The Comparison and Application of Corner Detection Algorithms

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Abstract—**Corners in images represent a lot of important information. Extracting corners accurately is significant to image processing, which can reduce much of the calculations. In this paper, two widely used corner detection algorithms, SUSAN and Harris corner detection algorithms which are both based on intensity, were compared in stability, noise immunity and complexity quantificationally via stability factor η, anti-noise factor ρ and the runtime of each algorithm. It concluded that Harris corner detection algorithm was superior to SUSAN corner detection algorithm on the whole. Moreover, SUSAN and Harris detection algorithms were improved by selecting an adaptive gray difference threshold and by changing directional differentials, respectively, and compared using these three criterions. In addition, SUSAN and Harris corner detectors were applied to an image matching experiment. It was verified that the quantitative evaluations of the corner detection algorithms were valid through calculating match efficiency, defined as correct matching corner pairs dividing by matching time, which can reflect the performances of a corner detection algorithm comprehensively. Furthermore, the better corner detector was used into image mosaic experiment, and the result was satisfied. The work of this paper can provide a direction to the improvement and the utilization of these two corner detection algorithms.**

Index Terms—**corner detection, quantitative evaluation, image matching, image mosaic**

I. INTRODUCTION

Corners are important local features in images. Generally speaking, they are the points that have high curvature and lie in the junction of different brightness regions of images. In a variety of image features, corners are not affected by illumination and have the property of rotational invariance. They are only about 0.05% in the whole pixels. Without losing image data information, extracting corners can minimize the processing data. Therefore, corner detection has practical value and it

plays an important role in scale space theory [1], motion tracking [2,3] , image matching [4,5], building 2D mosaics [6], stereo vision [7,8], preprocessing phase of outline capturing systems[9~11], image representation [12] and other fields.

A substantial number of corner detectors have been proposed by researchers. These methods can be divided into two main classes: contour based and intensity based. Contour based methods first recover image contours and then search for curvature maxima or inflection points along those contours. For example, Masood et al. detected corners for planar curves by sliding set of three rectangles along the curve and counting number of contour points lying in each rectangle [13]. Peng et al. introduced a boundary-based corner detection method using wavelet transform for its ability for detecting sharp variations [14]. The extended curvature scale space corner detectors [15] also belong to the category of contour based methods. Intensity based methods estimate a measure which is intended to indicate the presence of a corner directly from the image gray values [16~19]. This kind of method is characterized by its fast speed and its independence to other local features, using corners' own features to detect corners directly. Two representative algorithms of this kind method are SUSAN corner detection algorithm and Harris corner detection algorithm, which are the most widely used corner detection algorithms in practice. In this paper, these two corner detection algorithms were compared and analyzed quantificationally. The compared result was applied to an image matching experiment, which verified that the quantitative evaluations of these two corner detection algorithms were valid.

II. TWO CORNER DETECTION ALGORITHMS

A. SUSAN Corner Detection Algorithm

SUSAN (Smallest Univalue Segment Assimilating Nucleus) corner detector is realized by a circular mask [20]. If the brightness of each pixel within a mask is compared with the brightness of that mask's nucleus then an area of the mask can be defined which has the same (or similar) brightness as the nucleus. This
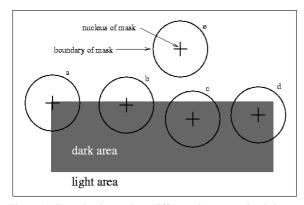
Figure 1. Four circular masks at different places on a simple image

area of the mask shall be known as the "USAN", an acronym standing for "Univalue Segment Assimilating Nucleus". Consider Fig. 1, showing a dark rectangle on a white background, five circular masks are shown at different positions on the simple image. Corners can be detected according to the area of USAN. Nucleus is on the corner when the area of USAN is up to the smallest, such as position "a".

