels, we suppose the target value of S, and the target value of four subblocks that compose S is to compare the value of with the sum of the four objective values of those four subblocks. Meanwhile, mark the maximum value as and record the corresponding beamlet decomposed by this method. Secondly, we move up one level to take 4-by-4 dyadic squares into consideration by the same methods as above until the entire image is analyzed. In the whole process, objective functions are repetitively compared. In other words, when the optimal objective function at small scale is given a solution, it shall continue to be compared with the target value at the next bigger scale while we can't decide whether the decomposition can be stopped or not under current conditions. Therefore, the "bottom to top" search strategy to some extent increases the computation complexity and needs more computing time.

Modified tree-structured algorithm

Algorithm principle

To reduce the computation complexity of "bottom to up" searching strategy brought forth by Donoho, we propose a "top to bottom" method to search the optimal value of objective function. That is to say, from the largest scale, gradually move downward level by level to compare objective value of next scale. If the objective function value at large scale is larger than the sum of the objective values of four subblocks, then stop the decomposition and take the beamlet corresponding to the target value at large scale as the objective of line feature, otherwise split the dyadic square into four subblocks to continue looking for the optimal value of objective function until all dyadic squares cannot be decomposed any more.

To make this easier to understand, taking the 256×256 image for example, at first, starting from the entire image, we suppose the target value of S (256×256) dyadic square is, the objective value of four dyadic subsquares is, then compare the objective value for the unsubdivided square with the sum of the four objective value of those four subsquares. If , stop decomposing and mark the maximum value of these two numbers as , or else move downward one level to go on decomposing; secondly, compare the objective values of 128-by-128 squares with the target values of four 64-by-64 dyadic subsquares. Accordingly, move downward one level

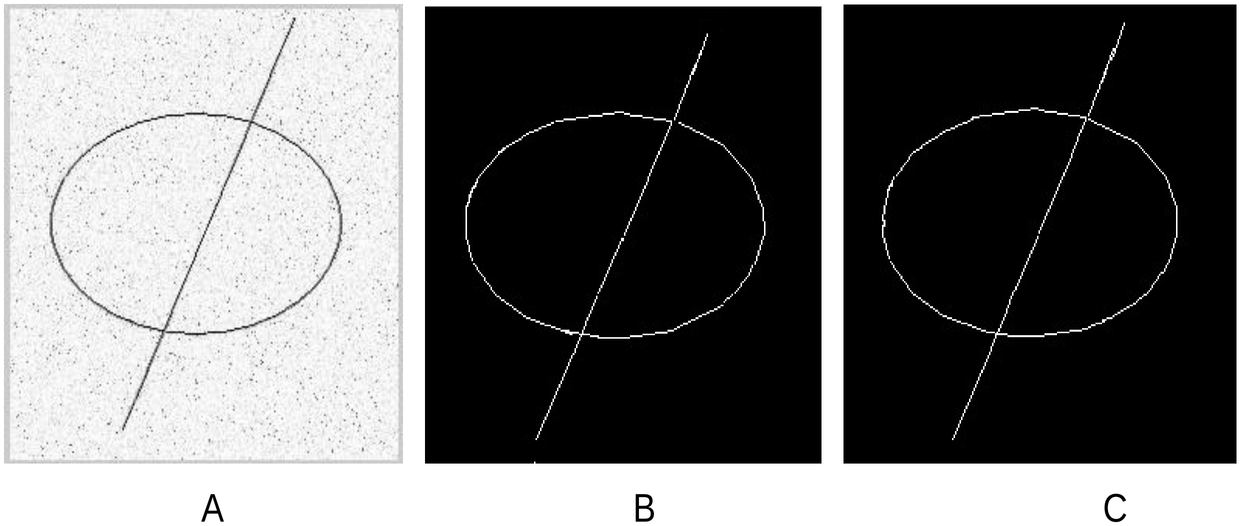


Figure 3. The test image and results.(A) Noisy image;(B) The result of Donoho algorithm;(C) The result of modified algorithm.

after another to consider whether dyadic subsquares should be retained or split into four pieces until all dyadic squares cannot be decomposed any longer.

