

CORNER DETECTION OF GRAY LEVEL IMAGES USING GABOR WAVELETS

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ABSTRACT

This paper proposes a novel method for corner detection of gray level images using Gabor wavelets. Wavelet transform is a tool that can provide multi-scale analysis while analyzing the local behavior of a signal. Gabor wavelets are known for their good localization in the time-frequency plane. Furthermore, they provide the shape and orientation information of local structures directly. In the proposed algorithm, the input image is decomposed at several wavelet scales and along several directions. The magnitude along the direction that is orthogonal to the gradient orientation represents the “corneriness” measurement. The proposed method is efficient since it has good localization, is robust to noise and achieves a high rate of true detection while keeping a low rate of false detection. Simulation results compare the proposed method with the two existing best approaches and show the good performance of the proposed method.

Index Terms – Corner Detection, Gabor Wavelet Transform, Modified Wavelet Transform Modulus Maxima (MWTMM).

1. INTRODUCTION

As a kind of low level image processing, corner detection is very important in many applications of computer vision and image processing. Corners are sparse and robust features of an image. Being sparse, they provide useful information and give important clues for shape representation and analysis [1]. Being robust, they are invariant to the changes of translation, rotation and scaling. They provide reliable clues regarding objects even under occlusion and varying background [2, 3]. Corner detection has wide applications such as object recognition, shape representation, image interpretation and motion analysis [2, 4].

Generally speaking, corner points have the following characteristics. First, they are local features of an image. Second, they may belong to structures of different sizes in an image. On the other hand, wavelet transform (WT) is a tool that can provide multi-scale analysis while analyzing the local behavior of a signal. Due to the above analysis, it is attractive to apply WT in corner detection. Because different wavelets have different properties, the selection of wavelet bases is of great importance.

There is no strict mathematical definition for corners. The judgement of a corner point is subjective. Thus, it is suitable to detect corners using filters that agree with the human visual system (HVS). Gabor wavelets are such filters. Furthermore, Gabor wavelets have the optimal localization in time-frequency plane. They transform the input images along multi-orientations. The magnitudes along the orientations provide more intuitive and useful information to describe the shape of the 2D structures. Consequently, we can expect to detect and localize corners accurately using Gabor wavelets.

In this paper, we propose a novel corner detection algorithm using Gabor wavelet transform. Using this detector, corners are detected and localized accurately. Meanwhile, this method provides us the magnitudes and orientations along the principal axes corresponding to the directions of the local eigenvectors of the local changes. The information is necessary when we deal with the affine transform applications in matching problems. Comparisons among the proposed method, Plessey corner detector [5] and SUSAN method [6] are also presented. Results demonstrate the good performance of our proposed method.

The rest of this paper is organized as follows. In section 2, we give a literature survey of the existing corner detection algorithms. Section 3 reviews the basic conception of the Gabor wavelets. In section 4, the proposed multi-scale corner detection method is presented in detail. Section 5 shows the simulation results. The conclusion and future works are discussed in Section 6.

2. LITERATURE SURVEY

According to the type of the processed images, corner detection of contour images and of gray level images are two main categories.

Corner detection of contour images is mainly used for shape description. Corner detection of gray level images has more applications in various tasks of computer vision and image analysis. There are many existing methods for corner detection of gray level images. We may categorize them into three types: template based corner detection, contour based corner detection and direct corner detection. There are advantages for direct corner detection and the best de-

tectors belong to it. As the proposed method belong to direct corner detection too, the review is mainly for it.