In order to detect corners, the similar comparison function between each pixel within the mask and mask's nucleus is given by (1):

$$c(r, r_0) = \begin{cases} 1, & |I(r) - I(r_0)| \le t; \\ 0, & otherwise. \end{cases} \quad (1)$$

Where r_0 is nucleus's coordinates and r is the coordinates of other points within the mask; $c(r, r_0)$ is the comparison result; $I(r)$ is the point's gray value; t is gray difference threshold which determines the anti-noise ability and the smallest contrast that can be detected by SUSAN detector. In fact, (1) is not stable in practice, and an improved comparison function (2) is more often used because of its efficiency.

$$c(r, r_0) = \exp\{-[\frac{I(r) - I(r_0)}{t}]^6\} \quad (2)$$

The size of USAN region is given by (3):

$$n(r_0) = \sum_{r \in c(r_0)} c(r, r_0) \quad (3)$$

And the initial response to corners is got from (4), which is in accord with the principle of SUSAN, that is, the smaller USAN region, the greater initial response to corners.

$$R(r_0) = \begin{cases} g - n(r_0), & n(r) < g \\ 0, & n(r) \ge g \end{cases} \quad (4)$$

In (4), g is geometric threshold which determines the acute level of a corner, the smaller the acuter. It enhances the corner information of an image. At last, corners can be found by non-maximum inhibition.

B. Harris Corner Detection Algorithm

Harris corner detection algorithm is realized by calculating each pixel's gradient [21]. If the absolute gradient values in two directions are both great, then judge the pixel as a corner.

Harris corner detector is defined as followed:

$$R = \det(M) - ktr^2(M) \quad (5)$$

$$M(x, y) = \begin{bmatrix} I_u^2(x, y) & I_{uv}(x, y) \\ I_{uv}(x, y) & I_v^2(x, y) \end{bmatrix} \quad (6)$$

$$I_u^2(x, y) = X^2 \otimes h(x, y),$$
$$I_v^2(x, y) = Y^2 \otimes h(x, y), \quad (7)$$
$$I_{uv}(x, y) = XY \otimes h(x, y),$$

$$h(x, y) = \frac{1}{2\pi} e^{-\frac{x^2 + y^2}{2}} \quad (8)$$

Where $I_u(x,y)$ and $I_v(x,y)$ are the partial derivatives of the gray values in direction u and v at point (x,y), and $I_{uv}(x,y)$ is the second-order mixed partial derivative; k is an empirical value; $h(x,y)$ is a Gaussian function; X and Y are the first-order directional differentials, which can be approximately calculated by convolving the gray values and difference operators in direction u and v. Gaussian function is used to reduce the impact of noise, because first-order directional differentials are sensitive to noise. If R exceeds certain threshold, then take the point as a corner.

An example of corner detection by SUSAN and Harris corner detectors on the house image is show in Fig. 2(a) and Fig. 2(b).

III. EVALUATION OF CORNER DETECTION ALGORITHMS

A variety of quantitative evaluation methods of corner detection algorithm have been proposed [22~24]. Here, SUSAN and Harris algorithms are compared quantificationally in 3 criterions, stability criterion, anti-noise criterion and complexity criterion, which can reflect an algorithm's performance objectively.

A. Stability Criterion

Assume that the camera is fixed, grab two frames in an image sequence and use the given algorithm to detect corners in these two frames. If the detected positions of corners are unchanged, the algorithm is "absolute" stability. In fact, even in the image sequence, the gray value of each pixel will be changed because of many factors impacting imaging. So applying the same algorithm to them can not ensure that the number and the positions of detected corners are exactly the same. Absolute stability is almost non-existent.

Define stability factor η to measure the stability of an algorithm, that is:

$$\eta = \frac{A_1 \cap A_2}{\min(|A_1|, |A_2|)} \times 100\% \quad (9)$$

Where A_1 and A_2 are the corner sets of the first frame

(a) SUSAN   (b) Harris
Figure 2. Corner detection on the house image

and the second respectively; $|A_i|$ represents the number of elements in A_i set; the numerator means the number of the same corners in two frames. From (9), it can be concluded that the greater η is, the stabler the corner detection algorithm is.

