The Harris Corner Detection Method Based on Three Scale Invariance Spaces

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Abstract

In order to solve the problem that the traditional Harris comer operator hasn't the property of variable scales and is sensitive to noises, an improved three scale Harris corner detection algorithm was proposed. First, three scale spaces with the characteristic of scale invariance were constructed using discrete Gaussian convolution. Then, Harris scale invariant detector was used to extract comers in each scale image. Finally, supportable and unsupportable set of points were classified according to whether the corresponding corners in every scale image support that of the original images. After the operations to those unsupportable set of points, the noised corners and most of unstable corners could be got rid of. The corners extracted by the three and the original scale spaces also had scale invariant property. The experiments results proved that, compared with the scale space on the whole Gaussian pyramid, the utilization factor of the image was increased, the calculation time is decreased, and the image was high recurrence rate and stability.

Keywords: *Harris corner detect, three scale spaces, scale invariant feature, Gaussian convolution, improved algorithm*

1. Introduction

Corners detection is the key step in the image processing, and the Harris comer detector is based on the gray scales of images, much sensitive to the change of the image scale. Based on the Lindberg [1]-[2] theory of the scale automatic selection, Mikolajczyk etc. [3]-[4] studied the construction of Harris scale invariant detector in the scale space of images. But the Harris scale invariant detector couldn't provide stable key points. The reference [5] researched systematically the parameter spaces constituted by the parameters capable of affecting the performance of the Harris scale invariant detector, and the experiments result corrected the conclusion that the Harris scale invariant detector is unstable. The reference [6] constructed multi-scale spaces using different integral scales. Combined with the image blocking method, the Harris comers were extracted, realizing the accurate location in small scale and removing false and remaining reality in large scale. But the proportional relations between the integral and the differential scales were not given, ignoring the role of the differential scales in the establishing of the scale space image.

Aiming at the problem of the traditional Harris detectors without the property of variable scales and is sensitive to noises, this paper proposed an improved three scale Harris corner detection method. Three scale spaces were constructed through selecting reasonably the parameters δ, S and t that influence the performance of the Harris scale invariant detector. Harris comers in each scale images were extracted by the Harris scale invariant detector and the supportable and unsupportable set of points were classified according to whether the corresponding corners in every scale image support that of the original images. The method could remove the noised corners and most of unstable corners effectively, and extracted and increased the corners with the characteristic of scale invariance.

2. Harris corner detect lgorithm

The equation of Harris corner detect algorithm [7] is:

$$M = G(\bar{s}) \otimes \begin{pmatrix} g_x^2 & g_x g_y \\ g_x g_y & g_y^2 \end{pmatrix} \tag{1}$$

Where, g_x is the gradient in x direction; g_y is the gradient in y direction; $G(\bar{s})$ is the Gaussian template.

The corner response function of Harris algorithm is:

$$R = \det M - ktr^2 M \tag{2}$$

Where, R is the response function of the corner required; det M is the Matrix determinant; tr M is the Matrix trace; k is the default constant, and is generally 0.04-0.06.

In the practice, the center value R of an image is calculated and if the value is the maximum in the neighborhood and larger than a given threshold, the point is regarded as a corner point.

In order that the second moment Matrix to detect Harris corners in the scale space was adaptable to the change of scales, the secondary moment Matrix after scale adjustment was adopted expressed followed:

$$M = \mu(x, y, \delta_I, \delta_D) = \delta_D^2 g(\delta_I) \begin{bmatrix} I_x^2(x, y, \delta_D) & I_x I_y(x, y, \delta_D) \\ I_x I_y(x, y, \delta_D) & I_y^2(x, y, \delta_D) \end{bmatrix} \quad (3)$$

Where, δ_I is the integral scale; δ_D is the differential scale, and $\delta_I = \delta_D$; S is the constant; I_x and I_y is the gradient in the x and y direction.

