Pavement Crack Detection Using the Gabor Filter

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Pavement Crack Detection Using the Gabor Filter

M. Salman, S. Mathavan, K. Kamal, M. Rahman

***Abstract*—Crack is a common form of pavement distress and it carries significant information on the condition of roads. The detection of cracks is essential to perform pavement maintenance and rehabilitation. Many of the highways agencies, in different countries, are still employing conventional, costly and very time consuming techniques which involve direct human intervention and assessment. Although automated recognition has been successfully performed for many pavement distresses, crack detection remains, to this date, a topic where reservations exist. A novel approach to automatically distinguish cracks in digital pavement images is proposed in this paper. The Gabor filter is proven to be a highly potential technique for multidirectional crack detection that was not done previously using the Gabor filter. Image analysis using the Gabor function is directly related to the mammalian visual perception, hence the choice of this method for crack detection. Results reported in this paper concentrate on pavement images with high levels of surface texture that makes crack detection difficult. An initial detection precision of up to 95% has been reported in this paper showing a good promise in the proposed method.**

I. Introduction

Pavements are primary elements of a transportation structure. A nation's highway network is supposed to be capable enough to maximize trade, industrial and social benefits. In order to ensure the required pavement performance, periodic road health monitoring surveys are indispensable to collect information about pavement conditions. Conventionally, road inspection surveys have been performed manually. However, with the ever increasing growth of road networks and the amount of traffic they handle, the time consuming visual analysis techniques are not preferred any more. In addition, manual highway surveys also suffer heavily from the associated subjectivity of human decision making. In contrast, automated pavement surveying systems, when designed and validated appropriately, are able to be very fast, accurate and remove the subjectivity involved.

Asphalt cracks are one of the most common road surface distress type encountered during road surveys. Cracks are generally produced by the partial or entire fractures of the pavement surface. There is an extensive variety of road cracks starting from single crack (longitudinal and traverse crack) to interrelated crack patterns spread over the complete pavement surface (block, crescent shaped and crocodile cracks). The load-spreading and water-resistant capacity of the road is lost due to these cracks which also speed up the deterioration process of pavement surface. If cracks are kept untreated, then the consequences become more severe and these cracks transform into potholes, deform the road and sometimes even produce differential settlement of road [1].

Both 2D and 3D imaging techniques have been used for distress measurements. Usually, 2D imaging can be performed by simpler hardware, hence is generally preferred. But 3D imaging becomes irreplaceable in certain situations, e.g. depth measurements. The automated detection of road cracks, the subject of this research, is a topical issue with numerous publications in recent years [2] [3]. The work reported in this paper uses pavement images (i.e. 2D) for cracks detection. A novel scheme based on the Gabor filter for accurate crack detection is proposed here. As the orientations of pavement cracks are arbitrary and unknown, a filter bank consisting of multiple oriented Gabor filters is used. In contrast to the previous studies, the algorithm presented in this study can detect every type of crack such as longitudinal, traverse, box or alligator crack despite of its orientation. The case study shown in the research is a part of alligator crack with crack spread in different directions and it is detected successfully [4].

II. Literature Review

Cracks are difficult to be identified from 2D images due to the randomness associated with their geometry and pixel intensities. The problem is even more compounded by the fact that they are embedded in road surfaces with intensive surface textures that are arbitrary as well. Several techniques have been experimented with. This section highlights some of them.

The Local Binary Pattern technique has been utilized for crack detection. It is a grey-scale and rotation invariant operator and widely used for texture classification. Huet al [5] used a similar approach by classifying local neighbors into smooth area and rough area. This classification has been carried out only on areas with coarse texture to know more about local structure. More work carried out on the same technique by training artificial neural networks and wavelet transformation for pavement distress image compression noise reduction and evaluation [6] [7].

Prah et al [8] used Bi-Directional Empirical Mode Decomposition (BEMD) for edges detection. Different techniques for edge detection like the Canny and Sobel methods have been compared with BEMD. They conclude that different edge detection techniques are more efficient for different types of surfaces. For example, it is reported that the Sobel method works better for Portland cement concrete while the Canny algorithm is found to be more efficient for asphaltic concrete.

