

An Adaptive Corner Detection Algorithm Based on Edge Features

Zhanli Li¹

College of Computer Science and Technology
Xi'an University of Science and Technology
Xi'an, Shaanxi 710054, P.R.China
lizl@xust.edu.cn

Junchao Wang²

College of Computer Science and Technology
Xi'an University of Science and Technology
Xi'an, Shaanxi 710054, P.R.China
kindy_wjc@163.com

Abstract—Harris algorithm is classical and high speed corner detection method, but the detect result is dependent on the thresholds and the coefficients of the corner response function, and it is easy to lose and error detect corners, so it has lower accuracy of corner detection. In summary, an adaptive corner detection algorithm based on edge feature was proposed in this paper, the purpose of improve detection algorithm is to promote corner detection accuracy and ensure algorithm performance. Firstly the Canny operator is used to extract the edge information of image, and calculated the characteristic value of edge region is calculated by optimizing the corner response function; then, the adaptive threshold is obtained by the OSTU algorithm to extract candidate corner region; Finally, according to block detection and scale-invariant ideas, we use the non-maximum suppression algorithm is improved to remove false corners. Our proposed algorithm not only overcomes somewhat non-adaptive threshold and easily loss corner and error detection problem, but also improves speed detection. The experimental results show that our algorithm can improve the accuracy of corner detection, and can have ideal detection effect in different environments.

Keywords—corner response function; adaptive threshold; non-maximum suppression; edge detection

I. INTRODUCTION

The corner points represent the important local feature information of the pixels with drastic changes or the intersection of edge contours in gray images[1], it contains not only the main image feature information, but also has the advantages of sample calculation and stable results. The quality of corner detection results directly affects the computer vision processing works such as image recognition [2], image stitching [3], and 3D reconstruction [4]. Therefore, corner detection has important technical value and practical significance in the field of Computer Vision Measurement and Pattern Recognition.

The existing corner detection methods can be roughly divided into two categories: gray level information corner detection and edge contour information corner detection [5]. The Moravec algorithm [6], Harris algorithm [7] and Harris algorithm [8] are classical algorithms based on the gray intensity of pixels of gray level information corner detection. Edge detection [9] based on image edge contour information generally divides the detection process into three parts: edge detection, template construction and corner detection, and the commonly detection methods are based on edge chain

code [10], wavelet transform [11], and curvature scale space [12]. Harris corner detection as a kind of classical detection algorithm, there are many scholars behind the further improvement on the Harris algorithm framework, such as Wu [13] et al. proposed based on local region and multi-scale Harris corner detection fusion algorithm to improve corner detection performance. The algorithm constructs a local detection area through information theory, and uses a multi-scale Harris algorithm as a detector. Therefore, it does not need to calculate the characteristic value for each pixel point, reducing the amount of calculation, but also effectively inhibits the generation of mistake corner points. Deng [14] et al. constructed a corner selection circle template, and compared the relationship between grayscale information of inner and outer ring template pixels points and gray value of central point of the ring to remove the wrong corner points in Harris detection results. Deng [15] et al. solved the problem of manually setting the threshold through the adaptive algorithm of the largest difference between classes (OSUT) algorithm, but the improved algorithm detected corners contain a large number of pseudo-corner points, which is not conducive to the detection of light noise images. Zhang [16] et al. proposed a method based on gray difference and template to solve the problem of pseudo corners and corner omissions, and obviously reduce corner detection time. Mikołajczyk [17] et al. combined the Harris operator with the Gaussian scale space to overcome Harris corner detection problem in a single image. Zhang [18] et al. proposed an improved Harris corner detection for the problem of manually entering corner clustering and pseudo corners in a single threshold, rather than the image gray changes and local window selection affect the number of corner detection and matching accuracy.

For the problem that the coefficient k in the corner response function and threshold of the Harris algorithm, in the paper, we proposed an adaptive corner detection algorithm based on edge features. The proposed algorithm is compared with classical corner detection algorithm (Harris and Harris) to verify the rationality and reliability of this algorithm.