B. Anti-noise Criterion

Noise immunity is measured by anti-noise factor ρ which is defined as followed:

$$\rho = \frac{B_1 \bigcap B_2}{\min(|B_1|, |B_2|)} \times 100\% \tag{10}$$

Where B_1 is the corner set of the original image and B_2 is the corner set of the image adding noise. The greater ρ is, the stronger the anti-noise ability of the algorithm is.

C. Complexity Criterion

The speed and complexity of an algorithm must meet the demand of real-time task, that is, the algorithm should be fast enough to be usable in the final image processing system. The runtime of an algorithm can describe its complexity.

D. Comparison Results

In the comparison experiment of corner detectors, 50 pairs of images with different contrast and brightness were gathered. Corners were detected by SUSAN and Harris algorithms respectively, where in SUSAN corner detector, a 37 pixels circular mask was selected; the similar comparison function adopted (2); gray difference threshold t=27; geometric threshold g=1/2n_{max}; and in Harris corner detector, gradient operators are [-2 -1 0 1 2] and [-2 -1 0 1 2]^T in direction u and v separately; Gaussian smoothing filter operator is Gaussian window function whose size is 7×7 and standard deviation is 2; and k=0.06. Stability factor and anti-noise factor were calculated, and the runtime of each corner detector was counted to measure the complexity of its algorithm.

The comparison result of stability factor is shown in Fig. 3, where the horizontal axis represents the serial number of images and the vertical axis represents the value of stability factor. As observed in Fig. 3, the average stability factor of Harris detector was 75.41%, yet that of SUSAN detector was 57.82%, which illustrates that the stability of Harris algorithm is better
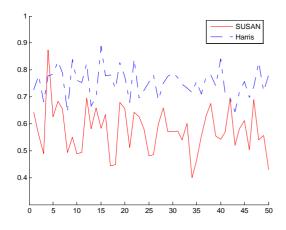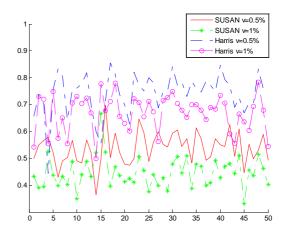

Figure 4.   Anti-noise comparison of SUSAN and Harris

than that of SUASN algorithm.

In the experiment of anti-noise comparison, the images were added different Gaussian white noise whose variance is 0.5% and 1%. The anti-noise factor curves are shown in Fig. 4. The anti-noise performance of Harris algorithm is also better than that of SUSAN algorithm on the whole, but both of them are lower when the noise is increased.

In order to compare the complexity of these two algorithms, counted the runtime of the test images (320×240 in size), 50 pairs in all, and the average runtime of SUSAN and Harris corner detectors was 4.2125s and 1.8686s respectively in Matlab7.0 environment. The speed of Harris algorithm is much faster than that of SUSAN algorithm.

As stated above, it can be concluded that Harris corner detection algorithm is superior to SUSAN corner detection algorithm whether on stability, or anti-noise ability, or complexity. The performance of SUSAN corner detector mainly depends on the similar comparison function $c(r,r_0)$ which is not immune to certain factors impacting imaging, such as strong luminance fluctuation, and noises. However, Harris corner detector is better because it draws a Gaussian smoothing function $h(x,y)$ into the detector, which makes great contribution to improving the stability and reducing the impact of noise.

E. Improvement of Susan Corner Detector

Since SUSAN corner detector mainly depends on the similar comparison function $c(r,r_0)$ where the gray difference threshold t is decisive, different threshold should be taken for different noise or contrast circumstance of images. An adaptive t is improved in different image contrast by (11):

$$t = \alpha \cdot \left(\frac{1}{n} \sum_i^n I_{i\,max} - \frac{1}{n} \sum_i^n I_{i\,min} \right) \tag{11}$$

Where I_{imax} and I_{imin} are the ith maximum gray value and the ith minimum of the whole image; n usually takes the value between 5~10; t can be valued among $\triangle I$ ($\triangle I = I_{imax} - I_{imin}$) which is the absolute contrast of the image; and the proportionality coefficient α is between 0.15~0.3,

Figure 3.   Stability comparison of SUSAN and Harris

which means corners can be detected well even in different contrast images when the threshold t is between 15%~30% of the absolute contrast.

