

Junction Detection using Multi-scale Gabor Filters

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Abstract—This paper proposes a novel junction detection algorithm which combines image intensity variation and edge contour information. Firstly, use the Canny edge contour detector to extract edge map. Secondly, imaginary parts of multi-scale Gabor filters (IPGFs) are used to smooth the input image, and then acquire the normalized information entropies at various scales. Finally, the multiplication of different normalized information entropies is served as a new interest point measure, which is used to detect interest point. The proposed method has two advantages: on one hand, the proposed method not only utilizes contour shape and local maximum curvature to extract junctions but also considers the gray variation information of edge pixels and their surrounding pixels; on the other hand, the multi-scale product is served as junction measure which can inhabit the non-junction. Compared with four other state-of-art methods, the proposed method showed excellent performance in terms of the average repeatability and the localization accuracy.

Index Terms—Junction detection, imaginary parts of the Gabor filters (IPGFs), normalized, information entropy, multi-scale product

I. INTRODUCTION

Junction, which often has unique structures, is a local invariant feature in an image. The detection and extraction of junction is very important in image analysis and computer vision, such as image matching [1], object recognition [2], feature tracking [3], among other applications. In true scenes, due to the perspectives and the environment change, the image may be turned by illumination, rotation and scale or be influenced by noise and other factors. Junction is independent to these variations, so we can extract image feature by detecting interest point. Generally, junctions are defined as the easy identified points in image [4], which also include corners and junctions.

Multiple junction detectors have been proposed in the literature [4-27], which can be broadly classified into three classes [4, 5]: intensity-based methods [6-13], template-based methods [4], [6] and contour-based methods

[14-27]. The intensity method which considers the corner's self-dissimilar property [6, 7] detects junctions in an image directly. The template-based method searches junctions by matching a small chip of an image to a previously given model. The contour-based method first uses some edge detectors to extract the edge contour and then analyzes the contour shape to find junctions. Furthermore, these detectors can also be divided into two groups [8]: single-scale detectors and multi-scale detectors. If the input image has the same scale feature, the single-scale detector has good detection property [9]. However, most input images contain multi-scale features that single-scale method may lose important junctions. To improve the defect of single-scale method, the multi-scale junction detector has been proposed. In this paper, we will combine the edge contour with intensity variation information to detect junctions.

The intensity methods detect junctions by using the first order or second order derivative of image. In the early stage, the second order derivatives are embedding in junction detectors, which proved to be sensitive to noise later. Inspired by Moravec's idea [10], Harris and Stephens proposed the prosperous Harris algorithm [6], which then is the foundation stone of follow studies. But Harris corner detector can only detect L-type corners, other complex corners cannot be detected well [11]. From then on, the steerable filters such as Log-Gabor wavelet [12] and the shearlet [13], which introduced multi-scale and multi-directional intensity variation information, were used to extract the fine local intensity variations for edge and junction detection.

The contour methods which proposed by Mokhtarian and Mackworth [14] are based upon curvature scale space (CSS) theory to detect junctions. Rattarangsi and Chin [15] first adopted CSS [14] principle to detect junction in entire scale space. Mokhtarian and Suomda [16] proposed its improved edition, which detects interest point in large scale and tracks curvature from large to small scale to improve positioning performance. The CSS detector works well in detecting junctions. However, The CSS detector is sensitive to noise or local variation. Meanwhile, it is a difficult task to choose a suitable Gaussian scale to smooth edge contours. To solve the aforementioned problems, Gao [18] proposed multi-scale method with local nature scale. Zhang [17] utilized the multi-scale curvature product to find junctions. Awrangjeb [19] proposed the discrete curvature estimate technique [20] based upon chord-to-point distance accumulation (CPDA). Literature [21] utilized polygon to approximate the contour shape, and then extract the polygon peak by curvature maximum through scale space. Meanwhile, gradient correlation matrices of planar curves [22], adaptive threshold method [23] and multi-chord curvature polynomial [24] are also proposed to extract junctions. Although these methods

Manuscript received Jan. 10, 2018; revised Feb. 8, 2018. This work was supported by the Control Science and Engineering Group Construction of Xi'an Polytechnic University (No.107090811), the Shaanxi Provincial Science and Technology Department of Natural Science Foundation research project funded project (2016JZ026), project of tackle key problems in Industrial technology of Shaanxi (2016GY-047).