We call the third type as direct corner detection because this type of detector does not depend on the edge detection or the mathematical models. It detects corner points directly from some computations. Usually, computations are based on the first or second derivative of the image. In [7], Beaudet derives a corner measurement from the Hessian matrix that needs the second derivative of the image. Noble [8] characterizes the 2D surface features (including corner points) by the differential geometry of a facet model. In [9], Kitchen and Rosenfeld multiply the rate of change of gradient direction by the gradient magnitude to detect corner points. In [5], Harris and Stephens develop Moravec's idea [10] into the famous Plessey corner detector. This method is based on the first derivative quantities. The basic idea of the Plessey corner detector is that the difference between the local image and its shift along any direction should be large only at corner points. Zheng *et.al.* [11] formulate a gradient-direction corner detector that is developed from the Plessey corner detector. In [12], Deriche and Giraudon analyze several existing edge and corner detection algorithms. They use two scale Beaudet's detector to estimate the delocalization and apply the zero-crossing of the Laplacian of Gaussian to get the accurate localization. In [6], Smith and Brady apply a circular mask to detect corners and this detector is called SUSAN. The SUSAN principle is based on the fact that the center pixel should be a corner point if the number of the pixels that have the same brightness as the center pixel in the circular mask is below a threshold. In [13], neural network is applied to detect corners. Wavelets are applied to detect corners in [14], [15], [16]. In [14], multi-scale transform information is used to judge corner points. The input image is decomposed using a B-spline wavelet at several scales. The sum of the frequency components from the decomposed low-high, high-low, and high-high subbands is thresholded to obtain the edge map. The corner point is then detected if the high-high component is larger than a threshold and belongs to the edge map. While in [15], the first derivative of the Gaussian function is used as the mother wavelet. The ratio of transform moduli of two scales is used to detect the edges and corners. Scale invariant property of corner orientation is applied to detect corner points. In [16], the modified Gabor filter (the difference of two low-pass filters of different bandwidths) is used to filter the input image iteratively. The iteration stops when the change of the output is below a threshold. All the existing corner detection algorithms using wavelet transform perform well only on simple synthetic images. They are not robust enough for the detection on natural images. In [17], gradient covariance matrix and gradient projection are studied and used to detect edge and corner points. Sojka's [18] corner detector measures the

variance of directions of the gradient. The weighting coefficients in the measurement function are computed based on Baye's Theorem. Based on the review, we find that the Plessey detector and the SUSAN detector have better performances. We compare our method with them in section 5.

3. GABOR WAVELETS

The 2D Gabor wavelets are known to give a good fit of the behavior of the receptive field of simple cells in mammals' primary visual cortex [19, 20, 21]. A 2D Gabor wavelet is obtained with a Gaussian window $g(x, y)$ modulated by a sinusoidal wave:

$$\psi_k(x, y) = g(x, y) \exp[-iW(x \cos \theta_k + y \sin \theta_k)]. \quad (1)$$

In (1), $\theta_k = k\pi/K$ is the orientation for $k = 1, 2, \dots, K$, where K is the total number of orientations.

The Fourier transform of the Gabor function is:

$$\Psi_{j,k}(\omega_x, \omega_y) = \sqrt{2^j} G(2^j \omega_x - W \cos \theta_k, 2^j \omega_y - W \sin \theta_k), \quad (2)$$

where, $G(\omega_x, \omega_y)$ is the Fourier transform of $g(x, y)$ and 2^j is the wavelet scale.

Gabor wavelets have the optimal energy concentration in the time and frequency plane. Furthermore, they provide multi-scale and multi-orientation information of the input image. Fig. 1 shows a cover of the frequency plane by such Gabor wavelets.

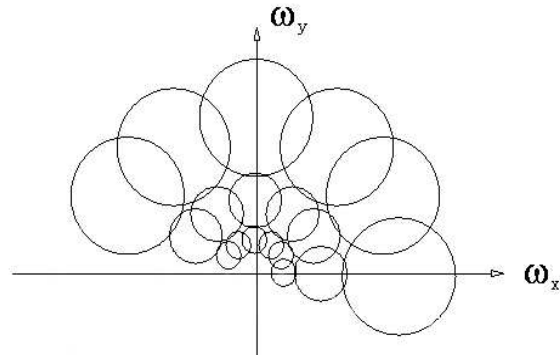


Fig. 1. Illustration of the frequency supports of Gabor wavelets.

4. THE PROPOSED CORNER DETECTION ALGORITHM USING GABOR WAVELETS

As corners are of 2D high frequency features, they should have high values along the two principal axes corresponding to the directions of the eigenvectors of local changes. Using the Gabor wavelet transform, we obtain first the magnitudes of every pixel along different directions at each scale. For each pixel, we detect the maximum value among all the magnitudes of different orientations. This value is called the modified wavelet transform modulus maxima (MWTMM).