II. HARRIS CORNER DETECTION PRINCIPLE

The basic idea of the Harris algorithm is to use the central pixel point and gradient of surrounding gradient to judge the corner points, and introduce the differential operator and autocorrelation matrix method to effectively

distinguish corner points, smooth points and edge points. Assuming that the gray value of the pixel at the image (x, y) is $I(x, y)$, the pixel is shifted in the x, y direction by the small displacement u, v respectively, and the generated gray change is:

$$E(u, v) = \sum_{x, y} w(x, y) [I(x + u, y + v) - I(x, y)]^2 \quad (1)$$

$$= \sum_{x, y} w(x, y) \left[u \frac{\partial I}{\partial x} + v \frac{\partial I}{\partial y} + O(u^2 + v^2) \right]^2$$

In the formula is a two dimensional Gaussian smoothing function, generally defined as $w(x, y) = e^{-(x^2 + y^2)/s^2}$.

The matrix form of $E(u, v)$ is

$$E(u, v) \cong [u, v] M \begin{bmatrix} u \\ v \end{bmatrix} \quad (2)$$

Where M is an autocorrelation matrix, is can be derived by formula (1):

$$M = \sum_{x, y} w(x, y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \quad (3)$$

The variation of $E(u, v)$ obtained by formula (2) is mainly determined by the autocorrelation matrix M . However, due to complex calculation of the eigenvalue of the autocorrelation matrix, the corner response function (CRF) is usually chosen to be constructed:

$$CRF = \det(M) - k * \text{trace}^2(M) = (AB - C^2) - k(A + B)^2 \quad (4)$$

Equation (4) is the determinant of matrix M , which is the trace of matrix M . Calculate Gaussian weights for I_x^2 , I_y^2 and $I_x I_y$ respectively yields three elements A , B and C , where $A = I_x^2 \otimes w(x, y)$, $B = I_y^2 \otimes w(x, y)$, $C = I_x I_y \otimes w(x, y)$. The CRF coefficient k is a classical constant of the Harris algorithm and is generally 0.04 to 0.06. A window with a radius of 3 is taken at the center of each pixel. If the CRF value of the pixel at the corner point is greater than the threshold set by a person and is the maximum value in the window, the pixel can be determined as a corner point.

III. IMPROVED ADAPTIVE HARRIS CORNER DETECTION ALGORITHM

A. Improve Algorithm Ideas

The classical Harris corner detection shows excellent performance in terms of brightness and rotation, but is still has the following deficiencies: 1) The size of the coefficient k needs to be set in advance when calculating the pixel point response function. 2) The corner point filtering needs constant trial and error, after the specified threshold size. 3) non-maximal suppression of the lack of local detail corner suppression. This paper proposes an adaptive corner detection algorithm based on edge features for the proposed three problems. For an image, firstly, the Canny operator is used to find the edge mapping of the input image. Then, according to the optimized corner response function the feature points of the pixels at the edge mapping are calculated. Finally, the candidate corner sets of the corner feature are extracted using the OSTU method, and the final set of best features is obtained by using the improved non-

maximum suppression algorithm for the candidate point set. The flow chart of this algorithm is shown in Figure 1.

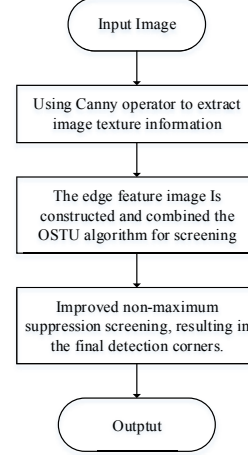


Figure 1. Texture feature corner detection algorithm flow chat

B. Improved Algorithm Implementation Steps

1) Extracting Edge Features and Constructing Corner Feature Images

Using classical Canny operator to obtain the image edge map, and calculate the horizontal and vertical gradient I_x and I_y , of the pixel point $I(x, y)$ at the edge mapping area (x, y) , and through the Gaussian smoothing function $w(x, y)$ computing (x, y) pixel autocorrelation matrix. After experiments verify that the Gaussian smoothing window size is not more than 5×5 , and the Canny operator threshold is 0.4 times the maximum pixel value. In order to avoid the need to artificially set the coefficient k in the calculation process of equation (3), the improved corner response function reduces the randomness of k selection and determines the position of the corner point:

$$CRF = \frac{\det(M)}{(\text{trace}(M))^2 + \varepsilon} \quad (5)$$

Since the autocorrelation matrix M of the corner points in the image is larger, the CRF value is also larger and pixel points are more likely to be corner points. In addition, the choice in formula (5) should be small enough to select 0.000001.

2) Getting Adaptive Threshold

The largest inter-class difference (OSTU) algorithm is a binary segmentation technique that find the threshold point of maximum variance. Assuming that the number of pixels of an image is N , the pixel value range is $[0, L]$, and the number of pixel points defining the image gray value i is n_i , indicating the probability of occurrence $p_i = n_i / N$ and the pixels in the image are divided into two major categories $T_1 = \{1, 2, 3, \dots, t\}$ and $T_2 = \{t + 1, t + 2, \dots, L\}$, then T_1 and T_2 have the probability w_1, w_2 :

$$w_l = \sum_{i=0}^l p_i = w(t) \quad (6)$$

$$w_2 = \sum_{i=l+1}^L p_i = 1 - w(t)$$

$\mu(t)$ is the pixel mean at $[0, t]$, and the formula is

$\mu(t) = \sum_{i=0}^t i * p_i$. μ_0, μ_1, μ_2 indicate the average pixel value of the T_1, T_2 and entire image, and the calculation formula is:

$$u_0 = w_1 \mu_1 + w_2 \mu_2$$

$$u_1 = \frac{1}{w_1} \sum_{i=0}^l i p_i = \frac{u(t)}{w_1} \quad (7)$$

$$u_2 = \frac{1}{w_2} \sum_{i=l+1}^L i p_i = \frac{u_0 - u_1}{w_2}$$

According to the knowledge of probability theory, the threshold value of t^* of the maximum variance between the pixels value $[0, L]$ is calculate to make the best diagonal image segmentation effect. The OSTU function is:

$$\sigma_i^2 = w_1(u_0 - u_1)^2 + w_2(u_0 - u_1)^2 \quad (8)$$

3) Improved Non-maximal Suppression Method to Extract The Optimal Corner

In order to collect high-quality corner points from the candidate corner points, this paper uses the modified non-maximum suppression algorithm to segment the candidate corner points and extract the optimal corner points based on the idea of block and scale invariant processing. The specific algorithm steps are as follows:

Firstly, we extract the regions with sharp changes in feature value of corner feature image, and divide these regions into $(n+1) \times (n+1)$ pixel square sub-blocks. Secondly, for each sub-block, a radius 2 circular template (figure 2) is used to search for feature points with maximal points, and the remaining pseudo-corner points are eliminated. Finally, all the candidate points in the image are tested with global non-maximum values to obtain the optimal corner points.

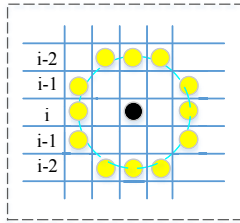


Figure 2. Improved non-maximum template method

IV. EXPERIMENTS AND ANALYSIS

This paper selects five images with different scene complexity from the classic corner image to verify the superiority inferiority of the proposed algorithm, experimental data includes classic grid image and building image. The results are compared using the classic Harris, SUSAN, and the improved algorithm. Experimental

environment inter(R) Core(TM) i7-4790 CPU processor, 8G memory, 64-bit win10 operating system, Matlab R2016a.

Figure 3 and 4 show the detection results of the classic grid and building images with clear corners of the three detection algorithm. It can be seen from simulation experiments that SUSAN detects the most corner points because the selection threshold is too small, and the screening template is too rough. Harris detects the least corner points because the Harris algorithm only uses image gray information and setting thresholds are not resonable. The improved algorithm uses the edge features of the image to accurately locate the corner points, and the threshold value is avoided by the adaptive threshold to avoid the problem of manual setting. The real corners detected by the improve algorithm are the most and pseudo corners are the least.