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have achieved better detection performance than the aforementioned detectors, there is still large space for improvement. The mentioned above contour-based method neglects the influence of gray variation information but only uses the contour shape to examine junctions, which leads to the detection performance depends on edge detection at large extent.

In literature [25], Gabor filter was proved to be the model of human visual system and it is further demonstrated [26][27] that Gabor filter is optimal to extract local feature such as edge and corner. Zhang [28] utilized imaginary part of Gabor filter (IPGF) to extract gray variation information and the normalized amplitude response at each direction is used to extract contour's junctions. Unlike the traditional CSS method, IPGF detector utilizes the contour shape information and gray variation information, which improves the detection reliability.

In this paper, we propose a new junction detection algorithm to overcome the aforementioned problems. The literature [28] pointed out that whether a pixel is the junction depends on the pixel and its neighbor pixels' gray value. Different from the literature [28], we use multi-scale IPGFs to extract gray variation information at multi-directions. Based upon the gray variation direction information at different scales, we compute the normalized information entropy of each contour pixel, and then the product of the normalized information entropies at multi-scale is embedded in contour framework to extract junctions. There is one main contribution in this paper: compared with the traditional contour-based method, the new algorithm uses not only contour shape information but also the pixel and its neighbor's gray change information. Hence, the new detector reduces the false junction detection rate, which is impossible for contour method. We also examine the effect of scale factors on the experimental results. It shows that scale multiplication makes the detector more robust to noise. Compared with four state-of-art methods, include Harris [6], Harris-Laplace[8], CSS [16] and He & Yung [23], our approach is more effective with respect to corner detection, localization, and noise-robustness.

II. MULTI-SCALE GABOR FILTERS AND JUNCTION MEASURE

In practical application, images are often the discrete two-dimensional signal, so the sequential Gabor filter should be discredited. In this section, we discuss the property of IPGF for interest point extraction.

A. Imaginary parts of Gabor filters

The discrete IPGF is expressed as

$$\varphi(m, n; f_s, \theta_k) = \frac{f_s^2}{\pi\gamma\eta} \exp\left(-\left(\frac{f_s^2}{\gamma^2}u^2 + \frac{f_s^2}{\eta^2}v^2\right)\right) \sin(2\pi f_s u),$$

$$u = m \cos \theta_k + n \sin \theta_k,$$

$$v = -m \sin \theta_k + n \cos \theta_k,$$

$$\theta_k = 2\pi k/K, k=0,1,\dots,K-1,$$

$$f_s = f_{\max} \times \sqrt{2}^{-(s-1)}, s=1,2,\dots$$

where γ , η are spatial width of filter along x-axis and y-axis, both of them determine the filter's shape, f_s is central

frequency under the scale s , f_{\max} is maximum central frequency, K is the number of direction of filter, θ is the rotation angle. Fig. 1 shows an example of imaginary part of Gabor filters at eight directions.

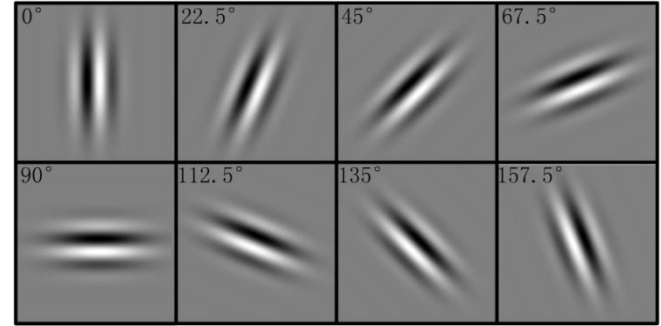


Fig.1 IPGF with $f_{\max}=0.25, s=0, \gamma=0.75, \eta=1, \theta_k=k\pi/8, k=0,1,2,3,\dots$