The corner detection result of the house image by improved SUSAN is shown in Fig. 5, and the performances of stability and anti-noise ability are shown in Fig.6 and Fig. 7 respectively. The average stability factor of the improved SUSAN detector was 61.56%, higher than that of the original 57.82%. Moreover, the average anti-noise factors of the improved SUSAN were 58.92 % and 46.63 % when adding different noises, higher than those of the original detector which were 54.89 % and 45.04 % correspondingly in different noise, but both of them were not satisfied. However, it's a good way to improve SUSAN detector by selecting an adaptive
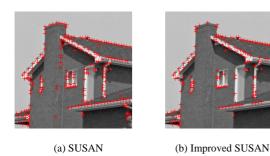
gray difference threshold.

F. Improvement of Harris Corner Detector

According to the comparison and analysis results above, Harris corner detector can be improved by changing its directional differentials. The improved directional differentials can be calculated by convolving the gray values and Gaussian first order differential operators in direction u and v which are more robust than the gradient operators, $[-2\ -1\ 0\ 1\ 2]$ and $[-2\ -1\ 0\ 1\ 2]^T$, as shown in (12).

$$f_u = \begin{bmatrix} 5 & 0 & -5 \\ 8 & 0 & -8 \\ 5 & 0 & -5 \end{bmatrix}, \quad f_v = \begin{bmatrix} 5 & 8 & 5 \\ 0 & 0 & 0 \\ -5 & -8 & -5 \end{bmatrix} \quad (12)$$

(a) SUSAN   (b) Improved SUSAN

Figure 5.   Corner detection on the house image by improved SUSAN

(a) Harris   (b) Improved Harris

Figure 8.   Corner detection on the house image by improved Harris

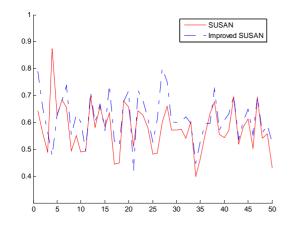Figure 6.   Stability comparison of original SUSAN and improved SUSAN

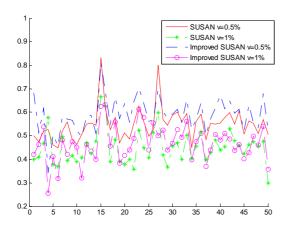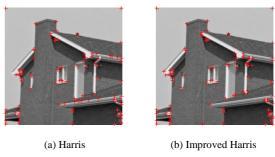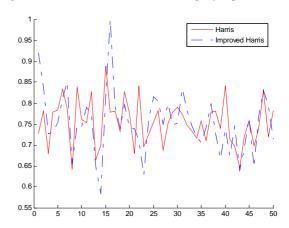Figure 9.   Stability comparison of original Harris and improved Harris

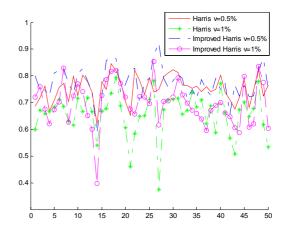Figure 7.   Anti-noise comparison of original SUSAN and improved SUSAN

Figure 10.   Anti-noise comparison of original Harris and improved Harris

The corner detection result of the house image by improved Harris is shown in Fig. 8. Moreover, compared with the original Harris corner detector, the performances of the improved corner detector in stability and anti-noise ability are shown in Fig. 9 and Fig. 10. The average stability factor of each detector was almost the same 75.4%, but the average anti-noise factors of the improved Harris detector were 77.48% and 69.6% when adding different noises, higher than those of the original detector which were 75.28% and 65.85% in different noises. Therefore, it has a certain improvement indeed.

IV. APPLICATIONS OF CORNER DETECTION

A. Image Matching

To evaluate corner detection algorithm is ultimately to guide utilizations. Image matching, recognizing the homologous pixels between two images or among multiple images by certain matching algorithm, is an important application field of corner detection through which can greatly reduce the matching data.