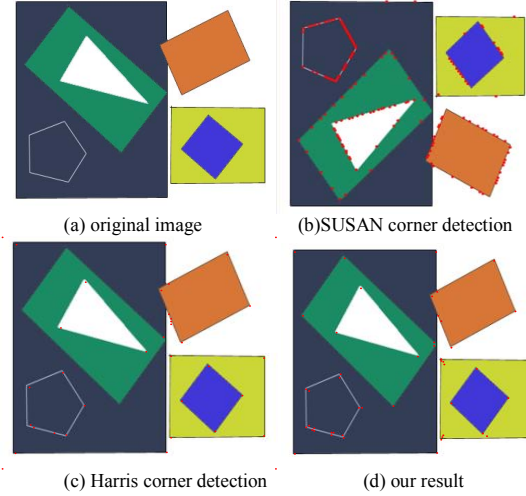


Figure 3. Corner detection of the classical grid image

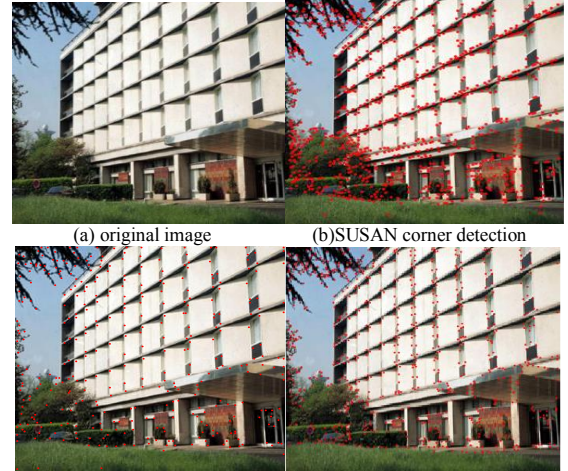


Figure 4. Corner detection of the building image

This article has been experimentally and intuitively concluded that the improved algorithm has a more robust detection result than the other two algorithms(eg. SUSAN, Harris) in detecting corner points. The specific experimental data is shown in Table 1.

TABLE I. LIST OF PARAMETERS

Figure Number	Algorithm	Coefficient k	Number of Corner Detection	Times
1	Harris	0.06	30	0.4687
	SUSAN	~	157	4.0469
	Improved Algorithm	~	51	0.2656
2	Harris	0.06	374	0.6562
	SUSAN	~	944	4.3438
	Improved Algorithm	~	729	0.6968

The above experimental data analysis can be concluded that the proposed algorithm is faster than the SUSAN algorithm in execution efficiency, and comparable or even better than the Harris algorithm. If the image edge information is the fastest detection speed, the execution speed is comparable to the Harris algorithm in complex cases. The number of corner detections is more than that of the Harris algorithm, which is less than the SUSAN algorithm. The reason is that the image edge features are introduced in this paper. The autocorrelation threshold and the improved non-maximum suppression algorithm are used to fundamentally guarantee the detection speed to improve the accuracy of corner detection results. In summary, the proposed algorithm can obtain better corner detection results in corner detection, and provide a reliable and stable data source for feature point matching of large-scale scene splicing and 3D reconstruction.

V. CONCLUSION

The main work of this dissertation is to solve the problem that the Harris algorithm is too dependent on the corner response function coefficient k and the threshold. The strategy of combining the edge feature construction corner feature map and the OSTU algorithm is to introduced to avoid the influence of jamming in the Harris algorithm on the corner detection result. In this paper, the main advantages of the improved algorithm are the following: 1) The corner feature map is constructed by the Canny edge detection algorithm, and the possible area of corner points is marked. 2) Automatic threshold segmentation through the OSTU algorithm reduces jamming interference and improves the reliability of the corner detection results. 3) Improved the non-maximal suppression algorithm by blocking and rotation invariance, and reduce the pseudo-corner of the image from refined to simple screening. Through a lot of experimental analysis, the robustness of the proposed algorithm in corner detection of various scenes are verified, and it has better practical application value.

