MULTISCALE CORNER DETECTION OF GRAY LEVEL IMAGES BASED ON LOG-GABOR WAVELET TRANSFORM

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ABSTRACT

This paper presents a novel corner detection method for gray level images based on log-Gabor wavelet transform(WT). The input image is decomposed at multiscales and along multi-orientations. The magnitudes of the decomposition are formulated into the second moment matrix. The smaller eigenvalue of the second moment matrix is used as the "cornerness" measurement. Compared with the most famous Harris detector, SUSAN detector and the recently published detector - Gabor wavelet transform based detector, the proposed method shows good localization and single response to the higher order corner structures. The simulation results also shows the higher detection rate of the proposed method.

Index Terms – corner detection, log-Gabor wavelet transform, second moment matrix.

1. INTRODUCTION

As a kind of low level image processing, corner detection is very important in many applications of computer vision and image processing. It is usually a front-end processing in a feature based image understanding system. Thus, the performance of corner detection has a great effect on the following processing and the whole system.

Generally speaking, corner points have the following characteristics. First, they are the 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.

As there is no strict mathematical definition for corners, the judgement of a corner point is subjective. Consequently, 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[1]. The magnitudes along the orientations provide more intuitive and useful information to describe the shape of the 2D structures. However, the maximum bandwidth of it is limited to approximately one octave. Furthermore, Gabor wavelets are not optimal for broad spectral information with maximal spatial localization. In [2], Field proposed the log-Gabor WT that is an improvement over Gabor WT. Log-Gabor wavelets can be constructed with arbitrary bandwidth and the bandwidth can be optimized to produce a filter with minimal spatial extent. Consequently, we can expect to detect and localize corners more accurately using log-Gabor wavelets.

In this paper, we propose a novel corner detection algorithm based on log-Gabor wavelets and second moment matrix. The input image is decomposed by log-Gabor wavelets at multiscales along multi-orientations. Then the magnitudes at different scales and orientations, are projected onto the x-axis and y-axis and formulated into the second moment matrix. Finally, the smaller eigenvalue of the second moment matrix is used to detect corner points. The proposed algorithm addresses three problems existing in the well-known Harris detector and SUSAN detector, i.e., (i) incomplete information based detection, (ii) delocalization problem, and (iii) multiple responses or no responses to higher order structures. That is, the proposed algorithm intends to solve the above three problems, while improving the detection rate. Comparisons among the proposed method, a recently presented Gabor-WT-based method[3], Harris method [4] and SUSAN method [5] are shown in the paper. The results demonstrate better performance by our proposed method.

The rest of the paper is organized as follows. Section 2 introduces the background theory of log-Gabor wavelets. The proposed algorithm based on log-Gabor WT and second moment matrix is presented in section 3. In section 4, the simulation results of the proposed method are presented, compared with the results of a recently presented Gabor-WT-based method, Harris detector and SUSAN detector. The conclusion is drawn in section 5.

2. LOG-GABOR WAVELETS

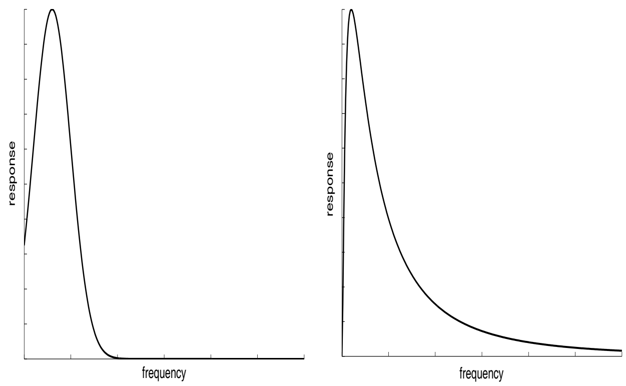
Although Gabor wavelets obtain the optimal localization in spatial and frequency domains simultaneously, the maximum bandwidth of a Gabor filter is limited to one octave. Otherwise, the zero frequency (low frequency) component is not small. In [2], Field proposes the log-Gabor wavelets that solve the problems existing in Gabor wavelets. Log-Gabor filters can be constructed with arbitrary bandwidth and the bandwidth can be optimized to produce a filter with minimal spatial extent [6].

Gabor functions have Gaussian transfer functions when viewed on the linear frequency scale. While log-Gabor functions have Gaussian transfer functions when viewed on the logarithmic frequency scale. Log-Gabor function has the following transfer function if viewed in the linear frequency scale.

$$G(f) = e^{-\frac{(log(f/f_0))^2}{2(log(\sigma/f_0))^2}}, \tag{1}$$

where, f_0 is the filter's center frequency. σ/f_0 controls the shape ratio of the filter.

