Orientation estimation for corner detection

Ling-wei Ye, Zhe Wang, Wei Feng
QingDao Area of NAAU
N AAU
QingDao, China
e-mail: lwyee@163.com

***Abstract*—Although many work have been done on corner detection, no generally accepted mathematical definition exists. This paper gives an explicit definition of corner which is based on the multi-orientation nature of corner and presents an algorithm for corner detection based on orientation estimation. Experimental results show that the proposed algorithm is more accurate and noise-robust compared with three popularly used corner detection algorithms.**

Keywords-Corner detection; Orientation estimation; orientation tensor; nonlinear diffusion

I. INTRODUCTION

Corners, which are also called junctions/ key points/ dominant points or interesting points, play an important role in many image analysis applications such as image registration, shape analysis, object recognition, motion analysis, scene analysis, stereo matching, etc. Therefore most of the work on two-dimensional features has concentrated on corner detection.

Although the notion of corner seems to be intuitively clear, no generally accepted mathematical definition exists. Different developed approaches give different computational definitions, for example, some defined the corner as a location where the curvature is high enough; some proposed that the curvature variation of the corner is high; some thinks that the direction of the boundary changes abruptly at the corner, etc. In this paper, we will give an explicit definition to corners and presents a corner detection algorithm based on orientation estimation. The paper is organized as follows: Section Ⅱ gives a short overview of the previous work on corner detection. We presents our algorithm in Section Ⅲ. The experimental results and analysis are demonstrate in sectionⅣ.

II. PREVIOUS WORK

In this section we divide the existing algorithms into two classes and enumerate some typical algorithms of each class. The first class can be called the direct methods containing the algorithms that work directly on the gray values of the image; the second includes the indirect algorithms that extract the edges firstly and analyze their curvature afterwards. An analysis of gray level corner detection has also been carried out in [15].

In the first class, Moravec (1979) [9]proposed an interest point detector which functions by considering a local window in an image and determining the average changes of intensity which results from shifting the window by a small amount in four directions. Harris and Stephens (1988) modified the Moravec's method to the Plessey corner detector by estimating the autocorrelation from the first-order derivatives[6]. SUSAN algorithm proposed by Smith and Brady (1997)[12] is a straightforward method which does not depend on image derivatives. Given a digital image, the USAN (Univalue Segment Assimilating Nucleus) area will reach a minimum when the nucleus lies on a corner point. SUSAN is not sensitive to noise and it is very fast as it only uses very simple operations.

In the second class, the earliest geometry-based corner detectors firstly segment the image, extract its boundary as chain code, and then search for significant turnings at the boundary [4]. This kind of corner detectors suffers the high algorithm complexity, as multiple steps are needed. What's more, any errors in the segmentation step will lead to great astray in the corner results. Hsin-Teng and Hu [7] used polygonal approximation method to detect corners. Medioni and Yasumoto used the cubic B-spline curve while Langridge employed the cubic polynomial curve. Mokhtarian and Suomela [8] proposed a curvature scale space technique which is much efficient than other curvature-based methods. Fei Shen and Han Wang [3] put forward an improved Hough transformation algorithm to detect the point of intersection and claim it as a corner. Shapes are characterized by their corners, which are extracted from the curvature function of their contours. Ray and Pandyan [11] suggested a technique for smoothing a curve adaptively based on the roughness of the curve, instead of smoothing a curve at multiple scales and integrating the information of various scales as conventional smoothing techniques. Wen-Yen Wu[14] used a method which determined the support region for each curve point using bending value. The points with local maximum smoothing bending value will be identified as a corner. Guru and Dinesh[5] proposed another model to determine the support region of a point useful for corner detection. Unlike other existing models this one is non-parametric and determines the support region adaptively. However, it does not take into account the effect of the noise and the location accuracy. Olague and Hernndez [10] proposed a parametric model based on Unit Step Edge Function and studied the location accuracy of "L"type corner. Vincent and Laganière [13]proposed a feature point detector which uses a wedge model to characterize corners by their orientation and angular width..

III. ALGORITHMIC ASPECTS

We can infer from lemma 1 that corners locate at the local maxima of the orientation variance. In practical computation, we can only take into account a certain neighborhood of a pixel, so digital curves can be approximated by straight lines considered in lemma 1. However, we must consider the effect of digitalization error, noise and computation error which make the orientation estimation results not so accurate and consistent as required in theory analysis. In order to solve this problem, we introduce the nonlinear diffusion to improve the performance and operate directly on orientation tensor to avoid the computation error of transforming the orientation tensor to angle.

The proposed corner detection algorithm is mainly divided into the subsequent steps:

Step 1. Detect the edges in the image using improved Canny edge detector,

Step 2. Estimate the orientation of edges by quadrature filters,

Step 3. Execute nonlinear diffusion to refine the orientation estimation results,

Step 4. Compute the orientation variance of edge pixels,

Step 5. Find local maximum in a search window whose orientation variance is bigger than its neighbors above a predefined threshold.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

The algorithm was implemented and extensively tested. We compared our algorithm with three popular corner detection algorithms published by (Harris and Stephen 1988, Smith and Brady 1997, Mokhtarian and Suomela 1998) in experiments. For all algorithms, the values of all their parameters (e.g. thresholds) were set to the values giving the lowest possible total error. The values were found by searching in the space of parameters of each particular detector.

