

Harris Scale Invariant Corner Detection Algorithm Based on the Significant Region

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Abstract

The traditional Harris corner detection algorithm is sensitive to scale change, corners detected throughout the entire image under complex background, thus extracting more false corners, lead to the follow-up of large amount of calculation and a high rate of error matching. To solve this problem, this paper proposes an optimized Harris corner detection algorithm. First, a significant region detection method is used to extract the target area, and take closing operation for the result figure, can effectively achieve target and background segmentation; second, scale invariant describing methods is applied to Harris algorithm, at the same time, combined with the non-maximum suppression methods to extract corners, get more right corners. Through experiment contrasts, the algorithm used in this paper can be improved more corner detection performance.

Keywords: *Harris; Significant area; Scale invariant; Non-maximum suppression*

1. Introduction

Corner is an important local feature of image, can be defined as the sudden changes pixel in gray value, or the intersection point of object contour edges, which retains the important feature information of objects at the same time effectively reduces the amount of data information. Corner has the characteristics of simple extraction process, stable result and strong adaptability to algorithm. Accuracy and stability of corner extraction has a direct impact on the subsequent visual processing tasks such as image matching, image stitching, object recognition [1], therefore corner detection plays a very important role in image processing and pattern recognition.

Currently, corner detection algorithm can be mainly divided into the follow two categories: the corner detection algorithm based on the edge and the corner detection algorithm based on the gray change. The first category, first extracting the chain code of image edge, according to the difference between adjacent code values to determine whether it is corner, the algorithm has the disadvantages of large amount of calculation and process instability [2]. The second category, calculating the curvature and gradient to detect corner, the typical representative algorithms: Moravec algorithm, Harris algorithm, SUSAN algorithm [3]. In which Harris algorithm has been widely used because of simple calculation, extraction corners ideal and high stability. But Harris algorithm exists the follow problems, corners spread throughout the entire image under complex background in the image, can not accurately extract the target, there is no guarantee the invariant of corners when image has large scale change, and common thresholds can not be set, etc[4].

Scale invariant feature theory is introduced into the Harris feature detection algorithm in literature [5] and [6], to realize the scale invariant of Harris feature corner detection, but this algorithm can not provide a large number of stable feature points. Through the

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study of Harris scale invariant key point detectors in literature [7], which corrects the wrong conclusions that Harris scale invariant detector is instable. In literature [8], the scale space combined with Harris operator, setting the threshold value can obtain relatively stable corner, but for the fixed threshold, which is not universal for different image. Literature [9] combines the scale space and the adaptive threshold method, to detect false corners less, but the corners extracted throughout the entire image, which it is not conducive to the target object detection. Based on the literature [9], in this paper, a optimize Harris detection algorithm based on significant region detection algorithm is proposed, to improve the accuracy of corner detection, doing comparative experiments with traditional Harris algorithm and the algorithm of literature [9], to verify that the algorithm is capable to effectively extract corner information of the image.

2. Harris Corner Detection Algorithm

The Harris operator is evolved on the basis of Moravec operator, by calculating the auto-correlation matrix and the gray value change to get the corners. Assumed $f(x, y)$ is gray value of pixel (x, y) , after moving (u, v) , the gray intensity change can be expressed by the following formula:

$$E_{u,v}(x, y) = \sum_{u,v} w_{u,v} [f(x+u, y+v)]^2 \quad (1)$$

By Taylor formula launching to:

$$f(x+u, y+v) = f(x, y) + f_x u + f_y v + O(u^2 + v^2), \text{ wherein,}$$

$$f_x = \frac{\partial f}{\partial x}, \quad f_y = \frac{\partial f}{\partial y}, \quad f_{xy} = \frac{\partial f}{\partial x} \frac{\partial f}{\partial y}.$$