Using the filters with large scale to smooth image can suppress noise well but may lose the detail of gray variation information. On the contrary, the filters with small scale can extract detail of gray variation information well but sensitive to noise. Hence, use the different scales to extract gray variation information can enhance the detection property. For a discrete image $I(m, n)$, under the scale S , the amplitude response ξ can be obtained by convolution:

$$\begin{aligned} \xi(m, n; f_s, k) &= I(m, n) \otimes \varphi(m, n; f_s, \theta_k) \\ &= \sum_{m_x} \sum_{n_y} I(m - m_x, n - n_y) \varphi(m_x, n_y; f_s, \theta_k). \end{aligned} \quad (2)$$

The magnitude response of the IPGF along the direction θ_k reflects the gray variation information of the input image. So, a bank of IPGFs along the different directions can give back the intensity variation regularities among edge contour pixels or interest points absolutely. For a step edge, L-type corner, Y-junction and X-junction, the magnitude response of the IPGF is shown in Fig. 2.

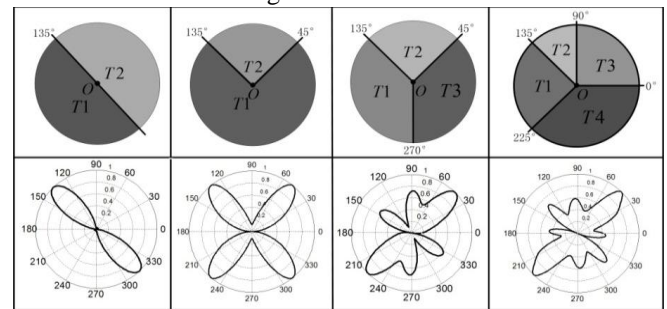


Fig.2 Magnitude responses of the IPGF of a step edge, L-type corner, Y-junction, X-junction

B. Junction measure of contour pixel

The traditional contour-based method usually extracts the junction by searching for the local curvature maximum in edge contour, which existing the noise-sensitiveness and contour dependency problems. Under the different scales, our method serves the gradient direction information entropy of contour pixel and its neighbor as the junction measure. The gradient direction corresponding to the gray variation maximum can be obtained by amplitude response of the IPGF:

$$(1) \quad \beta = \arg \max_{k=1,2,\dots,K} \{|\xi(m, n; f_s, k)|\}. \quad (3)$$

We take one pixel q and its neighbor Z_q arbitrarily which

contains K pixels, assuming that in this neighbor there were M_k pixels along the gradient direction β , so the corresponded probability of gradient direction is:

$$P = M_k / K, k = 1, 2, \dots, K. \quad (4)$$

The information entropy of pixel q is defined as:

$$H = -\sum_{k=1}^K P \log_2 P, P \neq 0. \quad (5)$$

In order to guarantee the sum of probabilities in one neighbor is equal to one, the window size of neighborhood should match with the filter's orientations. For example, if we choose 5×5 size of window, the number of filter's orientations should be 25. Under the scale s , normalizing the information entropies of all edge contours' pixels, then the i 'th pixel's normalized information entropy is:

$$H_{sq_i} = H_{si} / \max\{|H_{s1}|, |H_{s2}|, \dots, |H_{sn}|\}, \quad (6)$$

where H_{si} and H_{sn} denote the gradient direction information entropy of the i 'th and n 'th pixels, we use scale-product as the new interest point measure to search junction:

$$\mathcal{G} = \prod_{j=1,2,\dots}^{s_j} H_{s_j q_i} \quad (7)$$

where s_j denotes the j 'th scale, $H_{s_j q_i}$ denotes the normalized information entropy of contour pixel q under the j 'th scale.

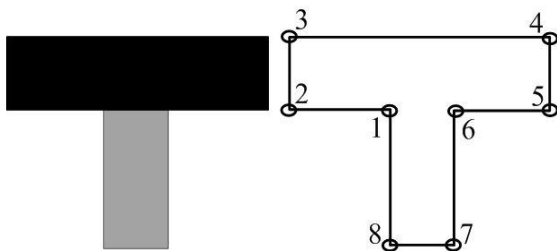


Fig.3 simple image and its contour.