When $R_{mazx} = \max(R)$, $R \geq 0.01 R_{\max}$, and the maximum value of 3×3neighborhood is got, the current point is a corner. It is the gradient that is calculated by Harris operators, so it is changed only in directions, independent of the image brightness, that is, the algorithm has the feature of rotational invariance.

3. Improved Harris corner detect algorithm with three scale invariance spaces

In order to solve the defects that the traditional Harris comer detector is sensitive to scale spaces and noises, an improved three scale Harris corner detection algorithm was proposed.

The theory of the scale space is first used to simulate the multi-scale features of images in the computer vision field. Lindeberg etc. demonstrated that the Gaussian kernel function is the only linear kernel. The Gaussian kernel function with the variable scales is [8]:

$$G(x, y, \delta) = \frac{1}{2\pi\delta^2} e^{-\left(x^2+y^2\right)/2\delta^2} \quad (4)$$

An image in a scale could be expressed the convolution of the image and the variable Gaussian kernel function, and the expression of the LOG operator is:

$$L(x, y, \delta) = G(x, y, \delta) * I(x, y) \quad (5)$$

Where, (x, y) is the space coordinate and the little δ represents the little smoothing of the image, and the corresponding scale is small. Large scales correspond to the general view of images, and small scales correspond to the details of images.

Traditional Method of Lowe [9]-[10] realized Harris scale invariance detector. In the process of establishing the Gaussian pyramid image, Harris corners of every points in every sub-scale space were calculated according to equations (1) and (2) , and compared them with the Harris corners of 26 neighborhood points located at 3 adjacent scales. If the Harris corner get the local maximum value and larger than a given threshold, it is extracted as the key point.

Experiments show that, establishing whole pyramid will cost much time, and the number of Harris corners extracted from every image is close related to the $R_{\max}$ of the image.
Generally, if the value of $R_{\max}$ is small in an image, the value of R at every point of the image is also small, impossible to be larger than all the 26 neighborhood points. So a little of the image in the pyramid is contributed, and the number of the corners extracted is small. Solving the problem would cost more time to establish more layers of pyramid. The value of $R_{\max}$ is determined by δ and S, and to different images, the different value of δ and S would also increase the calculation complex and the time.

In this paper, three Gaussian kernel functions with different scales $G_1(x, y, \delta_1)$, $G_2(x, y, \delta_2)$ and $G_3(x, y, \delta_3)$ were established, and the four images in their scale spaces including the original image were constructed. The corners of the four images were extracted by Harris, where $\delta_2 = t\delta_1$, $\delta 3 = t^2 \delta_1$. The unstable and noise corners without scale invariance were removed. Then the corners calculation was increased, assuring the numbers of the corners extracted. The steps were:

(1) Based on the original image L0, three space images L1, L2, L3 with different scales were established by three Gaussian kernel functions with different scales $G_1(x, y, \delta_1)$, $G_2(x, y, \delta_2)$, $G_3(x, y, \delta_3)$. Experiments showed that the suitable value of δ is 0.6-1.2 and the t is 1.5-2.5.

(2) The Harris corners of the four images were extracted according to the equations (1) and (2). Experiment showed that the suitable value of S is 0.4-1.0.

(3)If the corner a_0 in the image L0 could be found in other 5×5 neighborhood of other images with different scales, it would be regarded as being supported by corners in other scale spaces and the corner a_0 could be reserved.

Otherwise, the corner a_0 would be removed. The number of the reserved corners was z_1.
(4) Corners in the images L1, L2, L3 were separated into the corners supporting L0 and the corners not supporting L0. The corners collections not supporting L0 in the three images L1, L2, L3 were recorded as $a_1[n_1]$, $a_2[n_2]$, $a_3[n_3]$.
(5) For the corner a_1 in the $a_1[n_1]$, if it could be found that at least one corner was the corner a_1 in the $a_2[n_2]$ and $a_3[n_3]$ with 5×5 neighborhood of images L2, and L3, the corner a_1 of the $a_1[n_1]$ in the image L1 would be regarded as the corner with scale invariance.
(6)The step (4) was repeated to the L2 and L3 according to the same principle.
(7) Errors were calculated among the corners extracted from the images L1, L2, and L3 and the corresponding corners in the original image L0. The formula is:

$$\overline{x}_{L_i} = \frac{\sum_{j=1}^{n}\left(x_{0j} - x_{ij}\right)}{n} \tag{6}$$

$$\overline{y}_{L_i} = \frac{\sum_{j=1}^{n}\left(y_{0j} - y_{ij}\right)}{n} \tag{7}$$