Into the formula (1), to:

$$\begin{aligned} E_{u,v}(x, y) &= \sum_{u,v} w_{u,v} [f_x u + f_y v + O(u^2 + v^2)]^2 \\ &\approx \sum_{u,v} w_{u,v} [f_x u + f_y v]^2 \\ &= \sum_{u,v} w_{u,v} [(f_x u)^2 + 2f_{xy} uv + (f_y v)^2] \\ &= \sum_{u,v} w_{u,v} [u, v] \begin{bmatrix} f_x^2 & f_{xy} \\ f_{xy} & f_y^2 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} \\ &= \sum_{u,v} w_{u,v} [u, v] M \begin{bmatrix} u \\ v \end{bmatrix} \end{aligned}$$

Wherein, $M = w_{u,v} \begin{bmatrix} f_x^2 & f_{xy} \\ f_{xy} & f_y^2 \end{bmatrix}$, that is the auto-correlation matrix of pixel (x, y) . To

improve noise immunity, the window function selected the Gauss smoothing function,

$$w_{u,v} = e^{-\frac{(u^2+v^2)}{2\delta^2}}$$

Harris corner response function is:

$$R = \det M - k(\text{tr}M)^2$$

Wherein, $\det M$ is the determinant of matrix, $\text{tr}M$ is the trace of matrix, k is experience value, usually takes $0.04 \square 0.06$. Make λ_1, λ_2 as the two characteristic values of the matrix, which reflect the surface curvature of two principal axes in the image, diagonalizable processing obtains:

$$E_{u,v}(x, y) = D^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} D, D \text{ is the rotation factor.}$$

Therefore, $\det M = \lambda_1 \lambda_2, \text{tr}M = \lambda_1 + \lambda_2$. When λ_1 and λ_2 both are larger, shows that the local auto-correlation function has a peak, the curvature change of the pixel along any direction is larger. When Harris operator value is extreme value in the local region and is greater than the threshold, it is the corner that needed.

The corner detection results of above method are shown in Figure 1, We can know that, in practice, Harris operator is a kind of simple and stable corner detection operator, but for the complex background in the images, corners are detected that exist in the entire image, and Harris operator is sensitive to the change of scale, while the image scale changes (rotation, scaling, et), test results may be quite different. At the same time, the extraction effect of Harris corner algorithm is totally depended on the setting threshold, if the threshold too large will lose some corner information, and too small will detect more false corners.

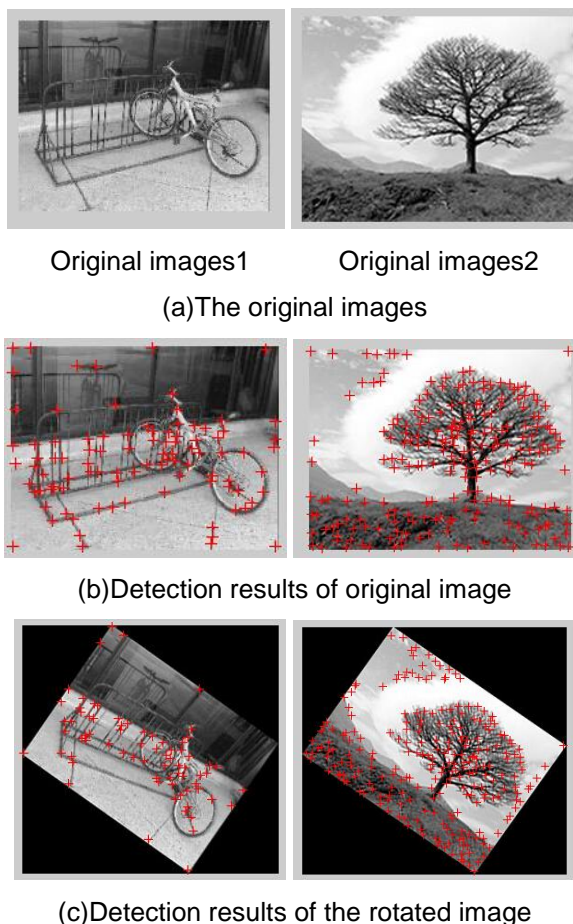


Figure 1. Results of Traditional Harris Corner Detection Algorithm

3. The Improved Harris Corner Detection Algorithm

According to above problem of Harris, the paper in algorithm can be divided into two parts: The first part, saliency detection method is used to extract the target in the image, corners are more concentrated in the target area. The second part: The method of scale space theory combing with the non-maximum suppression is used to detect corner, can improve the automation capabilities of the image.

