Edge Detection In Pavement Crack Image With Beamlet Transform

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Abstract. This paper proposed a beamlet-based method of extraction from pavement crack images. Fitstly, we transfer the collected pavement crack images to the binary images using Otsu's thresholding segmentation algorithm, then the beamlet transform was exploited to extract the linear features of cracks from the binary images with different scales and thresholds. Experiments show that the proposed algorithm can achieve satisfactory performance in the cases of low signal-to-noise ratios.

Introduction

Pavement distress, the various defects such as cracks illustrated in Figure 1, represent a significant engineering and economic concern. The traditional detection algorithms for pavement crack detection are generally based on pixel-level processing, and most of them have very poor signal-to-noise ratios. Generally, cracks in pavement images possess linear features, embedded in noise, and are discontinuous. In addition, pavement images have specific patterns, which make crack detection more difficult using traditional pixel-based methods.

Figure 1. Pavement crack images

The concept of beamlet transform was first introduced by David L. Donoho and X. M. Huo as a tool for multi-scale image analysis [1] .Beamlet transforms are proven to be insensitive to noise, computationally efficient, and able to detect features with high accuracy. beamlets are a simple dyadically organized collection of all line segments at different locations, orientations, and scales. The beamlet transform is the collection of line integrals along the set of all beamlets[2].

Beamlet Transform theory

Beamlet dictionary

The beamlet transform is performed in the dyadically partitioned squares of an image. Images are viewed as the continuum square $[0, 1]^2$ and the pixels as an array of 1/n by 1/n squares arranged in a grid in $[0, 1]^2$. The collection of beamlets is a multiscale collection of line segments occurring at a full range of orientations, positions, and scales [3], as illustrated in Figure 2. It is generated as follows:

1) *Dyadic Subdivision.*   We form all dyadic subsquares of $[0, 1]^2$ in the obvious way; to begin we divide the unit square into four subsquares of sidelength 1/2. Each subsquare is then divided into

four smaller subsquares, and so on. Figure 1 shows some subsquares after 0, 1, 2 or 3 steps of subdivision. We continue until we have created all dyadic squares of side 1/n by 1/n or larger.

2) *Vertex Labelling.* For deniteness, think of δ as 1/n, although in certain applications δ should be far smaller. Traversing the boundary of each subsquare, we mark out equally spaced vertices at spacing δ.

3) *Connect The Dots.* In each subsquare, form the collection of all line segments connecting any pair of vertices. Any such line segment is called a beamlet [4].
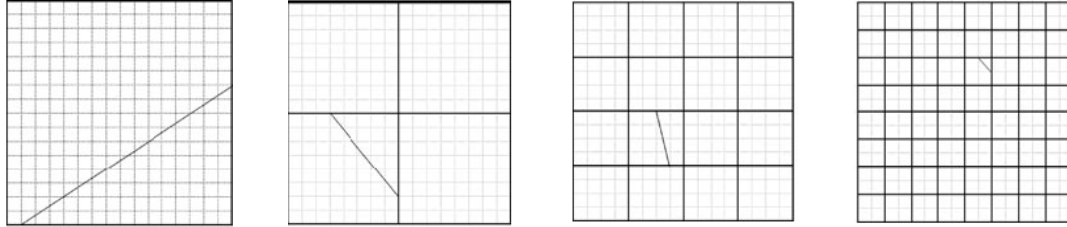

Figure 2. Four beamlets, at various scales, locations, and orientations.

Beamlet transform

The beamlet transform is defined as the collection of line integrals along the set of all beamlets. Let $f(x_1, x_2)$ be a continuous function on 2-D space, where x_1 and x_2 are coordinates. The beamlet transform T_f of function f is defined as follows:

$$T_f(b) = \int_b f(x(l))dl, \quad b \in B_E \tag{1}$$

where B_E is the collection of all beamlets.