Fig. 1 illustrates the difference between Gabor and log-Gabor transfer functions in the frequency domain.



(a) (b)

Fig. 1. Illustration of the frequency supports of 1D (a) Gabor transfer function, and (b) log-Gabor transfer function.

2D log-Gabor filters can be constructed in the frequency domain around some central frequency (f_i, θ_i), where θ_i is the orientation angle of the filter, and f_i is the central radial frequency [7, 8]:

$$G(f,\theta) = e^{-\frac{(log(f/f_i))^2}{2(log(\sigma_{f_i}/f_i))^2}} e^{-\frac{(\theta-\theta_i)^2}{2\sigma_{\theta_i}^2}}, \quad (2)$$

where, σ_{f_i} defines the radial bandwidth B in octaves with

$$B = 2\sqrt{2/log2}|log(\sigma_{f_i}/f_i)|, \quad (3)$$

and σ_{θ_i} defines the angular bandwidth

$$\Delta\Omega = 2\sigma_{\theta_i}\sqrt{2log2}. \quad (4)$$

Here,

$$G(f) = e^{-\frac{(log(f/f_i))^2}{2(log(\sigma_{f_i}/f_i))^2}}, \quad (5)$$

is the radial component, which controls the frequency band that the filter responds to, and,

$$G(\theta) = e^{-\frac{(\theta-\theta_i)^2}{2\sigma_{\theta_i}^2}}, \quad (6)$$

is the angular component, which controls the orientation that the filter responds to. The two components are multiplied together to construct the overall filter. Fig. 2 shows the magnitude responses of the 2D log-Gabor filters along eight directions.

3. THE PROPOSED CORNER DETECTION ALGORITHM BASED ON LOG-GABOR WAVELETS AND SECOND MOMENT MATRIX

In this section, we propose a novel corner detector based on log-Gabor WT and second moment matrix. The proposed method remains the good characteristics of the existing detectors. By utilizing the log-Gabor WT, the proposed method is robust to noise. By analyzing the eigenvalue of the second moment matrix, the proposed method has isotropic responses.

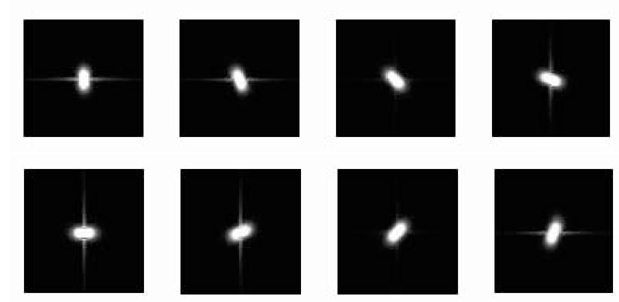


Fig. 2. 2D log-Gabor filters at different orientations.

Furthermore, the proposed method addresses three problems existing in Harris detector and SUSAN detector.

• First, Harris and SUSAN methods are based on single scale information. The proposed method is based on the multiscale information instead of single scale one. In practice, an image usually contains important details belonging to a range of scales [9]. Furthermore, between images of the same scene, they are usually related by the affine transform locally, and scaling is an important factor of the affine transform. Consequently, multiscale analysis is indispensable.

• Second, the delocalization problem which exists in Harris detector is minimized by utilizing the good localization property of log-Gabor wavelets. The localization accuracy is important in most of the applications. It affects the performance of the following processing directly. Therefore, it is desirable to have accurate localization in corner detection.

• Third, both Harris detector and SUSAN detector have certain problem to detect corners of higher order structures. For Harris detector, it can only detect "L" corners. For corners of higher order structures, such as "X", "T" and "Y" etc., it will handle them as 4 or 2 separate "L" corners. The reason is that the derivative is only along the x and y axis. For SUSAN detector, it cannot detect "X" junctions because the two kinds of gray levels in the neighborhood of junctions have the same amounts. To detect corners of higher order structures well, the multi-orientation decomposition of log-Gabor wavelets is exploited in the proposed method. As a result, the proposed method detects different types of corners well.

The log-Gaobr WT measures the intensity changes (high frequency components) along different directions. To get isotropic responses, the norm of the decomposition is formulated into the second moment matrix. As we know, the two eigenvalues of the second moment matrix characterize the intensity changes. If the small eigenvalue is large enough, it means that the intensity changes along any directions are large. Then, it corresponds to a corner point. Therefore, we take the small eigenvalue of the second moment matrix as the "cornerness" measurement in the proposed method.