3.1. Significant Region Detection Method

The image information can be divided into two parts: redundancy and change.

$$H(\text{image}) = H(\text{Innovation}) + H(\text{Prior Knowledge})$$

Since the human visual is sensitive to the change of the region, significant region detection retains conversion section of image, and remove redundant parts. Literature [10] and [11] proposed a simple calculation model based on image visual significance, by calculating the residual spectrum of logarithm to extract significant region.

For a natural image, \log amplitude spectrum is the amplitude spectrum that after the Fourier transform takes natural logarithm, it approaches a straight line, the average amplitude spectrum after Fourier transform and frequency is proportional:

$$E\{A(f)\} \propto \frac{1}{f}$$

Then, a significant area of an image is \log amplitude spectrum minus the average \log amplitude spectrum. Calculation process is:

$$R(f) = L(f) - A(f)$$

$$L(f) = \log(A(f))$$

$$A(f) = h_n(f) * L(f) \quad h_n(f) = \frac{1}{9} \begin{vmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{vmatrix}$$

$$S(f) = iFFT[\exp(R(f) + P(f))]^2$$

Among them, $R(f)$ is the residual spectrum of the image, $L(f)$ is \log amplitude spectrum, $A(f)$ is the \log average amplitude spectrum, $h_n(f)$ is a $n*n$ convolution kernel of mean filtering, in this paper n takes 3. $P(f)$ represents the phase spectrum, and $S(f)$ represents the final significant region.

In order to get the image saliency region, need to binary processing for significant figure, that needs a threshold to divide background and objective, binary image obtained is expressed as:

$$O(f) = \begin{cases} 1 & S(f) > Th \\ 0 & otherwise \end{cases}$$

The image is divided into background and the target two parts, if the ratio that target pixel occupies whole image is w_1 , average gray value of pixels is u_1 , then the

ratio that background pixel occupies whole image is $1-w_1$, average gray value of pixels is u_2 . t is the gray value of the image from small to large, g represents the total variance between classes of the image, the threshold that using traversal method obtains maximum variance is the threshold needed.

$$g(t) = w_1 w_2 (2u_1 - 1)^2 = \max$$

$$Th = t$$

There still may be many scattered, small salient region on the background part of the image to interfere with selecting for target part, to make the generated target figure not enough clear. Thus, after threshold segmentation, take the operation from corrosion to expansion for the binary figure, eliminate the small salient regions on the background part and fill small voids on the target part, to connect adjacent objects and smooth boundary. We use closing operation to erosion and dilation image.

$$E(x) = X \square B = \{z \mid B(z) \subset E\}$$

$$D(x) = Y \oplus B = \{z \mid B(z) \cap E\}$$

$$CLOSE(x) = E(D(x))$$

This method can effectively form a target figure, at the same time it will not change the original area of the object, so that the segmentation is more accurate. By this method, the segmentation results based on the significant region detection are shown in Figure 2.