The whole process simplifies the process that repeatedly compares objective function value by traditional algorithm. Only if we compare its objective function value with that at next smaller scale can we determine whether dyadic squares at current scale shall be stopped decomposing or continued to be divided into four sub-blocks. Therefore, compared with traditional tree-structured Donoho algorithm (called Donoho algorithm for the sake of simplicity); our improved method reduces calculation complexity and time.

Implementation steps of modified Beamlet tree-structured algorithm

Concrete steps of modified Beamlet tree-structured algorithm are as follows:

(1) Calculate beamlet transform coefficients of all dyadic squares on each scale by rapid Beamlet transform proposed in Yang et al. (2007);
(2)Construct discrete Beamlet tree structure and calculate the optimal value of objective function by using “top to bottom” searching strategy proposed by last section and comparing objective values of each scale. When the optimal value of objective function exceeds zero, record the decomposition method.
(3) Draw a line segment to depict the discrete beamlet corresponding to the optimal value of objective function that is greater than zero. That is to say, the gray value of all pixels of beamlets is set 1 as the target while others are set 0 as background.

Comparison of experiment results

In order to verify the efficiency of the algorithm, we test computer synthesized images by using Donoho algorithm and modified tree-structured algorithm.

As shown in Figure 3, it is a computer synthesized image with curve and line features and its size is 256×256. Meanwhile, the image is added the salt and pepper noise with the strength of 0.02 and Gaussian noise with the variance of 0.01. Figure 3B shows the line features extraction results by using the Donoho algorithm, Figure 3C reflects the extracted line features results after using our modified tree- structured algorithm. It can be seen from experiment results that Donoho algorithm can effectively extract line feature from low SNR and fully prove the advantages of Beamlet transform. Figure 4 shows a real image and results. Figures 4B and C show the results by using Donoho algorithm and the proposed method. As shown in the results, the modified tree-structured algorithm in this paper can perform well.

The comparison of the computing time

We implement the algorithm of Donoho and the improved Beamlet tree-structured algorithm by Matlab7.8 on a computer with 2.20HZ CPU and 2GB memory. Computing time is concerned with the size of image, as the tree-structured algorithm should traverse dyadic squares on all scales to search the optimal BD-RDP. Considering that, we choose 20 images of different sizes for comparison, and we get the average time of 20 images. Computing time is shown in Table 1(In this paper, only the comparison of computing time between tree-structured algorithm and Donoho algorithm is made).

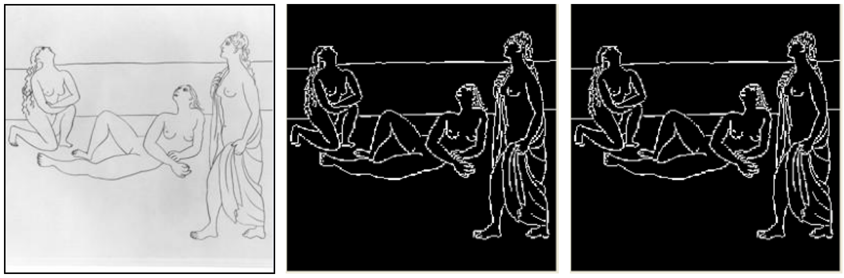


Figure 4. The picasso and results. (A) Picasso image; (B) The result of Donoho algorithm; (C) The result of modified algorithm.

Table 1. The time comparison of computing Beamlet tree structure by different algorithms.

Image size	Donoho algorithm (s)	The proposed algorithm (s)	The proposed algorithm/ Donoho algorithm (%)
128 x 128	0.080	0.001	1.25
256 x 256	0.161	0.002	1.24
512 x 512	0.406	0.005	1.23
1024 x1024	1.044	0.013	1.24

We can see from Table 1 that the time cost by proposed algorithm in this paper only accounts for about 1.24% or so of the time taken by Donoho algorithm.