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Nguyen [9] used brightness and connected concurrency for detection of cracks on roads and pavements. In another effort, Ma et al [10] employed the Forward Differential Wavelet transform. In the first phase of their algorithm, fractional differentiation has been applied for high, medium and non-linear low frequencies. Subsequently a wavelet transform is applied for noise reduction. Neighboring Qingquan et al [11] used Difference histogram method (NDHM) for the pavement cracks detection. They use classical thresholding methods like the Otsu method for calculating between-class variance, the Kapur method for probability distribution and finally (NDHM) for image segmentation.

Henrique and Paulo Lobato, 2009, used a supervised approach for crack detection and classification. To handle the high amount of input data in their research, the image database was split into image subset. The system was trained by human experts who manually selected the crack regions from training image subset. Three parametric and three non-parametric supervised classification strategies were introduced to conclude the cracks. The cracks were then classified to longitudinal, traversal and mixed by exploring the 2D feature space [12].

Kelvin Wang used a matched filtering approach to detect the cracks aligned at different orientations. The matched filtering algorithm uses 12 different oriented filters. The author used Chaudhuri's matched filtering method which illustrate the intensity profile of the kernel by predetermined Gaussian curve. It was assumed in this paper that the background is brighter than the crack so the alien object and oil marks are likely to be mismatched [13].

In recent years, crack detection research has started to use relatively newer techniques available in image processing producing some good outputs; examples are Free Form Anisotropy (FFA), Conditional Texture Anisotropy (CTA) and Continuous Wavelet Transform.

In 2010, Roberto Medina et al only addressed the pavements cracks which are parallel to road or at 90 degrees in the pavement image (longitudinal cracks) and the cracks which are at 0 or 180 degrees in the image(traverse cracks). The automatic filter selection method or automatic crack detection algorithm is not discussed for both kinds of cracks. It seems that the filters are selected manually for each type of crack after visual inspection [4].

III. Gabor Filter

Fourier transformation is the most commonly used tool in signal processing for the analysis of frequency characteristics of a given signal. However, after signal transformation, the features from different parts of the image are mixed together and the time information of the signal is lost and it is almost impossible to identify the position of the frequency and in study. To counter this problem, joint domain analysis can be used. In 1946, a joint domain function, the Gabor filter namely, was proposed by Gabor. The Gabor function is proved to achieve the lower bound and performs the best analytical resolution in the joint domain [14].

The Gabor filter based techniques have been widely used in a wide range of vision based applications like textures analysis and segmentation [15] [16] [17] [18] [19], edges detection [20], object recognition [21] [22], illustration of images [23], and handwritten digits and alphabet recognition [24]. The Gabor Kernels are band pass filters and are govern by the basic conception of vision information processing by multiple channel filtration in the mammalian visual structure [25].

A. 2D Gabor Filter

In 1985, Daugman extended the design of 1D Gabor filter to 2D filter. the 2D Gabor kernel family have eight degrees of freedom in: x_o and y_o specify the position of the kernel in 2D spatial domain; u_o and v_o are modulation coordinates specify the position of the filter in 2D frequency domain, θ is desired orientation, ω is spatial frequency, ψ is the phase offset of the modulation factor, which decides the symmetry or anti-symmetry of the filter and the width (a) and the length (b) of the elliptical Gaussian (2D) envelope and the angle between orientation of sinusoidal wave vector and the two dimensional Gaussian axes [26] [27]. The general form of the Gabor filter is shown (1)

$$g(x,y) = s(x,y)w(x,y) \tag{1}$$

Where the Gaussian envelope can be termed as:

$$s(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{1}{2}\left[\left(\frac{x'}{\sigma_{x'}}\right)^2 + \left(\frac{y'}{\sigma_{y'}}\right)^2\right]} \tag{2}$$

Where $x' = xcos\theta + ysin\theta$ and $y' = -xsin\theta + ycos\theta$

Here σ_x and σ_y are the scale factors of the neighborhood.