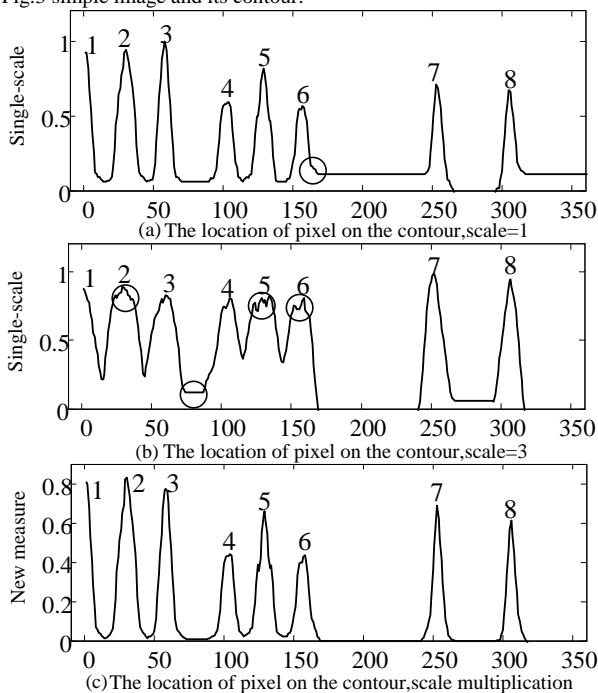


Fig. 4 (a) single-scale response, $s=1$, (b) single-scale response, $s=3$, (c) scale-multiplication.

In order to prove multi-scale measure has better

performance than single-scale, in Fig.3, we use a simple image and its contour to examine the property of junction measure. Fig.4 (a), (b) and (c) show the junction measure under single-scale and scale multiplication. We can see that single-scale responses mix with some other points (marked by "o") such as noise or edge pixels; this method could not distinguish junction well. On the contrary, scale multiplication can suppress non-junction well and its response is almost approach to zero. In addition, the multiplication makes the algorithm more robust that can distinguish junctions from others.

C. Outline of the proposed method

Based upon the content above, we give the algorithm's steps:

--First, extract edge map from the input image by Canny[29] edge detector, and fill gaps to form a complete edge contours.

--Second, smooth the input image by multi-scale IPGF to obtain the magnitude response as well as gray variation information.

--Third, under the different scales, compute the edge contour pixels' normalized information entropies in 7×7 neighborhoods by Equation (6).

--Fourth, Multiply the normalized information entropies at different scales and then apply the non-maximum suppression to the multiplication. We use a local window with the size of 13×13 to smooth through all the pixels of the edge contour. If the central pixel is the local maximum, then the pixel is kept; conversely, it would be set to zero.

--Fifth, to remove weak and false junctions, compare the candidate junctions acquired in step 4 with a threshold.

III. PERFORMANCE EVALUATION AND EXPERIMENTAL RESULT

In this section, we focus on the performance evaluation and experiment results. We compare the proposed interest detector with four state-of-art methods (Harris [6], Harris-Laplace [8], CSS [16] and He&Yung [23]) by means of the average repeatability and localization error criterion [19], [30].

A. The database

As is shown in Fig.5, eighteen images acquired from the database [31] and other magazines are used to evaluate the parameters and properties of four detectors.



Fig. 5 Twenty-eight images for computation of the average repeatability and localization error.

The test images are acquired by using the six different types of transformation on each original image: rotation,

uniform scaling transform, non-uniform scaling transform, shear transform, lossy JPEG compression and Gaussian noise.

B. The database

The evaluation criterion [19], [30] adopts average repeatability and localization error to analyze the performance of the different detectors.

The average repeatability R_{avg} reflects the repeatable degree between test image and origin image. It is defined as:

$$R_{avg} = 0.5 \times N_r \times (1/N_o + 1/N_t) \tag{8}$$

where N_o denotes the number of detected interest points from original images, N_t denotes the number of detected interest points from test images and N_r denotes the number of repeated interest points. Imagine that an interest point was detected in origin image and if its corresponding point in geometric transformation were within four pixels, N_r should be added to one, and so on.

