Compass Detection Algorithm based on Image Corner

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Abstract

To improve the Features from Accelerated Segment Test (FAST) algorithm such as artificial threshold setting and the choice and ordering of continuous points on circle, a novel compass detection algorithm is proposed. The algorithm uses four compasses as the test mask and calculates threshold value based on image intensity feature. Four compasses are used to pre-detect corners. In order to improve the location accuracy of corners, pseudo response on skewed edges is eliminated. Finally, multiple adjacent responses are tackled by keeping only points which have extremal value of Laplacian. Comparative experiments between FAST and the proposed algorithm are carried out with respect to validity, robustness and efficiency. The results show that the detected corners by the proposed algorithm are accurately located and well-distributed.

Keywords: *adaptive threshold, corner detection, compass detection, FAST, skewed edge*

1. Introduction

Corner detection is used as the first step of many vision tasks such as tracking, localization, SLAM (simultaneous localization and mapping), image matching and recognition [1]. Corner is typically detected and matched into a database, thus it is important that the same real-world points are detected repeatedly from multiple views [2]. Corner detection algorithm can be divided into three categories:

(1)Edge based corner detector, an edge in an image corresponds to the boundary between two regions. At corner, this boundary changes direction rapidly. Such algorithms include chain code corner detector [3], maximum curvature corner detector [4], *etc.* In corner detection process, the success of algorithm depends on edges. If the edge line is broke, the error of corner detection is bigger. The whole computational process is very complex.

 (2)Corner detection algorithms work by calculating the value of corner response function across the image. Such algorithms include Moravec [5], Harris [6], Shi-Tomasi [7], *etc.* Corners can be defined as points with low self-similarity in all directions, but algorithms are sensitive to noise.

(3)Corners are detected by examining a small patch of an image to see if it "looks" like a corner. Such algorithms include SUSAN [8], Trajkovic and Hedley [9], *etc.* Since second derivatives are not computed, a noise reduction step (such as Gaussian smoothing) is not required. Consequently, these corner detectors are computationally efficient since only a small patch of an image is examined for each corner detected. But detecting speed will be always affected owing to more pixels in a small patch of an image.

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All the detector algorithms described above are slow with speed and complex with computation, Features from Accelerated Segment Test(FAST) [10-11] proposed by Rosten and Drummond in 2006 can be detected the corner of the image in limited computing resources. But there are two problems with the FAST algorithm. First, threshold selection is a key for the success of corner detection. The threshold depends on the property of the actual image, so the threshold is difficult to determine. Second, the choice and ordering of the contiguous pixels are a key step for affecting the algorithm efficiency.

To improve the FAST algorithm, adaptive threshold compass detection (ATCD) is proposed in this paper. The selection of threshold and the choice and ordering of the contiguous pixels can be effectively solved with the proposed algorithm.

2. Adaptive Threshold Compass Detection

2.1. Compass Corner Detection

FAST test criterion operates by considering a circle of sixteen pixels around the corner candidate *p*, as illustrated in Figure 1.
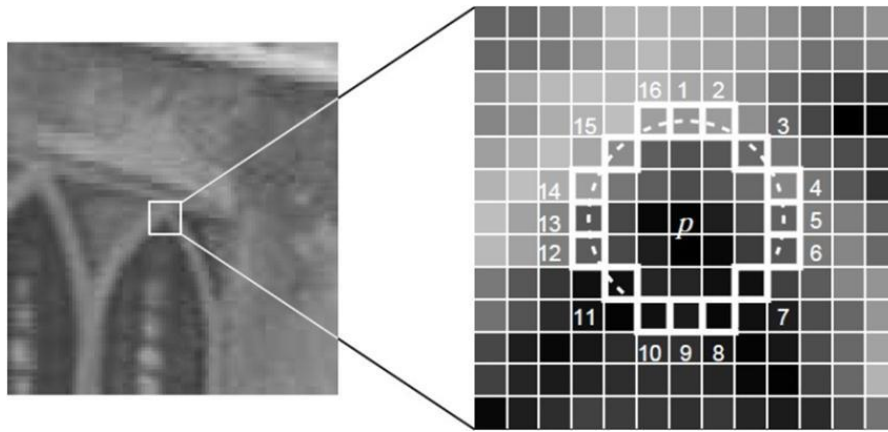
Figure 1. The Template for Corner Detection Based on Bresenham Circle