A complex sinusoidal with a phase offset ψ is given by:

$$w(x,y) = e^{j(2\pi\omega_0 x' + \psi)} = cos(2\pi\omega_o x' + \psi) + j\,sin(2\pi\omega_o x' + \psi) \tag{3}$$

From equations (1), (2) and (3), the Gabor consists of a real component and an imaginary component. The real part is,

$$g_r(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{1}{2}\left[\left(\frac{x'}{\sigma_{x'}}\right)^2 + \left(\frac{y'}{\sigma_{y'}}\right)^2\right]} \{\cos[2\pi\omega_0\,(xcos\theta + ysin\theta) + \psi]\} \tag{4}$$

And the imaginary component of the complex Gabor filter is

$$g_i(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{-\frac{1}{2}\left[\left(\frac{x'}{\sigma_{x'}}\right)^2 + \left(\frac{y'}{\sigma_{y'}}\right)^2\right]} \{\sin[2\pi\omega_0\,(xcos\theta + ysin\theta) + \psi]\} \tag{5}$$

Equations (4) and (5) can be jointly written in terms of aspect ratio γ (i.e. the ellipticity of the Gabor filter) and wavelength λ of the sinusoidal factor.

$$g(x,y) = \frac{\gamma}{2\pi\sigma^2} e^{-\frac{1}{2}\left[\frac{x'^2 + \gamma^2 y'^2}{\sigma^2}\right]} e^{j(\frac{2\pi x'}{\lambda} + \psi)} \tag{6}$$

Where $\gamma = \frac{\sigma_x}{\sigma_y}$

A Gabor filter of wavelength of 20, variance = 4, phase offset = 0 is shown in Fig. 1.

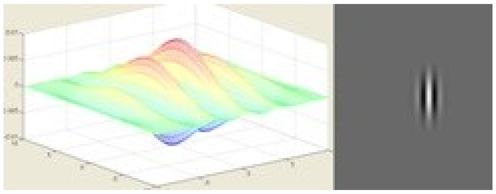

Figure 1. Gabor filter at 0 degree orientation

The Gabor frequency response is illustrated in Fig. 2.

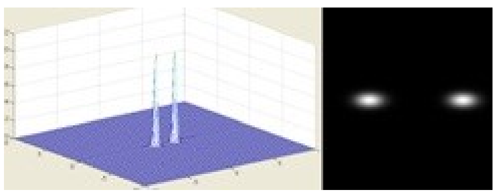

Figure 2. Frequency response of filter in Fig. 1

IV. Implementation and Results

A. *Proposed Algorithm*

The proposed algorithm for pavement cracks detection by Gabor filter bank is presented below in Fig. 3. The algorithm was implemented on a personal computer using MATLAB.

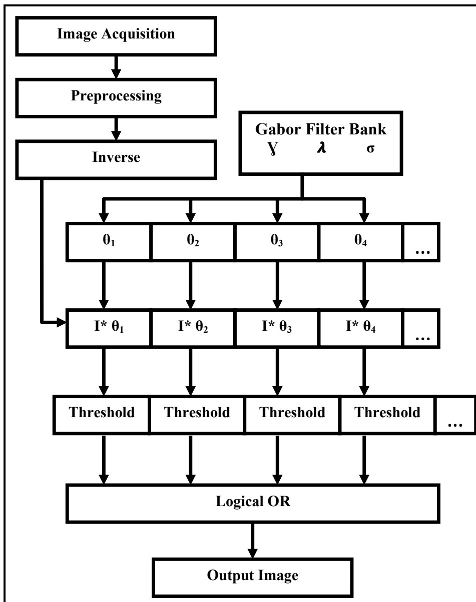

Figure 3. Proposed algorithm *(Flow chart)*

A filter bank is generated using Gabor filter. The filter bank contains multi orientation filter. Generally, the number of orientations depends on the application where the Gabor filter is applied. As the orientations are increased, the output results are more accurate. But raise in number of orientations also increases the computational time and complexity of the system. All other parameters used to generate Gabor kernels are predefined and were obtained by extensive experimentations. The Gabor filter of a given orientation is then convolved with the input preprocessed image. After the completion of convolution, the real component of the response out of the kernel is thresholded to generate a binary output image. Finally, the binary images resulting from the differently oriented filters are combined by logical OR operation to produce an output image that contains detected crack segments.