Figure.1 illustrates the experimental results on a synthetic image without noise. Figure.1(a) shows the original image; Figure.1(b) is the reference image containing only the corners; Figure.1(c)-(f) demonstrate the images processed separately by the proposed algorithm (Corner Detection based on Orientation Estimation, CDOS for short), Harris and Stephens' algorithm (Harris), Smith and Brady's algorithm (Susan), Mokhtarian and Suomela's algorithm (CSS). TABLE Ⅰ summaries the qualification comparisons. In this experiment, the parameters for Harris are set as the Gaussian $\sigma_{gauss} = 0.7$, non-maxima suppression radius $\lambda_{scale} = 0.04$, the relative minimum threshold $\lambda_{relative\_\min} = 0.00001$; the geometry threshold for Susan algorithm is $B_{th} = 20$; In CSS, the original gauss filter $\sigma_{original} = 4.0$, the gauss filter for Canny $\sigma_{canny} = 1.0$, the double threshold is $T_{high} = 35.0$ and $T_{low} = 1.0$; while in our algorithm, the anisotropic gauss is $\sigma_x = 0.3$ and $\sigma_y = 0.7$, noise threshold $T_{noise} = 0$, the double threshold is decided by the edge ratio of the image, here it is estimated to be 0.2 and the proportion $T_{low}/T_{high} = 0.4$, the iteration time for non-linear diffusion $t = 20$.

To test the robustness to noise, we add some gauss noise to image#1 and get a synthetic image with noise. This time the parameters for Harris and Stephens' algorithm is $\lambda_{relative\_\min} = 0.4$ and the rest remains the same; Susan algorithm's geometry threshold is $B_{th} = 25$; the lower threshold of CSS is changed to 2.0; in the proposed algorithm the noise threshold is set as $T_{noise} = 5$ and the iteration time $t = 50$. As illustrated by Figure.2, the Harris and Stephens' algorithm detected 136 corners, Susan algorithm detected 112 corners, CSS algorithm detected 31corners, while our algorithm still detected the same 26 corners.

TABLE I. QUANTIFICATION COMPARISON OF EXPERIMENTAL RESULTS ON IMAGE#1

Algorithm	**Correct detection ratio**	**False detection ratio**	**Repetitious detection ratio**	**Mean localization error**
Harris	100%	9.68%	11.54%	1.67
Susan	100%	23.68%	6.90%	1.12
CSS	100%	9.68%	7.69%	1.15
CDOS	100%	0	0	0.69

TABLE II. QUANTIFICATION COMPARISON OF EXPERIMENTAL RESULTS ON IMAGE#2

Algorithm	**Correct detection ratio**	**False detection ratio**	**Repetitious detection ratio**	**Mean localization error**
Harris	96.15%	84.18%	19.23%	2.40
Susan	92.31%	88.17%	25%	1.81
CSS	96.15%	9.68%	6.46%	2.13
CDOS	100%	0	0	0.97

REFERENCES

[1] Bae, Sun Cheol, Kweon, In So, Yoo, Choong Don, COP: a new corner detector. Pattern Recognition Letters, 2002.23, 1349-1360.

[2] Brox, Thomas, From pixels to regions: Partial differential equations in image analysis, PhD Thesis, Mathematical Image Analysis Group, Department of Mathematics and Computer Science, Saarland University, 2005. Germany.

[3] Fei Shen, Han Wang, Corner detection based on modified Hough transform. Pattern Recognition Letters, 2002.23, 1039-1049.

[4] H.Freeman, L.S.Davis, A corner finding algorithm for chain code curves. IEEE Trans. on Computers, 1977.26, 297-303.

[5] D.S.Guru, , R.,Dinesh, Non-parametric adaptive region of support useful for corner detection: a novel approach. Pattern Recognition, 2004.37, 165-168.

[6] C.G.Harris, M.Stephens, A combined corner and edge detector. In: Proc 4th Alvey Vision Conf. Manchester, 1988. pp189-192.

[7] Hsin-Teng, W.C.Hu, A rotationally invariant two-phase scheme for corner detection. Pattern Recognition, 1996. 28, 819-828.

[8] F.Mokhtarian, R.Suomela, Curvature Scale Space Based Image Corner Detection. In: Proc. European Signal Processing Conference, Island of Rhodes, Greece, 1998.pp. 2549-2552.

[9] H.P.Moravec. Visual mapping by a robot rover. In: Proc. of the 6th International Joint Conference on Artificial Intelligence, 1979. pp 598-600.

[10] Olague, Gustavo, Hernndez, Benjamn, A new accurate and flexible model based multi-corner detector for measurement and recognition. Pattern Recognition Letters, 2005. 26:27-41.