The localization error L_e is defined as the average distance on all the matched pairs. Let $\langle (P_k, \bar{P}_k), k = 1, 2, \dots, N_r \rangle$ be the matched pairs in original and test images. Then, the localization error is computed by:

$$L_e = \sqrt{\frac{1}{N_r} \left(\sum_{k=1}^{N_r} \|P_k - \bar{P}_k\|_2^2 \right)} \tag{9}$$

C. Experimental results

In this section, we first concentrate on the experimental parameter setting for the proposed detector. Then, we give the relative results between the proposed and four other detectors: Harris [6], Harris-Laplace [8], CSS [16] and He & Yung [23]. The parameters setting are: $f_0 = 0.19$, $\gamma = 0.55$, $\eta = 0.55^2$, $K = 49$, the multi-scale of Gabor filters is [1, 3], the threshold is $Thr = 0.7$, the size of non-maxima suppression window is 13×13 .

The whole comparative results among the proposed and four other detectors (Harris [6], Harris-Laplace [8], CSS [16] and He & Yung [23]) are put forward in this section. Here, all the parameters of the detectors use their default values.

Table I shows the average repeatability and localization error under the different geometric transformations, lossy image compression and Gaussian noise. In rotation

transformations, the proposed method has high average localization; the Harris-Laplace has the worst performance in rotation transformation. Meanwhile, in average repeatability aspect, the proposed method is outperform other methods in Gaussian noise. In localization error aspect, the proposed method performs worse than the Harris-Laplace method, but achieves better performance than other four methods.

The statistics performance index of the five detectors are as follows: the average of the Harris is 4, Harris-Laplace is 2.333, He&Yung is 3.333, CSS is 3.417 and the proposed is 1.833, respectively. It can be seen that the proposed method shows the best performance, Harris-Laplace is second, He & Yung is third and Harris is the poorest.

IV. CONCLUSION

We have proposed a new junction detector based on the multi-scale IPGFs. It combines the edge contour pixels' shape information and their surrounding pixels' gray variation, which improves the property of the junction detector. Meanwhile, the scale-multiplication also suppresses the non-interest point. Compared with four other detectors, the proposed detector performs well in geometric transformations and it has precise localization of the repeated interest points. Future work may consider the more accurate localization performance and noise robustness.

ACKNOWLEDGMENT

This work was supported by the Control Science and Engineering Group Construction of Xi'an Polytechnic University (No.107090811), the Shaanxi Provincial Science and Technology Department of Natural Science Foundation research project funded project (2016JZ026), project of tackle key problems in Industrial technology of Shaanxi (2016GY-047).

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TABLE I
 AVERAGE REPEATABILITY AND LOCALIZATION ERROR RESULTS UNDER DIFFERENT TRANSFORMATIONS.

Test classes	Quantity	He & Yung	Harris -Laplace	CSS	Harris	Proposed
Rotation transformation	Average repeatability (%)	0.63	0.45	0.55	0.7	0.72
	Average localization (pixel)	2.23	2.57	1.85	1.98	1.55
Uniform scaling transformation	Average repeatability (%)	0.57	0.59	0.62	0.61	0.64
	Average localization (pixel)	2.71	3.05	2.81	2.63	2.55
Nonuniform scaling transformation	Average repeatability (%)	0.56	0.49	0.52	0.58	0.6
	Average localization (pixel)	2.85	3.12	2.89	2.73	2.66
Shear transformation	Average repeatability (%)	0.61	0.52	0.59	0.63	0.65
	Average localization (pixel)	1.99	2.11	1.95	1.89	1.73
Lossy compress	Average repeatability (%)	0.73	0.7	0.72	0.75	0.83
	Average localization (pixel)	1.59	1.81	1.63	1.57	1.52
Gaussian noise	Average repeatability (%)	0.75	0.65	0.73	0.65	0.18
	Average localization (pixel)	1.46	1.98	1.54	1.35	1.35

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