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ABSTRACT

We proposed a new line detection method in noisy images using Mexican hat wavelet filters. In our approach, we applied the wavelet transform in a multiresolution sense by forming the products of wavelet coefficients at the different scales to locate and identify lines at different scales. In addition, we also considered shifting line locations through multiple scales for robust line detection in the presence of noise. We found that our approach leads to an effective method to form the basis of a line detection approach.

Keywords: wavelet transform, line detection, multiresolution

1. INTRODUCTION

The line detection of gray-level discontinuities is an essential part to identify linear features in an image. Many researchers use filters that have small masks to detect lines in an image.[1,2] However, the choice of the size of the masks is important because the optimal mask size varies with the image. In general, the smaller masks are sensitive to noise and suffer from excessive unwanted line fragments whereas the larger masks cannot resolve fine detail. A robust method for edge detection was proposed where it hardly responds to thin lines and it does not respond at the middle but at each side of larger lines.[3] Moreover, lines in noisy images are often difficult to detect because line detection algorithms may be sensitive to noise. To overcome these problems, we propose a line detection algorithm based on a multiresolution approach using the wavelet transform.

When an image is examined for intensity variations, several scales generally are of interested. The detection of certain feature in an image is optimal at a certain scale. This scale depends on the characteristic scale contained in the object to be detected. Optimal processing of an image thus requires the representation of an image at different scales. In order to detect lines in an image, it is necessary to perform and combine information of line detection at multiple scales. Since the WT is clearly related to multi-scale analysis, the WT could play an important role in multi-scale line detection. Practically, the fine scale of the WT gives detailed information, whereas the coarse scale adds global information. To perform and combine information at multiple scales, it can improve the robustness of road detection.

In our approach, we developed a line detection method using a multiresolution approach by forming the products of wavelet coefficients on different scales to locate and identify lines. In addition, we also considered shifting line locations through multiple scales for robust line detection in the presence of noise

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2.WAVELET TRANSFORM

Wavelets are finited duration waveforms or short waves that have an average value of zero. The wavelet transform is the breaking up of a signal into basis function same as Fourier transform (FT). For the FT, the Fourier domain consists of basis functions that are sines and cosines. While the wavelet domain contains more complex basis functions known as mother wavelets $w_{jk}(t)$, where parameter a corresponds to the scale while b is the shift parameter.[4]

$$w_{jk}(t) = \frac{1}{\sqrt{a}} w\left(\frac{t-b}{a}\right) \tag{1}$$

The analysis function of forward transform continuous wavelet transform is defined by the integral where b_{jk} are the wavelet coefficients, j and k are real number refer to the scale and shift of the mother wavelet $w_{jk}(t)$.

$$b_{jk} = \int_{0}^{\alpha} f(t) w_{jk}(t) dt \tag{2}$$

In the discrete case, we take the discrete values of the scale parameter a and the shift parameter b in a different way. The basis function is shrunk by a factor of two, dyadic sampling, at each increasing scale where we take parameter a to be the form of 2^{-j} and b to be the form of $k2^{-j}$. So, we can written in discrete case as,[6]

$$W_{jk}(t) = 2^{j/2}\, w_{jk}(2^{j}\, t - k) \tag{3}$$

3. LINE DETECTION

We used the Mexican hat wavelet that corresponds to the second derivative of the Gaussain. We concentrate on line detection based on a multiresolution approach. In general, forming the product of the wavelet coefficients between each scale is the simplest way to examine the consistency of wavelet coefficients at different scales. Since line locations may shift according to changing scales, we can modify the product between shifted versions of the wavelet coefficients.[3] We may consider line positions that can be shifted by two pixels between scales. For instance, considering lines that shift up to two pixels between the wavelet transform of two scales b_1 and b_2, we get five products, b_1b_2, b_1b_{2R1}, b_1b_{2R2}, b_1b_{2L1} and b_1b_{2L2}, where b_{2R2} and b_{2L2} refer to shifts of b_2 to the right and left by two locations, respectively. In our approach, we formed the product with shift method on the wavelet transform at scales one and two, b_1 and b_2 to identify the line locations.