THE APPLICATION OF IMPROVED ALGORITHM IN PAVEMENT CRACK DETECTION

Generally speaking, the pavement distress image includes background, pavement crack, pebble and asphalt. Moreover, it is considerably influenced by non-uniform illumination and random noise. Pavement crack detection distinguishes crack pixels from non- crack pixels mainly based on the basic idea that the gray value in crack area is lower than that in non-crack area (Cheng et al., 1999).

IMAGE PREPROCESSING

The grey values of the pavement image background will change within a big interval because of non-uniform illumination and surface reflectance. They cause small difference between the gray value of background and pavement crack and lead to false pavement crack detection.

In order to get correct pavement crack detection results, the non-uniform background shall be removed. The basic idea of pavement image preprocessing is to divide the image into several subblocks by adopting the method mentioned in Cheng et al. (1999); secondly, adjust the pixel value of each subblock by a multiplicative factor to change the non-uniform background into uniform background and eliminate the possibilities of false pavement crack detection (Cheng et al., 1998). Concrete steps are as follows:

(1) Partition the entire image into several subblocks. The size of subblocks will affect the result of preprocessing. If the block is too big, it can't achieve the effect in eliminating the non-uniformity of background. On the contrary, the background can be uniform if the block is divided too small. However, it appears over smooth and some cracks are even removed when the crack covers the entire subblock. Therefore, the principle of partition is trying to ensure that each sub-block contains the target (crack) and background in concentration area of crack.

(2) Respectively calculate average gray value (G_{mean}), the maximum ($G_{\max}$) and minimum ($G_{\min}$) of image's gray scale value of each subblock;

(3) Set a threshold range for each subblock while the pixels out of threshold range are supposed as crack pixels、noise pixels or other interference factors on pavement image. The threshold range $[r_l, r_h]$ is represented as shown below:

$$r_h = G_{mean} + (G_{\max} - G_{mean}) * th \quad (4)$$

$$r_l = G_{mean} - (G_{mean} - G_{min}) * th \quad (5)$$

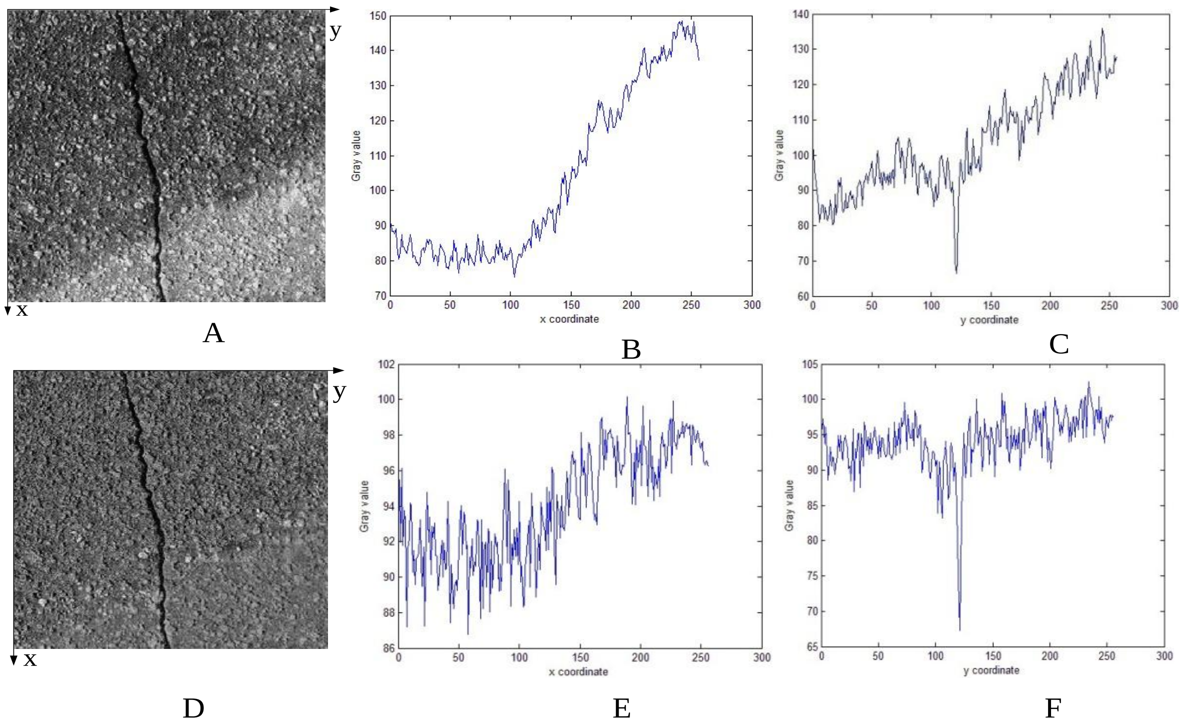


Figure 5. Image preprocessing. (A)Original image;(B) Gray level in the x-direction of the original image;(C) Gray level in the y-direction of the original image; (D) Rectified image; (E) Gray level in the x-direction of the corrected image; (F) Gray level in the y-direction of the corrected image.

Where, $0 < th < 1$;

(4) Calculate average gray value ( ) of all pixels for each subblock within the limits of $[r_l, r_h]$.

(5) Define a multiplicative factor

$$f = G / G'_{mean} \qquad (6)$$

Where, *G* is the average gray value of the entire image.

(6) Suppose $I(x, y)$ means the gray value of the point (x, y), then adjust gray value of all pixels in subblocks.

Traverse each pixel of subblocks when $f < 1$. If the gray value is less than r_l , then $I'(i, j) = I(i, j) * f$, or else the pixel assignment is *G* when the gray value is equal to or greater than r_l .

Traverse each pixel of subblocks when $f \geq 1$. If gray value is more than r_h , then the pixel assigns *G*, or else the original gray value is maintained unchanged.

By means of judging multiplicative factor of each subblock, on one hand, gray level of crack area can be corrected to enable the gray value to be smaller and enhance the contrast between the image crack area and non-crack area to make the image be clearer. On the other hand, in terms of non-crack area (the noise resulted from non-uniform background, pebble or asphalt), change the gray value into constant value or keep the original value. Thus, the background is transformed from non-uniformity to uniformity and the possibilities of false detection are eliminated.

Figure 5A shows a pavement crack image with non-uniform background. Figures 5B and 5C respectively present the changes of gray level in *x*-direction and *y*-direction of the original image. It can be seen that the background gray value in *x*-direction and *y*-direction changes within a bigger range and non-uniform background forms because of non-uniform illumination. Figure 5D reflects the pavement image after the non-uniform background is removed by using multiplicative factor to rectify gray level. Figure 5E displays the changes of gray level in *x*-direction of corrected image. It can be seen that the gray value in *x*-direction changes within a local range. Figure 5F displays the changes of gray level in *y*-direction of corrected image, while it can be seen that the range of background gray value of rectified images in *y* direction changes within a smaller range. When the value of *y* takes about 120, the gray value reaches the smallest, namely the gray value of crack pixels. Comparing Figure 5C with Figure 5F, contrast between the crack area and non-crack area is increased after rectification. The experiment results show that the method removes the non-uniform background and increases contrast between the crack area and non-crack area as well after preprocessing. Moreover, the pavement crack image becomes clearer.