[11] Ray Bimal Kumar, Pandyan Radhika, ACORD—an adaptive corner detector for planar curves. Pattern Recognition, 2003 . 36, 703-708.

[12] S.M.,Smith, J.M.,Brady, SUSAN - A new approach to low level image processing. International Journal of Computer Vision, 1997. 23, 45-78.

[13] Vincent Etienne, Laganière Robert, Detecting and matching feature points. Journal of Visual Communication and Image Representation, 2005.16, 38-54 .

[14] Wen-Yen Wu, Dominant point detection using adaptive bending value. Image and Vision Computing, 2003 .21, 517-525.

[15] Zhiqiang Zheng, Wang Han, Eam Khwang Teoh, Analysis of gray level corner detection. Pattern Recognition Letters, 1999. 20, 149-162.

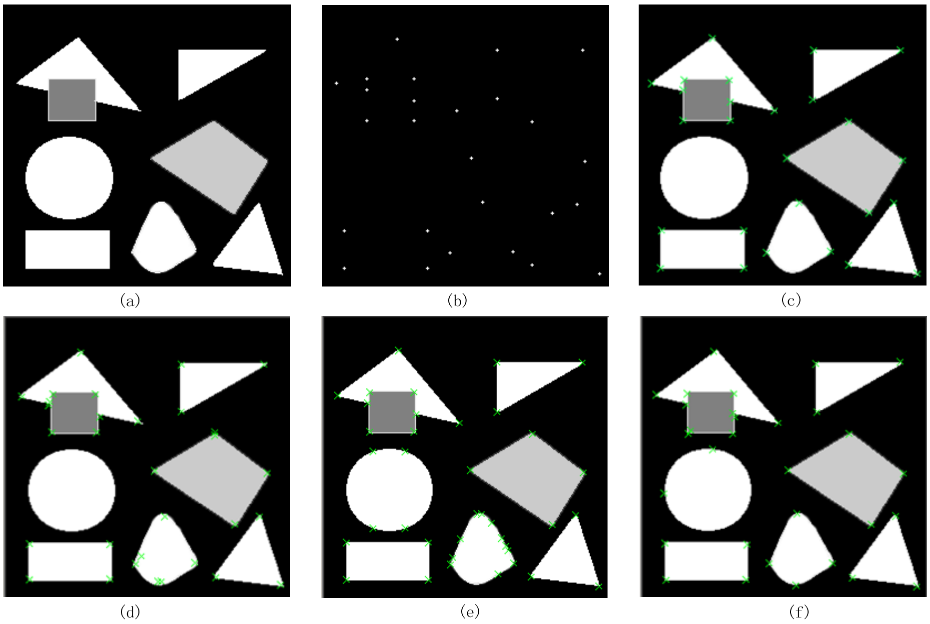

Figure 1. Experimental results on image1.
(a)image#1; (b)reference corner image ; (c)CDOS; (d)Harris; (e)Susan; (f)CSS.

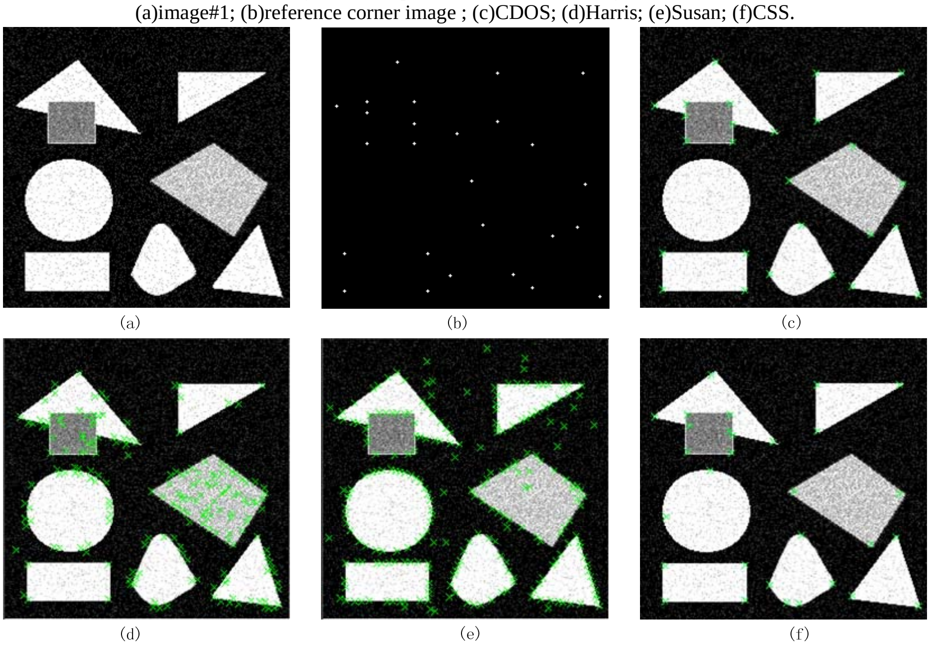

Figure 2. Experimental results on image2
(a)image#2; (b)reference image; (c) CDOS; (d)Harris; (e)Susan; (f)CSS.