This detection is efficient because the maximum value is robust to noise. Then the value along the direction that is orthogonal to the direction of the MWTMM is selected as the “cornerness” measurement. The proposed corner detection method is described as follows.

- Step 1. The input image $I(x, y)$ is first transformed using the Gabor wavelet along K orientations for s scales, given by

$$W_{j,k}(x, y) = \int I(x, y) \psi_{j,k}^*(x - x_1, y - y_1) dx_1 dy_1, \quad (3)$$

for $j = 1, 2, \dots, s$, and $k = 1, 2, \dots, K$. In (3), ‘ $*$ ’ denotes the complex conjugate, whereas $W_{j,k}(x, y)$ represents the wavelet coefficients for the decomposition using the Gabor wavelet.

- Step 2. At each scale, select MWTMM among the magnitudes of the K directions and record the direction for each pixel. It can be denoted as $W(j, k_1)$. k_1 denotes the direction of the MWTMM. The value of the MWTMM is proportional to the gradient which is along the principal axis.

- Step 3. Select the value along the direction that is orthogonal to the gradient (i.e. k_1), which is denoted as $W(j, k_2)$. Here, k_2 is the other principal direction. $W(j, k_2)$ is proportional to the differential value along the other principal axis. The relationship between k_1 and k_2 is $|k_1 - k_2| = K/2$.

- Step 4. Apply non-maximum suppression to the result obtained in Step 3. Non-maximum suppression is a simple but efficient post processing technique in image processing. It uses a local window sliding through all the pixels in the image. If the center pixel of the window is the local maximum within the window, then the central pixel value is kept; otherwise, it would be deleted.

- Step 5. To suppress the false detection, the corners are detected by applying a threshold to the results obtained in Step 4. The threshold is selected experimentally.

Due to the inherent denoising properties of the wavelet transform, this proposed detection method is less sensitive to noise. The magnitudes and orientations information obtained in Step 2 and Step 3 can be used further in other applications, such as affine invariant detection.

5. ILLUSTRATIVE RESULTS AND COMPARISONS

In this section, the robustness of the proposed algorithm is evaluated. We have also compared the performance of the proposed method with the Plessey corner detector and the SUSAN detector. We adjust the parameters carefully for each detector to obtain the best results.

In Fig. 2, a synthetic reference image called as “checkerboard” is used for evaluation. Fig. 2(a) shows the original image, whereas Fig. 2(b) presents the detection results of our proposed method. According to Fig. 2(b), all the corners points are detected successfully without having any false detection. Similarly, Fig. 2(c) shows the results of detection

for the corresponding noisy image having SNR=13 dB. As it is shown in Fig. 2(c), the method still can perform well for such a noisy image, which is corrupted with additive white noise.

In Fig. 3, a natural, gray-level Lab image is used for simulation which is more complex than the image shown in Fig. 2(a). In this example, we perform corner detection using our proposed method, Plessey method and SUSAN method. According to the results shown in Fig. 3, it can be shown that the proposed method has a comparable performance as the Plessey method, while it performs much better than the SUSAN method. The proposed method provides the shape information for a local structure. The shape information can be further used in some matching problems.

It is noted that the simulation results as presented in this paper are obtained by using the second scale (i.e. $j=2$) and the total number of orientations of 8 (i.e. $K=8$). Also, the size of the non-maximum suppression window used for the post-processing is 11×11 .

6. CONCLUSION AND FUTURE WORKS

In this paper, we propose a multi-scale corner detection method using the Gabor wavelet. Experimental results show that this new method is efficient and robust to noise.

As the proposed method provides the magnitudes along the principal axes, this method is useful also for affine invariant detection applications. In the future work, we will exploit these information to develop an affine invariant corner detector and apply it in some matching applications, e.g. in stereo matching. In the future, we also would like to combine various information from the multi-scales in order to achieve better performance for corner detection instead of the single scale information as used in this paper.