Binarization based on Otsu method

Otsu (Otsu, 1979) is a kind of self-adaptive threshold segmentation. It makes use of least square method to find the optimal segmentation threshold by giving the solution of the maximum between-cluster variance (Zhang et al., 2005). The basic idea of the method is as follows: firstly, the image is divided into two parts, namely background and target which are respectively marked C_0 and C_1. We suppose the grayscale of background C_0 ranges within $0 \sim k$, while the grayscale of target C_1 ranges within $(k+1) \sim L$ (where L is the largest gray value of the entire image). Secondly, solve average gray values of two regions and the entire image, while correspondingly record them as μ_0, μ_1 and μ according to Otsu (1979). In addition, solve the probability of occurrence of each region and between-cluster variance (namely objective functions), while respectively record them as ω_0, ω_1 and σ^2. At last, traverse within the grayscale from 0 to L and solve the k which enables the between-cluster variance to be the maximum, namely the optimal threshold value in grayscale segmentation. We use equation (7) to calculate the between-cluster variance σ^2 as follows:

$$\sigma^2 = \omega_0(\mu_0 - \mu)^2 + \omega_1(\mu_1 - \mu)^2 \quad (7)$$

The algorithm steps of pavement crack detection

Concrete steps of pavement crack detection based on improved Beamlet tree-structured algorithm are as follows:
(1) After grayscale processing of collected color image, preprocess pavement crack image by the way mentioned in image preprocessing to get rid of the influence of non-uniform illumination and increase the image contrast; (2) Use the Otsu method to realize the binarization;
(3) Calculate Beamlet transform coefficients of dyadic squares on all scales to get a set of Beamlet transform coefficients by fast Beamlet transform (Yang et al., 2007);
(4) Construct discrete Beamlet tree structure by improved Beamlet tree-structured algorithm and solve the optimal value of objective function. Meanwhile, record the decomposition method and corresponding discrete beamlet when the optimal value exceeds zero;
(5) Display the obtained discreet beamlets as line features. In other words, the gray value of all the pixels in beamlet is set 1 as target while others are set 0 as background.

RESULTS

Experiment 1

To prove the validity of the proposed algorithm, we implement some tests for different kinds of cracks images. The first column of Table 2 are some initial crack images with size of 256×256 while the images after preprocessing and binarization are displayed in the second column. Meanwhile, the crack detection results by the proposed algorithm in this paper are shown in the last column. The first two rows are images with ordinary cracks. Look at line number three, the image with strong texture background and some shadows. And the last two images have an alligator crack. From the experimental results, we can see the Otsu's images are affected by a great deal of noise, but when we adopt our algorithm to deal with these images, it can be indicated from the detection results that noises have been basically eliminated. The pavement crack is so clear that we can distinguish it easily. Moreover, it not only keeps the continuities of the crack but also has the detection results be basically identical to practical shapes of the crack.