B. *Experimentations*

The first image is a mixed crack on asphalt layer of a pavement. The image has been captured with a Canon IXUS 80 IS commercial camera under natural lighting conditions [28].The overall surface condition is highly non-uniform with the bitumen coating is almost worn out. This makes the surface highly textured. In addition, the intensity difference between crack and aggregate is very low. Fig. 4 is the image after preprocessing i.e. compressed to 336 ×339 from 1070 ×1080 to reduce the size and to reduce the computing time. The image is then processed by Gabor filter. In this case only 6 orientations, in 30° increments, are used.

Figure 4. Mixed crack on asphalt

Fig. 5 shows the first convolution with the input image at 0 degree orientation. The other parameters are wavelength = 16, Gaussian spread = 4, aspect ratio = 1 (round kernel) and phase offset = 0.

It can be visualized that various parts of the randomly shaped crack are responding to its corresponding orientation filter. In Fig.5 all of the vertical parts of the crack are responding. In Fig. 6 and 7, in the upper side of the image, only the left side crack has responded well, while the other part is suppressed. In Fig. 8 only small horizontal segments have responded and so on.

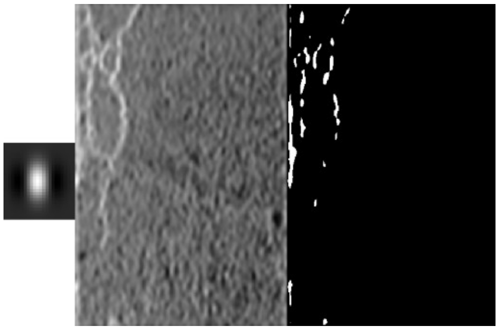

Figure 5. Gabor filter at 0° orientation; real part of the response (left) and thresholded image (right)

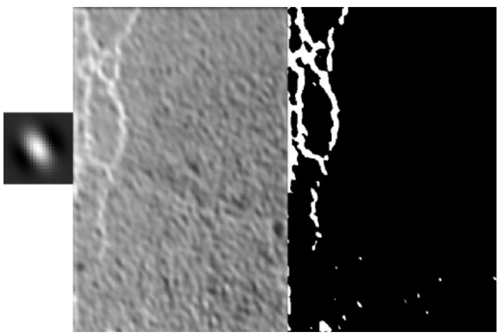

Figure 6. Gabor filter at 30° orientation; real part of the response (left) and thresholded image (right)

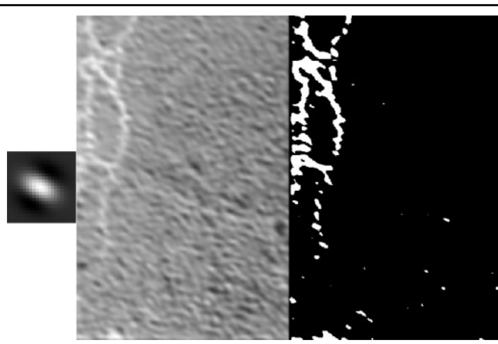

Figure 7. Gabor filter at 60° orientation; real part of the response (left) and thresholded image (right)

Fig. 9 and 10 show the real parts of the responses from the Gabor filter at 120° and 150° respectively. In Fig. 9 and 10, the right halves are their respective threshloded images.

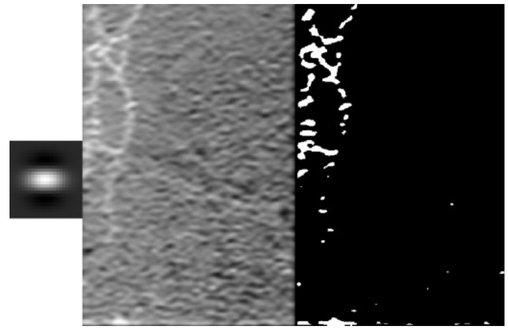

Figure 8. Gabor filter at 90° orientation; real part of the response (left) and thresholded image (right)