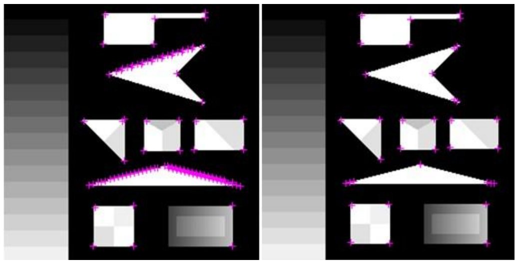
Where, $\overline{x_{Li}}$, $\overline{y_{Li}}$ were the error in the directions x and y ; x_{ij}, y_{ij} were the corner s' coordinates; n is the number of supporting corners.
(8) The pixel coordinates in the original image were recovered through the steps (4) and (5). If the calculated errors by the step (7) were less than given values, the corners were regarded as the corners with scale invariance. The number was z_2, and the whole number of the corners with scale invariance were recorded $z_1 + z_2$.

4. Experiments and Analysis to the algorithm

In order to prove the superiority of the algorithm, the improved algorithm of Harris corners extraction were tested in a variety of circumstances, compared with traditional method of Harris corners detection.

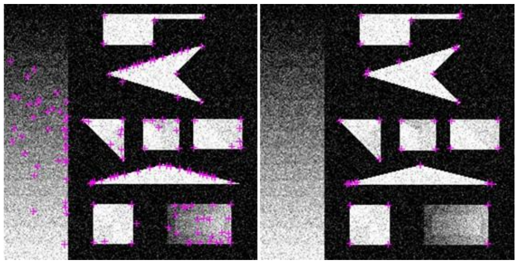
Four pictures with the various changes were used in the experiments, and the compared results were given, where (a) was the picture which corners were extracted by traditional Harris algorithm, (b) was the picture which corners were extracted by the improved Harris algorithm. We set δ=0.8, t=$\sqrt{2}$, and S=0.8 in the experiments.

The first image series shown in the Fig.1 and the Fig. 2 adopted the classical testing image and the corresponding image with additional noises.



(a) (b)

Fig.1 Compared pictures before adding noises



(a) (b)

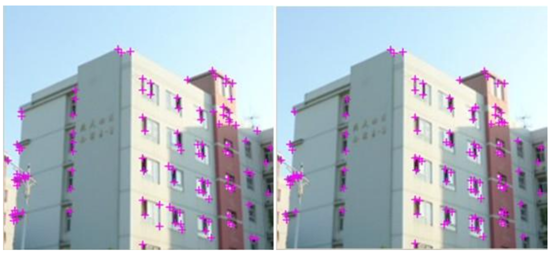
Fig.2 Compared pictures after adding noises

It could be seen from the Fig.1 and the Fig. 2 that, noised points and the edge points not required were removed by the improved Harris algorithm.

The second compared image series shown in the Fig.3 and the Fig.4 were the images before and after the change of scale zooming.
It could be seen from the Fig.3 and the Fig.4 that, through the improved algorithm, the extracted Harris corners from the image after scale zooming were much stable all the same, and the characteristics of the corners were not influenced by the change of scales, verifying that the Harris corners extracted by the improved method had the scale invariance.