The steps of the proposed algorithm are as follows.

• Step 1. The input image $I(x, y)$ is first transformed using the log-Gabor wavelets along k directions for s scales. Then the magnitude of the transformation is taken as

$$W_{i,j}(x,y) = |\int I(x,y)\psi_{i,j}^*(x-x_1, y-y_1)dx_1dy_1|, \quad (7)$$

for $i = 1, 2, \cdots, s$, and $j = 1, 2, \cdots, k$. In (7), ' * ' denotes the complex conjugate, whereas $\psi_{i,j}$ represents the log-Gabor wavelet filter at scale i and along orientation j. $|\cdot|$ denotes the norm operator.

• Step 2. Then the measurement at each point is computed as follows.

$$a = \sum_i \sum_j (W_{i,j} cos(\theta_j))^2, \tag{8}$$

$$b = \sum_i \sum_j W_{i,j} cos(\theta_j) W_{i,j} sin(\theta_j), \tag{9}$$

$$c = \sum_i \sum_j (W_{i,j} sin(\theta_j))^2. \tag{10}$$

In Eqs. (8)-(10), θ_j is the angle of the orientation j. $W_{i,j}$ represents the magnitude of the log-Gabor WT coefficient at scale i and orientation j. The second moment matrix is then constructed as follows.

$$M = \begin{bmatrix} a & b \\ b & c \end{bmatrix}. \tag{11}$$

• Step 3. The eigenvalues of the above matrix is

$$\lambda_{1,2} = \frac{1}{2}(a+c) \pm \frac{1}{2}\sqrt{4b^2 + (a-c)^2}. \tag{12}$$

We take the smaller eigenvalue as the "cornerness" measurement, i.e.,

$$m = \frac{1}{2}(a+c) - \frac{1}{2}\sqrt{4b^2 + (a-c)^2}. \tag{13}$$

• Step 4. The non-maximum suppression and threshold is applied as the post processing.

The flowchart of the algorithm is illustrated in Fig. 3

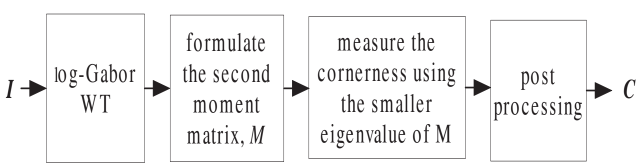


Fig. 3. Flowchart of the proposed algorithm based on log-Gabor WT and second moment matrix. I is the input gray level image, and C is the detected corners.

4. ILLUSTRATIVE RESULTS AND COMPARISONS

In this section, we compare the performance of the proposed methods with Gabor-WT-based method, Harris detector and SUSAN detector.

In Fig. 4, a synthetic image called as "model" is used for evaluation. The "model" image contains corner types of "L", "Y", "T" and "X". From the results, we see that the proposed method detects all types of corners correctly. Furthermore, the proposed method can achieve good result with easy-setting parameters. Although the Gabor-WT-based method also detects all the corners correctly, the parameters of it, i.e., the size of the nonmaximum window and the threshold need to be set carefully. The result of Harris detector shown in Fig. 4 (c) treat the "T" and "X" corners as 2 and 4 separate corners, respectively. If we increase the size of the non-maximum suppression window, the over detection of the