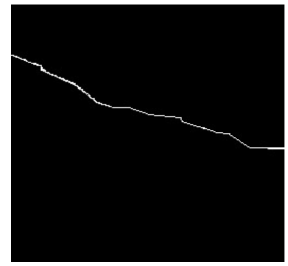
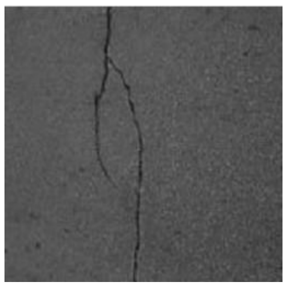
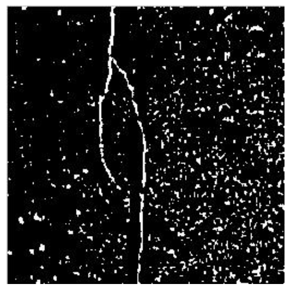
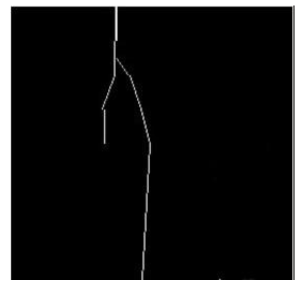
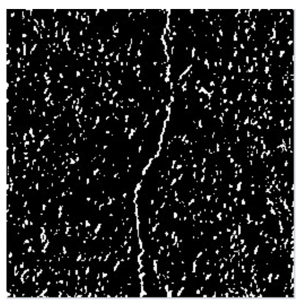
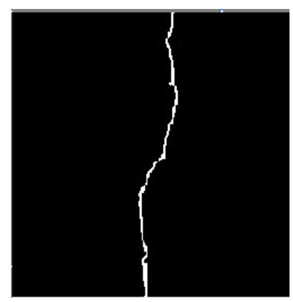
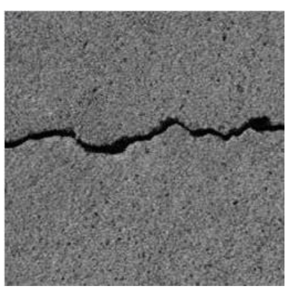
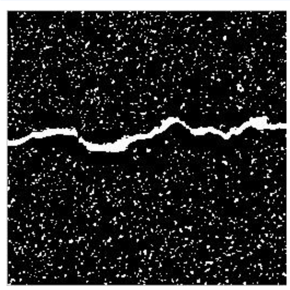
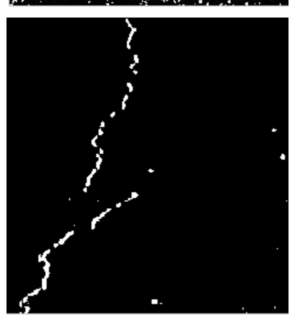
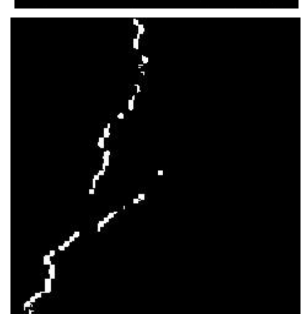
Experiment 2

In order to prove the superiority of the proposed algorithm in this paper, we carry out another comparative test on detection effect and computing time among four algorithms and the proposed algorithm in this paper.

As shown in Figure 6A, it is an initial pavement distress image with the size of 256×256, and the pavement image with non-uniform illumination. Figure 6B is the result which has been detected by Canny operator. It can be seen from the Figure 6B that there is still a great deal of noise and we cannot easily identify the characteristics of the crack in the image. Figure 6C is the image detected by wavelet. Though the result obviously shows no noise interference, the continuity of the crack is destroyed to some extent. Figure 6D shows the result got from the pavement crack image based on morphological approach. It can be seen that the crack keeps good continuities, but there are some shortcomings that punctiform and false cracks in the image can't be distinguished. Figure 6E displays the result which is detected by the method based on line singularity in Wang et al. (2006), it shows good continuities of the crack, and also suppress the noises. Figure 6F is the crack detected by the proposed algorithm, while it can be seen from the Figure 6F that the proposed algorithm can not only eliminate the noise but also ensure the continuities of cracks. Thus, the superiority of the proposed algorithm in this paper is fully presented.

We used 20 images to evaluate the proposed method. The averge time of whole 20 images is shown in Table 3. And the operation time taken by the other four different algorithms is also listed in Table 3. By comparison, it can be seen that detection needs shorter time when we use Canny algorithm, morphological algorithm and the proposed algorithm. However, the pavement crack detection using Canny algorithm has relatively lower noise resistance and it is difficult to detect cracks. When we use morphological algorithm, the interference by punctiform noise can't be eliminated and the crack is not

Table 2. Experimental images and results.

Original images	Binary images by Otsu	Results by proposed images
		
		
		
		
		

effectively detected. Therefore, the proposed algorithm in this paper has huge superiority in veracity, noise immunity and low time consumption.