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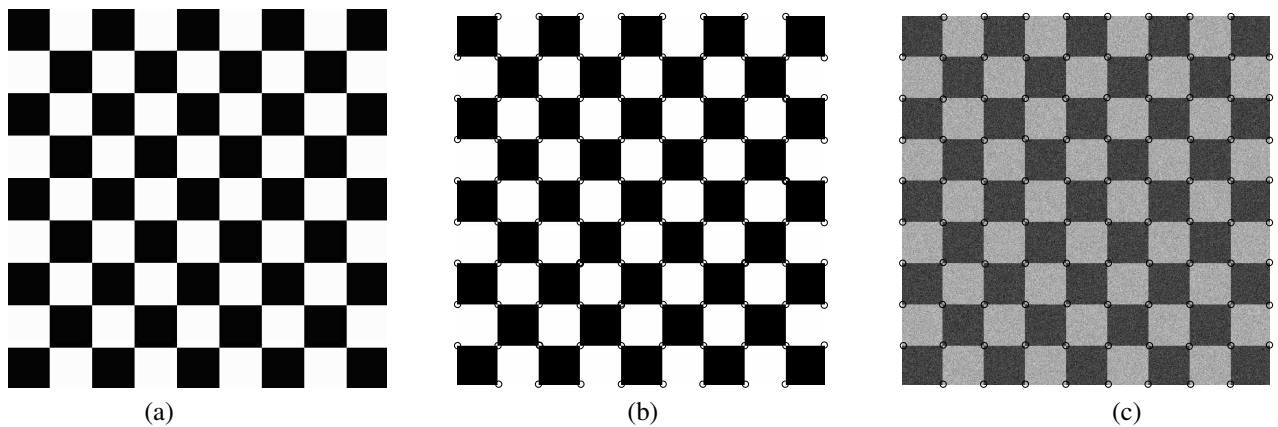


Fig. 2. Simulation using proposed Gabor wavelets corner detector on a synthetic image, (a) the original image, (b) result of the test image without noise, (c) result of the test image with additive white noise, SNR=13 dB.

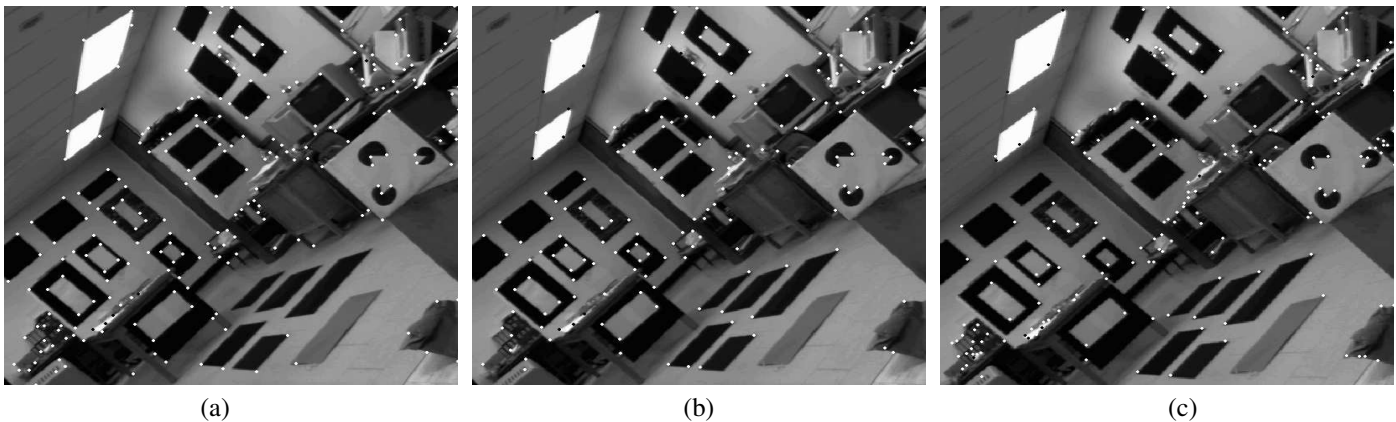


Fig. 3. Results of corner detection using (a) proposed Gabor wavelets corner detector, (b) Plessey detector, (c) SUSAN detector.

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