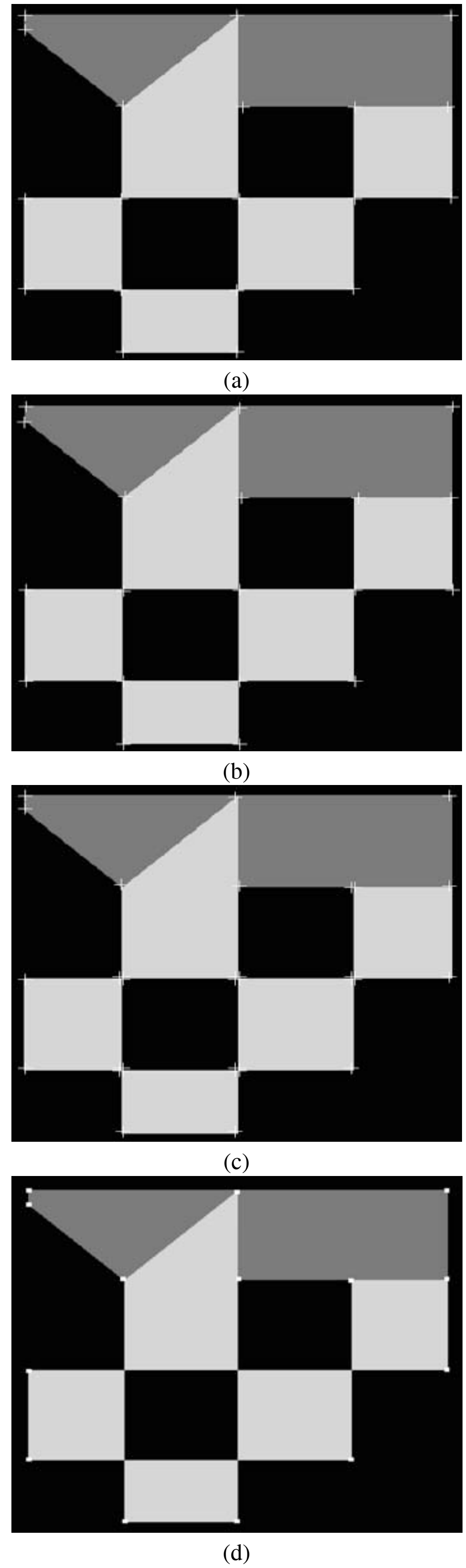
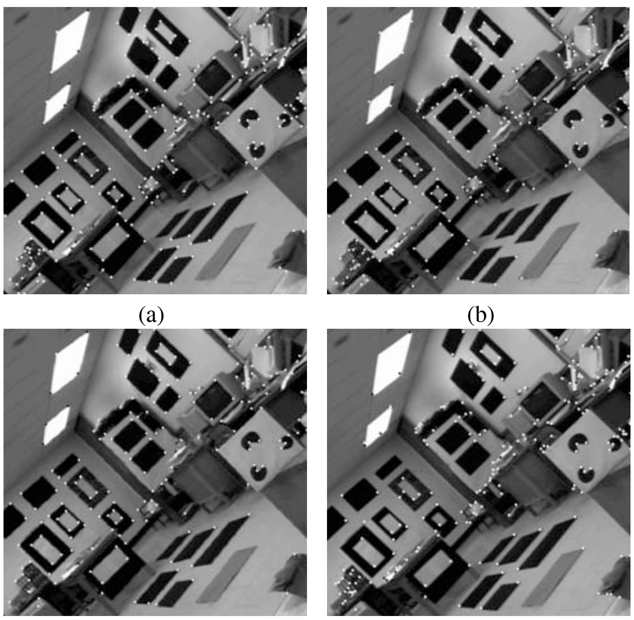


Fig. 4. Results of corner detection using (a) the proposed multi-scale corner detector based on log-Gabor WT and second moment matrix, (b) Gabor-WT-based detector, (c) Harris detector, and (d) SUSAN detector.

"X" corners can be removed, but the over detection of the "T" corner still sustains. Fig. 4 (d) gives the result of SUSAN detector, showing better localization accuracy than the proposed method, the Harris method and the Gabor WT based method. However, all the corners of "X" type have missed. It is because the numbers of the pixels belonging to the two gray levels in the neighborhood of "X" corner are the same, SUSAN takes it as an edge point.

In Fig. 5, the "Lab" image is used for simulation. The results of the proposed methods are obtained using the same parameters as in the simulation of the "model" image. For the Gabor-WT-based detector, Harris detector and SUSAN detector, we adjust the parameters to get the best results. The proposed method achieves better performance than all the other three methods. More correct corners are detected. SUSAN detector misses many corners.

It is noted that the simulation results as presented in this section are obtained by using three scales, i.e. s=3, and the total number of orientations of 8, i.e. k=8.



(a) (b) (c) (d)

Fig. 5. Results of corner detection using (a) the proposed multi-scale corner detector based on log-Gabor WT and second moment matrix, (b) Gabor-WT-based detector, (c) Harris detector, and (d) SUSAN detector.

5. CONCLUSION AND FUTURE WORKS

In this paper, we propose a multi-scale corner detection method based on log-Gabor WT. The localization is improved by utilizing the optimal localization property of the log-Gabor WT. To achieve isotropic response, the proposed method exploits the multi-orientation decomposition of log-Gabor WT and constructed the second moment matrix. The smaller eigenvalue of the second moment matrix is used to detect corners. The proposed method provides a unique response for the corner of higher order structure. Simulation results compare the proposed methods with one recently presented method and two existing well-known approaches and demonstrate the better performance of the proposed method.

The proposed method can be evaluated objectively through application based method, e.g. stereo matching. Due to the limit of the length of the paper, the quantitative evaluation results have not shown in this paper, which further demonstrate the better performance of the proposed method [10].

6. ACKNOWLEGMENT

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