For a digital image, the beamlet transform is a measure of the line integral in the discrete domain. As figure 3 shows, the beamlet transform for all the points along the beamlet b is defined as,

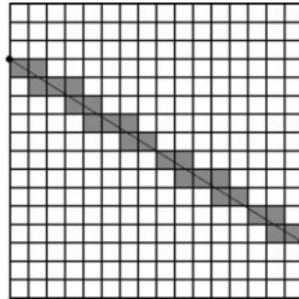$$f(x_1, x_2) = \sum_{i_1, i_2} f_{i_1, i_2} \Phi_{i_1, i_2}(x_1, x_2) \tag{2}$$

Fig. 3. Beamlet transform as a weighted sum of pixel values along the s headed line.

Where f_{i_1, i_2} is the gray level value of pixel (i_1, i_2) and $\Phi_{i_1, i_2}(x_1, x_2)$ is considered to be the weight function for each pixel. If $p(x_1, x_2)$ represent $[i_1/n, (i_1+1)/n] \times [i_2/n, (i_2+1)/n]$, choose function Φ_{i_1, i_2} fulfill the equation:

$$n^2 \int_{P(x_1, x_2)} \Phi_{i_1, i_2}(x_1, x_2)dx_1 dx_2 = \delta_{i_1, i_2} \tag{3}$$

δ_{i_1, i_2} is Kroneker symbol. Then f_{i_1, i_2} is a function that obeys:

$$f_{i_1, i_2} = Ave\{p(x_1, x_2)\} \tag{4}$$

Line feature extraction base on beamlet transform

Suppose we have a noisy n-by-n image, perhaps containing somewhere within it a faint image of a line segment of unknown length, orientation and position. And the noise image pixel-level data y_{i_1, i_2} expressed as:

$$y_{i_1,i_2} = A\tilde{\phi}_{i_1,i_2} + \varepsilon \bullet z_{i_1,i_2} \qquad 0 \leq i_1, i_2 < n \qquad (5)$$

Where ε is a noise level, z_{i_1,i_2} is a white Gaussian noise, A is an unknown amplitude parameter and $\tilde{\phi}_{i_1,i_2} = \tilde{\phi}(i_1,i_2;\overline{v_0 v_1})$ is the observed effect at the sensor array of an unknown beam $\overline{v_0 v_1}$. And the we suppose simple null hypothesis:

$$H_0 : A = 0 \qquad (6)$$

against the composite alternative:

$$H_1 : A > 0, \quad v_0, v_1 \in [0,1]^2 \qquad (7)$$

and consider the maximum beam statistic

$$Y^* = \max\{Y[v_0,v_1] : v_0, v_1 \in [0,1]^2\} \qquad (8)$$

Here the maximum is taken over all beams $\overline{v_0 v_1}$ with endpoints in $[0,1]^2$. We then reject H_0 if Y^* exceeds a certain threshold [5]. This is often called the Generalized Likelihood Ratio Test, because it takes the standard Likelihood Ratio Test (deriving from the above H_0 and a simple alternative hypothesis $H_{1,\overline{v_0 v_1}}$) and then optimizes over all choices of $H_{1,\overline{v_0 v_1}}$ in order to test the composite alternative.

Edge detection algorithm for pavement crack image

Otsu threshold Segmentation algorithm [6], using the extremum principle of least squares method to find the best segmentation threshold by the largest variance between the demand classes. The specific methods are: firstly, we divide the images into two regions, region A and B, and region A gray-scale range 0 from k and region B grayscale range (k +1) from L (L is the max gray values); then calculated the average gray of each regions m_a, m_b and the average gray scale of the whole image; thirdly calculated the probability of each region P_A, P_B. Finally calculate the between-class variance (the objective function) σ^2:

$$\sigma^2 = P_A(m_A - m)^2 + P_B(m_B - m)^2 \qquad (9)$$

The specific algorithm is described as follows:

1) Grayscale processed the collected pavement crack image, and then use of the OTSU law translated the gray image into a binary image.

2) Using beamlet transform to the resulting binary image and calculate the binary box beamlet exchange coefficient. According to the characteristics of the cracks and different analysis requirements, select the appropriate decomposition scale.

3) Test the maximum beamlet for each binary box, which is determine by the following energy function:

$$Y = \max\{T_f(b)/\sqrt{L(b)}\}, \quad b \in B_{n,1/n} \qquad (10)$$

Where $T_f(b)$ is the beamlet transform coefficient, $L(b)$ is the corresponding length of beamlet, $B_{n,1/n}$ is binary box beamlet Collections at different scales. Amplitude normalized Y and set a threshold T for it, according to the visual effects, the T value is generally defined as 0.5, which can free adjust [7].