Alternatively, to overcome the computational expense of the product with shift method, we consider initially finding the result of two scales, then combining the result with each additional scale, one scale at a time. For example, considering wavelet coefficients at scale b_1, b_2, b_3, and b_4, we initially formed the product with shift method on the two largest scales, b_3 and b_4. Then, we combined the result with b_2 using the product with shift method. Finally, the result of that step was combined with b_1 using the product with shift method to identify the line locations.

The block diagram of our algorithm is illustrated in Figure 1. First, we applied the wavelet transform to the levels 1-4 of the original image in both vertical(V1-V4) and horizontal(H1-H4) directions separately. In order to avoid the misrepresentation in each subimage and make the size of each subband same as original, we did not use downsampling. Then, we have to merge the different scales by using our approach and labeled the results as Wcv and Wch, followed by thresholding to get the binary images (Wh and Wv). We then formed the product with the wavelet coefficients at the first scale to get the directional line images in both vertical and horizontal images (Mv and Mh). Finally, the modulus sum, M(x,y), of Mv and Mh is used for the final result.

$$M(x,y) = \left(|w_h b_{1h}|^2 + |w_v b_{1v}|^2 \right)^{1/2} \tag{4}$$

4. EXPERIMENT

The main purpose of the experiment is to test the performance of our line detection approach that uses the combination of wavelet coefficients at different scales, multiresolution approach, by comparing with the line detection results using only one resolution or scale. Mean square error (MSE) is used to determine how well the method worked effectively when the size of lines width changed as well as how well the method reduced the effect of noise while detecting and looking for possible line pixels.

The test images, we used circle2, circle6 and circle10 that have different width at 2, 6 and 10 pixels wide respectively. Circle images are good images for testing because they can be used to test how well the detection approach can detect the lines at different angles. We used the wavelet filters at the first, second and third scales to detect circle2, circle4 and circle10 images respectively and compared the results with the multiple scales results. In addition, we added Gaussian noise to the image (SNR=10) for considering in noisy line detection case. The experiments of line detection are shown in Figure 3.

5.CONCLUSION

In this paper, we proposed a wavelet-based method for road detection from aerial images. We found that our approach leads to an effective method to form the basis of a road extraction approach.

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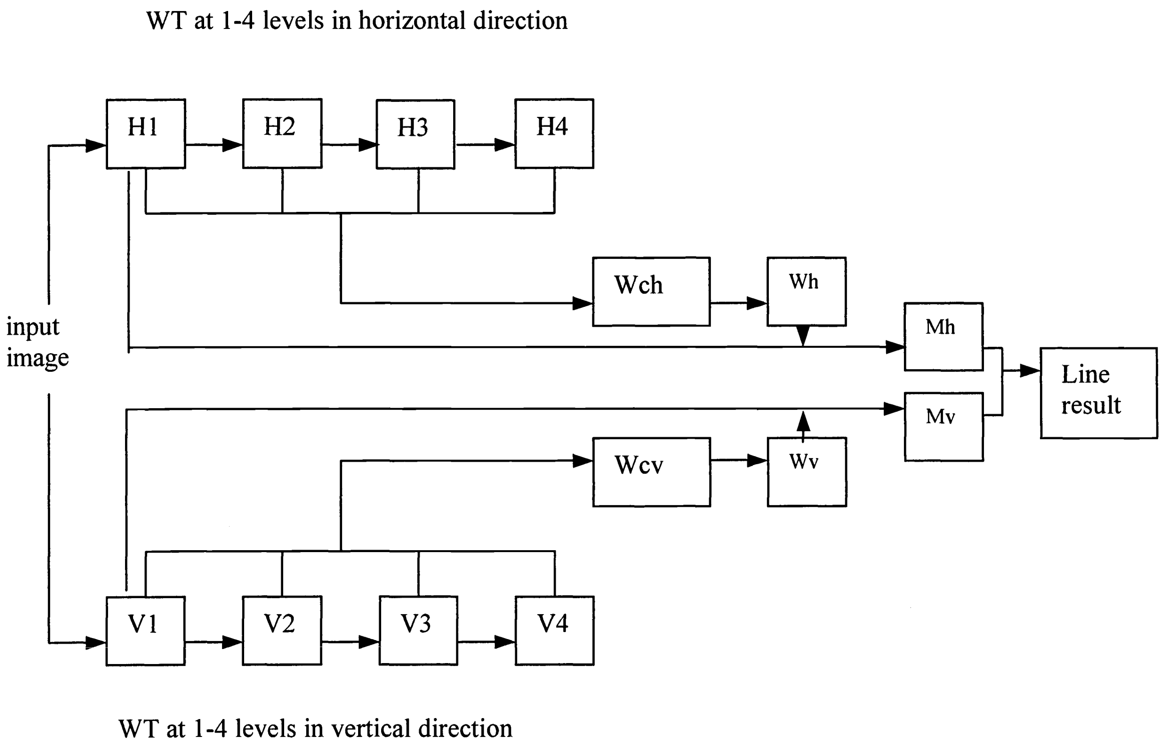