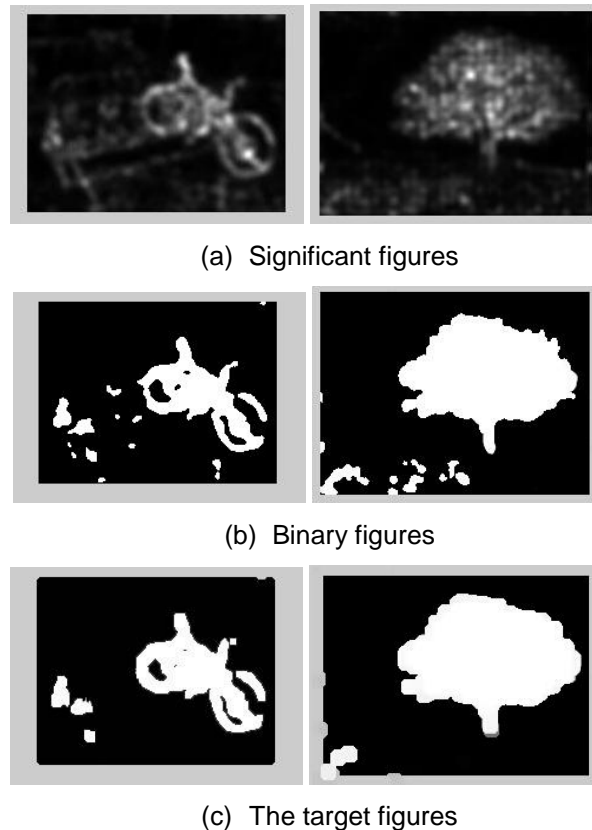


Figure 2. Significant Region Detection Segmentation Results

3.2. The Scale Invariant Harris Corner Detection Algorithm

Scale space describes the image characteristics at different scales. Lindeberg pointed out that the Gaussian kernel is the only transform core to realize scale transformation, owns linear, shift invariant, rotation invariant etc [12]. Mikolajczyk *et. al.*, in the theoretical basis of the scale automatic selection, put forward with the scale invariance of the Harris operator [13].

Harris detection is based on the auto-correlation matrix to calculate, when the differential scale is δ_D , Gauss kernel differential function is $w(x, y; \delta_D)$, then,

$$f_x(x, y; \delta_n) = f_x \otimes w_x(x, y; \delta_n),$$

$$f_y(x, y; \delta_n) = f_y \otimes w_y(x, y; \delta_n).$$

Autocorrelation matrix of multi-scale Harris operator defines as follow [14]:

$$M = \delta_D^2 w(x, y; \delta_D) \otimes \begin{bmatrix} f_x^2(x, y; \delta_D) & f_x(x, y; \delta_D) f_y(x, y; \delta_D) \\ f_x(x, y; \delta_D) f_y(x, y; \delta_D) & f_y^2(x, y; \delta_D) \end{bmatrix}$$

Where, δ_I is integral scale, $\delta_I = s\delta_D$, s is constant. By the two order matrix, to determine the response function value of the improved Harris operator is:

$$R = \text{Det}(M) - k(\text{tr}M)^2$$

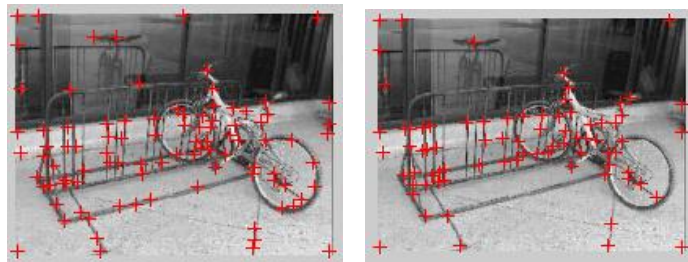
In this paper, using non-maximum suppression processes the response function, to avoid calculating the threshold value, automation capabilities of the algorithm is improved. Select 3*3 square template and get maximum points in the template area, mathematical expression describes as follows:

$$\begin{aligned} &R(i, j) > 0.01 * R_{\max} \&\& R(i, j) > R(i-1, j-1) \&\& R(i, j) > R(i-, j) \&\& R(i, j) \\ &> R(i-1, j+1) \&\& R(i, j) > R(i, j-1) \&\& R(i, j) > R(i, j+1) \&\& R(i, j) > \\ &R(i+1, j-1) \&\& R(i, j) > R(i+1, j) \&\& R(i, j) > R(i+1, j+1) \end{aligned}$$

The point that gets the maximum $R(i, j)$ is the Harris corner, record its position (i, j) , to facilitate marking and matching corners. Corners obtained by this method are not particularly dense, very uniform dispersion on the image.

4. Experimental Results and Analysis

In order to verify the effectiveness of the proposed algorithm, use two images to simulate. In this paper, significant regional is used to optimize scale invariant Harris algorithm, the corner detection results of the algorithm are compared with the traditional Harris and the algorithm of literature [8], at the same time, use the algorithm of this paper to detect the rotation image, as shown in Figure 3.