4) visualized the beamlet. If Y is greater than threshold T, it means that the corresponding location in the source image is linear Characteristics, then dash the line of the beamlet.

Experiments

Suppose a bloc of size 256×256 pixels in a pavement crack image is under investigation (Fig.4(a)). We consider the 2-D Gaussian function as a filter kernel and compare our method with the widely used canny operator, and obtained the edge map as shown in Fig.4(b). The discontinuities on the edges mainly result from the threshold in the Canny edge detector against

high amplitude of local gradients due to image noise [8]. We present an alternative approach to the problem by application of the multi-scale up-to-do beamlet analysis. Comparing detection results of (b) and (c), our method achieves a higher SNR and position accuracy, and provides more complete edge than Canny operator.
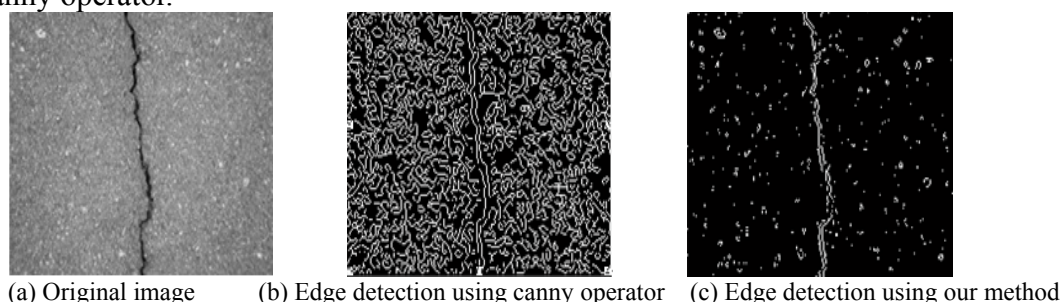

(a) Original image   (b) Edge detection using canny operator   (c) Edge detection using our method

Fig. 4. Edge detection of pavement crack image

Conclusions

This paper presents a Beamlet transform-based technique to extract crack features from pavement images. It can be applied on noisy pavement images with a high rate of detection and very low rate of false detection. It could be available alternative to common pixel-based approaches for crack extraction. Compared with common pixel-based approaches, it is more effective and robust to noise. Edge detection results on pavement crack images have shown significant improvements over classical local operators, and the template matching result based on edge information also validates this method.

References

[1] David L. Donoho, and Xiaoming, Huo. Image Beamlet and Multiscale Image Analysis. *International Journal of Computer Science and Network Security*, vol. 8, No. 1, 2008.

[2] Huo Xiaoming, Donoho L David. Recovering filamentary objects in severely degraded binary images using beamlet driven partitioning. *IEEE International Conference on ICASSP*, 2002.

[3] Yang Ming, Yin Yon, Peng Yuhua, et al. Beamlet transfrom and multiscale linear feature extraction. *Acta Electronica Sinica*, 2007, 35(1).

[4] David Donoho and Xiaoming Huo. Beamlet pyramids: A new form of multiresolution analysis, suited for extracting lines, curves, and objects from very noisy image data. *In Proceedings of SPIE*, volume 4119, July 2000.

[5] Kelvin C. P. Wang, Qiang Li, and Weiguo Gong. Wavelet-Based Pavement Distress Image Edge Detection with Trous Algorithm. *Transportation Research Record*. Journal of the Transportation Research Board, No. 2024, 2007.

[6] Herrera J,Pajares G,Guijarro M. A segmentation method using Otsu and fuzzy K-Means for stereovision matching inhemispherical images from forest environments. *Applied soft computing*, 2011, 8 (11):4738-4747.

[7] H. D. Cheng, J. R. Chen, C. Glazier, and Y. G. Hu. Novel approach to pavement distress detection based on fuzzy set theory. *J. Comput. Civ. Eng.*, 13(4), 1999, p. 270–280.

[8] Canny J. A computational approach to edge detection [J]. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 1986, 8(6): 679-698.