Figure 1 Block diagram of the line detection algorithm

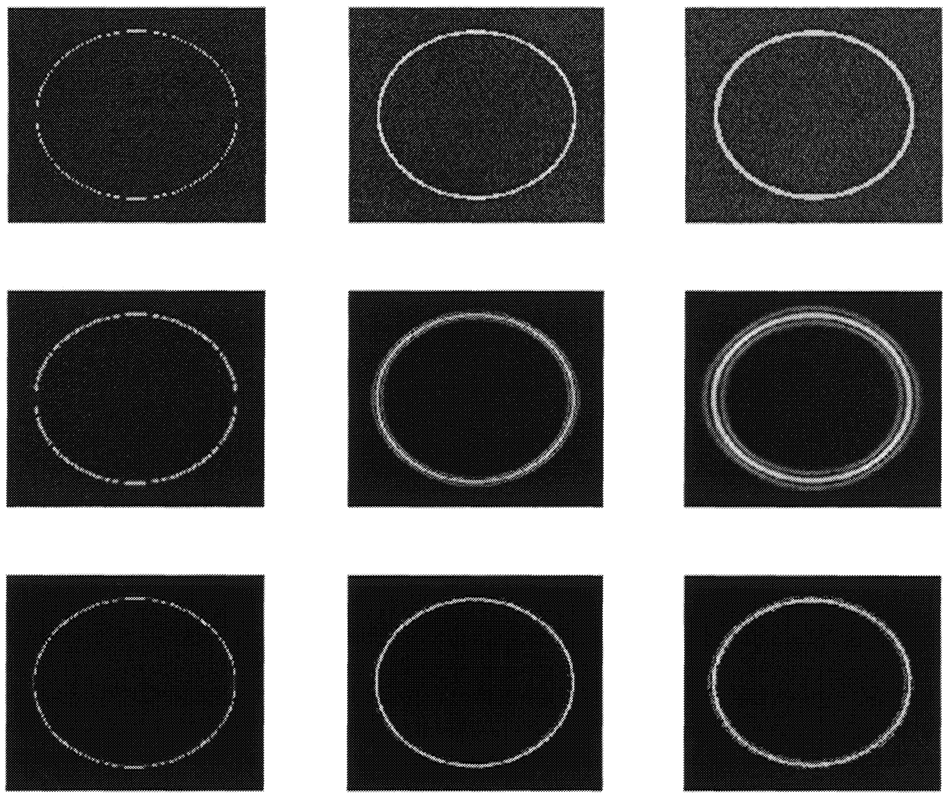

Figure 2 Experiment results of line detection using single scale and multiple scales at SNR=10

SNR=10	MSEs of single scale	MSEs of multiple scales
circle2	0.5603	0.3892
circle6	0.5686	0.393
circle10	0.5924	0.4275

Table 1 MSEs comparison between single and multiple scale of line detection