REFERENCES

- [1] Chen J, Zou L, Zhang J, et al. The Comparison and Application of Corner Detection Algorithms[J]. Journal of Multimedia, 2009, 4(6):435-441.
- [2] Kitti T, Jaruwan T, Chaiyaporn T. An Object Recognition and Identification System Using the Harris Corner Detection Method[J]. 2012.
- [3] Zhou Z, Yan M, Chen S, et al. Image registration and stitching algorithm of rice low-altitude remote sensing based on Harris corner self-adaptive detection[J]. Nongye Gongcheng Xuebao/transactions of the Chinese Society of Agricultural Engineering, 2015, 31(14):186-193.
- [4] Bagchi P, Bhattacharjee D, Nasipuri M. A robust analysis, detection and recognition of facial features in 2.5D images[J]. Multimedia Tools & Applications, 2015, 75(18):1-38.
- [5] Y. X. Xing, D. Y. Zhang and J. H. Zhao, An Adaptive Threshold Corner Detector Based on Multi-scale Chord-Angle Sharpness Accumulation [J]. Geomatics and Information Science of Wuhan University, 2015, 40(5):617-622.
- [6] Moravec H P. TOWARDS AUTOMATIC VISUAL BBSTACLE AVOIDANCE[C]// International Conference on Artificial Intelligence. 1977.
- [7] Harris C J. A combined corner and edge detector[J]. Proc Alvey Vision Conf, 1988, 1988(3):147-151.
- [8] Smith S M, Brady J M. SUSAN—A New Approach to Low Level Image Processing[J]. International Journal of Computer Vision, 1997, 23(1):45-78.
- [9] Y. L. Zhao, W. C. Zhang and Y. H. Li, Novel contour-based corner detection with adaptive threshold [J]. Journal of Image and Graphics, 2016, 21(11):1502-1514.
- [10] Zhang W C, Shui P L. Contour-based corner detection via angle difference of principal directions of anisotropic Gaussian directional derivatives[J]. Pattern Recognition, 2015, 48(9):2785-2797.
- [11] H. Y. Zhao and Y. L. Zhu, A Method of Fuzzy Set Registration Based on Wavelet Transform and Harris Corner Detection[J]. Electronics Optics & Control, 2016(5):45-49.
- [12] J. D. Sun, Q. Q. Guo and Z. S. Zhang, Contour Corner Detection Based on Curvature Scale Space [J]. ELECTRONIC ENGINEERING, 2009, 36(7):78-82.
- [13] P. W. H. L. X and W. L. L., Multi-scale Harris-corner detection algorithm based on region detection [J]. Journal of Harbin Engineering University, 2016, 37(7):969-973.
- [14] Q. Y. Deng, C. W. Qu and Y. J., Improved corner detection algorithm based on circle mask via Harris [J]. Systems Engineering and Electronics, 2016, 38(4):949-954.
- [15] X. D. Deng, Y. Q. Du and C. Y. Wang, An adaptive threshold corner detection algorithm based on auto-correlation matrix of image pixel [J]. Transactions of the Chinese Society of Agricultural Engineering, 2017, 33(18):134-140.
- [16] L. T. Zhang, X. L. Huang, L. L. Lu and Z. K. Xu, Fast Harris corner based on gya difference and template[J]. Chinese Journal of Scientific Instrument, 2018, 39(02):218-224.
- [17] Mikolajczyk K, Tuytelaars T, Schmid C, et al. A Comparison of Affine Region Detectors[J]. International Journal of Computer Vision, 2005, 65(1-2):43-72.
- [18] J. S. Zhang, H. M. Zhang and Y. T. Luo, Image registration method based on improved Harris corner detection algorithm [J]. Laser & Infrared, 2017, 47(2):230-233.