(a) (b)

Fig.3 Compared pictures before scale zooming



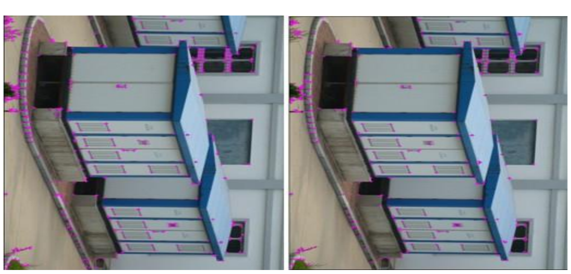
(a) (b)

Fig.4 Compared pictures after scale zooming

The third image series shown in the Fig.5 and the Fig. 6 were the images before and after the change of rotating.
It could be seen from the Fig.5 and the Fig.6 that, through the improved algorithm, the extracted Harris corners from the image after rotating were much stable all the same, and the characteristics of the corners were not influenced by the change of rotating, verifying that the Harris corners extracted by the improved method had the rotating invariance.

(a) (b)

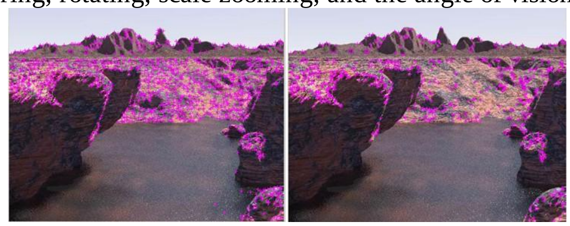
Fig.5 Compared pictures before rotating



(a) (b)

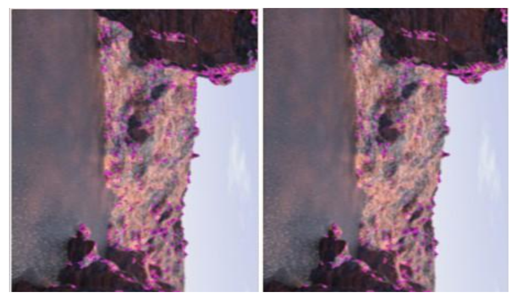
Fig.6 Compared pictures after rotating

The fourth image series shown in the Fig.7 and the Fig.8 were the images before and after the complex changes of blurring, rotating, scale zooming, and the angle of vision.



(a) (b)

Fig.7 Compared pictures before complex changes



(a) (b)

Fig.8 Compared pictures after complex changed

It could be seen from the Fig.7 and the Fig.8 that, through the improved algorithm, the extracted Harris corners from the image after changes were comparative stable, and the characteristics of the corners were not much influenced by the changes.

From the experiments above, the traditional Harris algorithm regarded noised points and edge points unwanted as useful corners and extracted them. But the improved algorithm could remove the noised points and edge points unwanted, and the Harris corners extracted had the performances of scale invariance, rotating invariance, and anti-interference.

The recurrence rates were calculated according to the equation (8).

$$r = 2n_3/(n_1 + n_2) \tag{8}$$

Where, n_1 and n_2 are the numbers of key points in the pictures before and after changes. n_3 is the number of the detected corresponding key points actually.

The compared table was shown in table 1 and table 2. From the tables, the recurrence rates were large extracted by the improved algorithm, stating that the detector was more stable, beneficial to the subsequent match.

Table 1: The comparing of the recurrence rates to the picture with the change of zooming

	Traditional method	***Improved method***
n_1	304	232
n_2	131	97
n_3	105	88
$r(\%)$	48.3	53.5

Table 2: The comparing of the recurrence rates to the picture with the change of rotating

	Traditional method	***Improved method***
n_1	509	341
n_2	470	339
n_3	406	321
$r(\%)$	83.0	94.4

5. Conclusion

Traditional Harris operator hasn't the property of scale variation and is sensitive to noises. This paper improved the Harris detector by establishing three scale spaces using variable Gaussian convolution kernel. Compared with the method of establishing the whole Gaussian pyramid scale spaces, the Harris corners extracted removed most noised points, and the utilization factor of the image was increased, the calculation time is decreased, and the image was high recurrence rate and stable. The corners detection by the improved method would make a favorable basis for the image reconstruction follow-up.

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