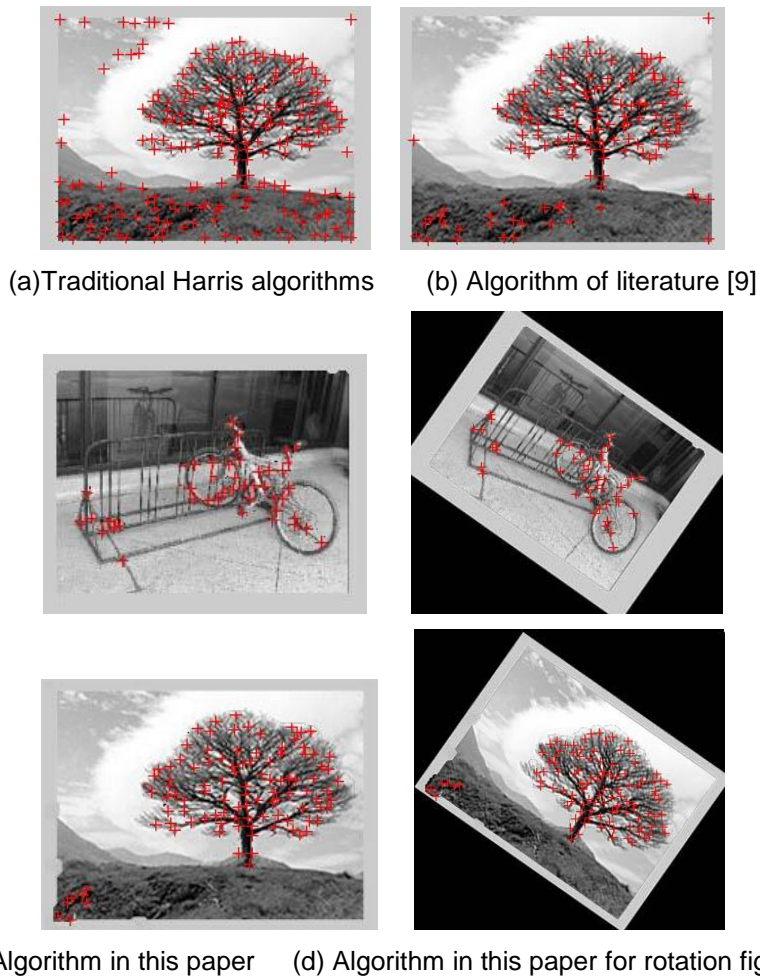


Figure 3. Comparison Figures of Three Algorithms Experimental Results

Experiment result figures and the **Table 1.** show that using the algorithm of this paper, the corners more focus on the object, and improve the corner detection accuracy, also can effectively overcome the Harris algorithm scale sensitivity, to reduce the amount of subsequent calculation. The **Table 2.** shows that algorithm of this paper can improve the speed for corner detection, when the more complex background and corners, the more quickly using the optimized Harris algorithm.

Table 1. Comparison of Corners of Three Algorithms and Rotated Image

	Original images1	Original images2
Traditional Harris algorithms	143	221
Algorithm of literature[9]	92	126
Algorithm of this paper	42	105
Algorithm of this paper for rotation figure	45	105

Table 2. Comparison of Time of Three Algorithms

	Original images1	Original images2
Traditional Harris algorithms	0.35509	0.46753
Algorithm of literature[9]	0.30217	0.41361
Algorithm of this paper	0.28476	0.40249

5. Conclusion

The paper combines some advantages of existing algorithms, aiming at some shortcomings of Harris corner detection algorithm, such as be sensitive to scale change, corners distribute in the entire image, and influence the detection of the target. By using the method of significant region detection, can effectively extract the target, so that feature points are concentrated on the target, at the same time, scale space combines with the non-maximum suppression, can optimize Harris corner detection algorithm, and reduce the amount of detected corners. Experimental results show that the detection algorithm is more quickly and reasonable.

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