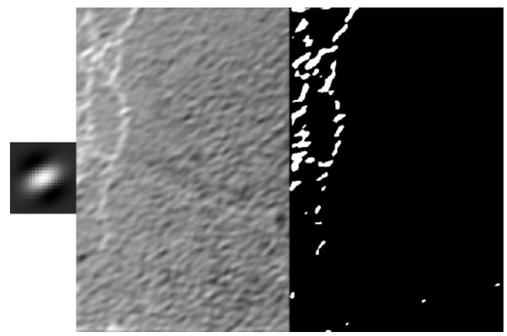

Figure 9.Gabor filter at 120° orientation; real part of the response (left) and thresholded image (right)

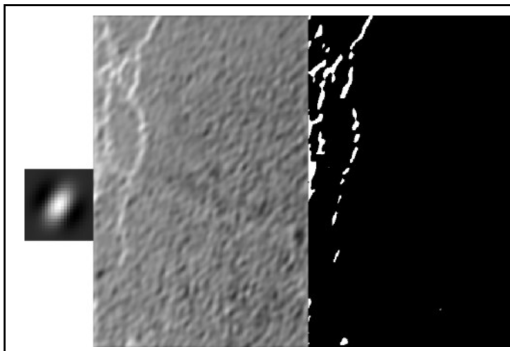

Figure 10. Gabor filter at 150° orientation; real part of the response (left) and thresholded image (right)

The image resulting from the OR operation on the thresholded images shown in Fig. 5-10 is given in Fig. 11. In Fig. 11, the image on the right consists of the original image embedded with red squares representing the detected crack segments for easy visualization. The squares are 10 pixels in size. In addition the red tiles are also used to analyze the accuracy of the algorithm, the results of which are presented in Table 1.

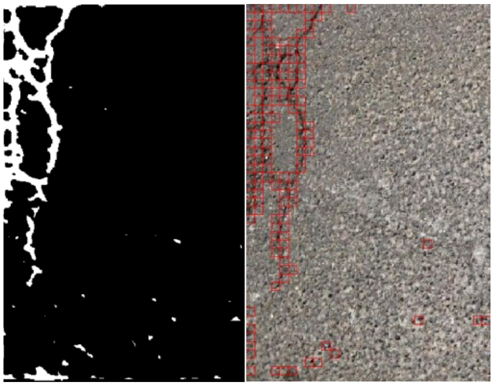

Figure 11. Gabor filter overall response (left) and detected Overall Power spectrum

The pavement shown in Fig. 12 is an industrial quality image. The image is from the LRIS (Laser Road Imaging System) system produced by Pavemetrics Inc, Canada. The picture on the left in Fig. 12 depicts the detection.

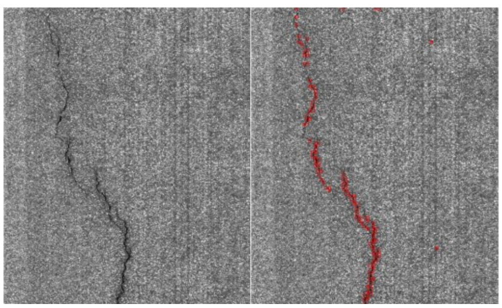

Figure 12. Input Image case 2 (left), Output image showing crack (right)

Table 1 shows the results for 5 images. The first two are industrial images acquired by the LRIS system. The last three are captured by the Canon IXUS 80 IScamera. The total number of crack tiles and the non-crack tiles are based on manual estimation. The algorithm's precision for the industrial images is 95%. The corresponding recall is 78%. For the images with the commercial camera a precision of 66% and a recall of 90% are obtained.

TABLE I. CRACK DETECTION RESULTS USING GABOR FILTER

Image Number	Number of crack tiles	Number of false negatives	Number of non-crack tiles	Number of false positives
1	150	24	9373	13
2	195	53	11147	2
3	91	26	1361	24
4	64	0	420	32
5	118	0	1158	69

V. CONCLUSION

Experimental results shows that, by applying proposed Gabor filter bank on pavement images, up to 95% precision has been achieved. These detection rates have been achieved despite the fact that the flexible pavements have very complex and random texture. Gabor based crack detection could be a feasible substitute to conventional crack detection techniques. The existing algorithm is planned to be enhanced by analyzing connected components and by introducing some further post-processing techniques.

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