In this paper, the image matching experiment firstly used SUSAN and Harris corner detectors to extract key points of images, then extracted 7 invariable moments in their neighborhood as eigenvector, and took Euler distance as similarity measurement of the key points, that is, getting one key point in the image waiting for matching and searching for two nearest points in reference image, if the ratio of the nearest distance to the sub-nearest distance is below the given threshold, then accept they are a pair of matching points.

Fig. 11 and Fig. 12 show the results of corner detection and image matching by SUSAN and Harris corner detectors respectively, and Table I shows the statistic data of these two detectors in the image matching experiment, where matching efficiency, defined as correct matching pairs dividing by matching time, can reflect the performances of a corner detector comprehensively. It can be seen from Table I that the matching efficiency of Harris is higher than that of SUSAN, which verifies the comparison result of these two corner detection algorithms.

B. Image Mosaic

According to the comparison and analysis results above, Harris corner detector is better than SUSAN, so we use Harris corner detector to complete a future application, image mosaic which is to stitch two or more small images that have overlapping areas with their neighbors into a large, high-resolution synthesis image. The automatic construction of image mosaics is an active
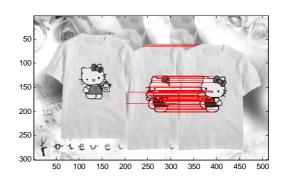

Figure 11.   Results of corner detection and image matching by SUSAN corner detector
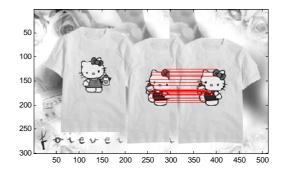

Figure 12.   Results of corner detection and image matching by Harris corner detector

TABLE I.
STATISTIC DATA OF TWO CORNER DETECTORS IN IMAGE MATCHING EXPERIMENT

Detector	Corners in left image	Corners in right image	Correct matching pairs	Time	matching efficiency
SUSAN	220	89	52 pairs	8.8120s	5.9010 pairs/s
Harris	132	56	25 pairs	3.9850s	6.2735 pairs/s

area of research in the fields of photogrammetry, computer vision, image processing, and computer graphics. It usually has two basic steps, image matching (or image registration) and image fusion.

Let (x,y) be the coordinates of the pixel in the image waiting to match and (x',y') be the coordinates in the reference image. Therefore, the relationship between them can be represented by a planar perspective transformation, as (13), which warps an image into another image plane.

$$x' \sim Mx = \begin{bmatrix} m_0 & m_1 & m_2 \\ m_3 & m_4 & m_5 \\ m_6 & m_7 & m_8 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{13}$$

where $x = (x,y,1)$ and $x' = (x',y',1)$ are homogeneous or projective coordinates, and "~" indicates equality up to scale. Equation (13) can be re-written as:

$$x' = \frac{m_0 x + m_1 y + m_2}{m_6 x + m_7 y + m_8}$$
$$y' = \frac{m_3 x + m_4 y + m_5}{m_6 x + m_7 y + m_8} \tag{14}$$

And then these two images are stitched together. In order to smooth the overlapped area, linear weighted model, a kind of image fusion method, was used. The mosaic result by Harris corner detention algorithm is shown in Fig. 13, and satisfied in visual effect.

V. CONCLUSIONS

From the above comparison results of these two corner detection algorithms, it is known that Harris algorithm is superior to SUSAN algorithm on the whole. The main disadvantages of SUSAN algorithm are:

(1) A fixed global threshold is not suitable for general situation. The corner detector needs an improved adaptive threshold and the shape of mask can be improved, too;

(2) The anti-noise ability is weak and the robustness of the algorithm should be strengthened.

Similarly, there is still much space for Harris algorithm to be improved, such as how to choose difference operators and Gaussian smoothing filter operators better and so on. The work of this paper can provide a direction to the improvement and the utilization of these two corner detection algorithms.

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Figure 13. Image mosaic result

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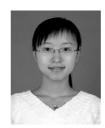
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