DISCUSSION

This paper firstly proposed an improved Beamlet tree-

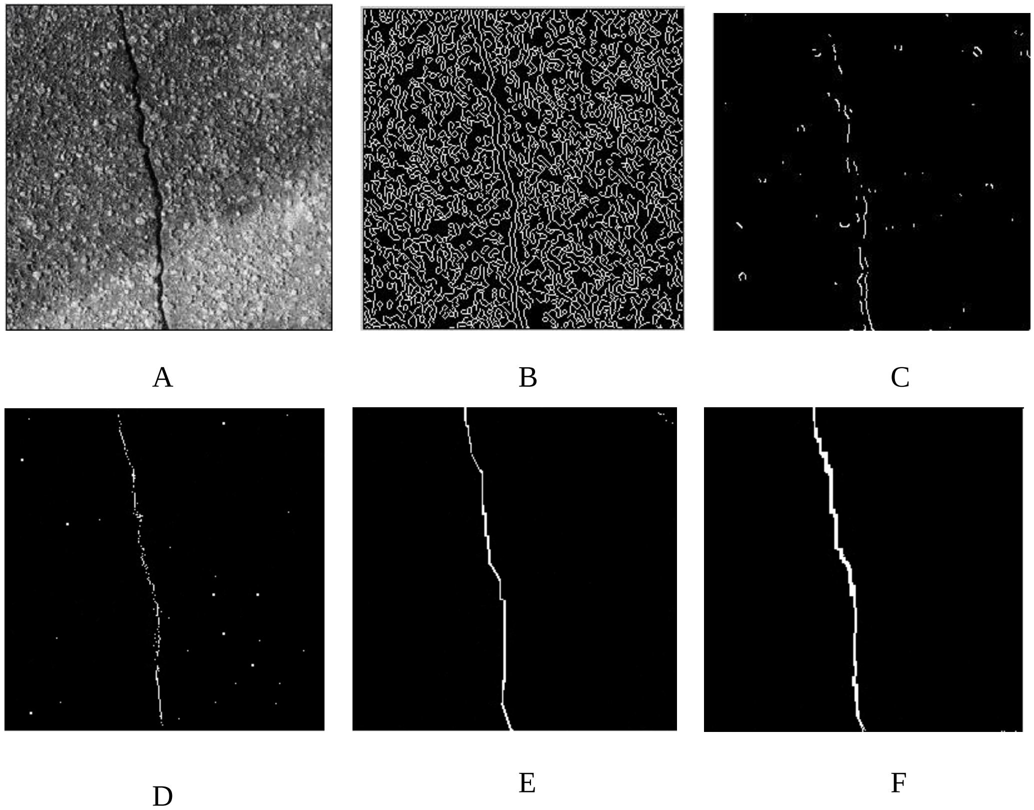


Figure 6. The comparison of different algorithms. (A) Original image; (B) Canny algorithm; (C) Wavelet transform; (D) Morphological algorithm; (E) Wang et al. (2006) algorithm; (F) Proposed algorithm.

structure algorithm. Integrating multi-scale tree structure of Beamlet transform, we adopted a “top to bottom” searching strategy to seek the optimum value of the objective function and obtained line feature of the image so as to decrease the calculation complexity and reduce the runtime. Then, we applied the improved beamlet tree-structured algorithm to pavement crack detection. The experimental result shows that the proposed method in this paper can obtain clear crack image quickly from noise jamming and do well in keeping continuities of the crack as well. The next step is to classify the cracks into different types. In addition, we will study to Beamlet algorithm to improve execution time and accuracy instead of using some preprocessing methods.

ACKNOWLEDGMENT

This work was supported partially by the National Natural Science Foundation of China (Grant No. 61165011), the science and technology support program of Jiangxi province, China (Grant No. 20112BBG70092), Aerospace Science and Technology Innovation Fund of China (Grant No. CASC201102), Aviation Science Foundation of China Grant No. 20085556017 & 2010ZC56006) and Project supported by the Key Lab of Image Processing & Image Communications, Jiangsu Provincial, China.

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