For each location on the circle $x \in \{1... 16\}$, the pixel at that position relative to *p*, denoted by $p{\rightarrow}x$, can have one of three states. Corner Response Function (CRF) is:

$$CRF_{p\rightarrow x} = \begin{cases} dark, & I_{p\rightarrow x} \leq I_p - t \\ similar, & I_p - t < I_{p\rightarrow x} \leq I_p + t \\ bright, & I_p + t < I_{p\rightarrow x} \end{cases} \quad (1)$$

Where, I_p is the intensity of the candidate pixel *p*; $I_p{\rightarrow}x$ is the intensity of a pixel *x* relative to *p*; *t* is the threshold.

The candidate pixel *p* is a corner if there exists contiguous pixels in the circle which are all brighter than the intensity of the candidate pixel I_p plus a threshold *t* ($CRF_{p\rightarrow x} = d$), or all darker than $I_p - t$ ($CRF_{p\rightarrow x} = b$). The number of contiguous pixels is 8, 9, 10, 11 or 12. But Edward proved there is a most stable result if the number of contiguous pixels is nine.

There are some defects in the whole detection algorithm of FAST as follows:

1. From the equation (1), the value of $S_{p\rightarrow x}$ is strongly influenced by the threshold *t*. If the value of *t* is too small, it will lead to detect more pseudo corners. The

accuracy of image matching will be reduced. If the value of t is too large, it will miss many important corners. It will lead to failure between image matching.
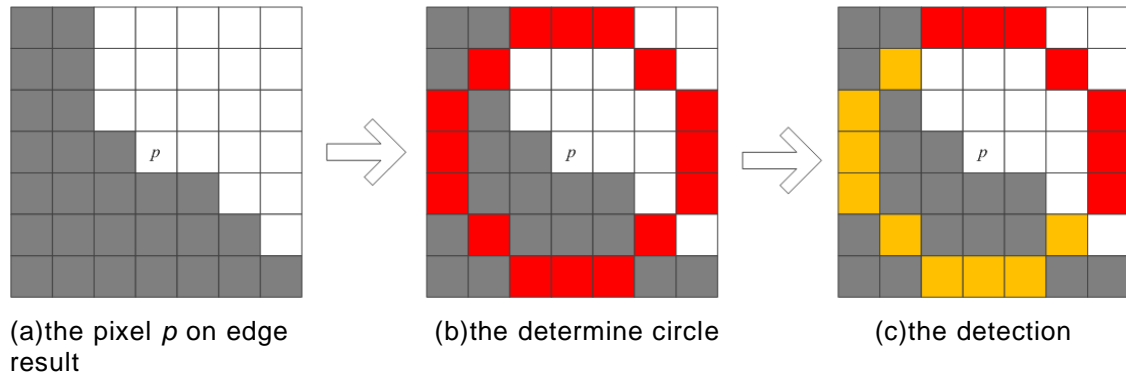
2. The selection order of nine consecutive pixels on Bresenham circle is uncertain (In Figure 2.The total of selection order are 16 kinds. The different order will lead to different value of $CRF_{p \to x}$.

3. Skewed edge pseudo corner cannot be eliminated, as illustrated in Figure 3.In Figure 3.(a), the pixel p is on edge. In Figure 3.(b), the Bresenham circle is used to detect the pixel p.In Figure 3.(c), there are nine contiguous pixels satisfied the $CRF_{p \to x}$.Through this detection process, the pixel p on Skewed edge will be detected to a corner.

In order to avoid the choice and ordering of nine contiguous pixels, as illustrated in Figure 4, candidate corners are constructed by compass corner detection.


(a)choice 1   (b)choice 2

(c)choice 3   (d)choice 6
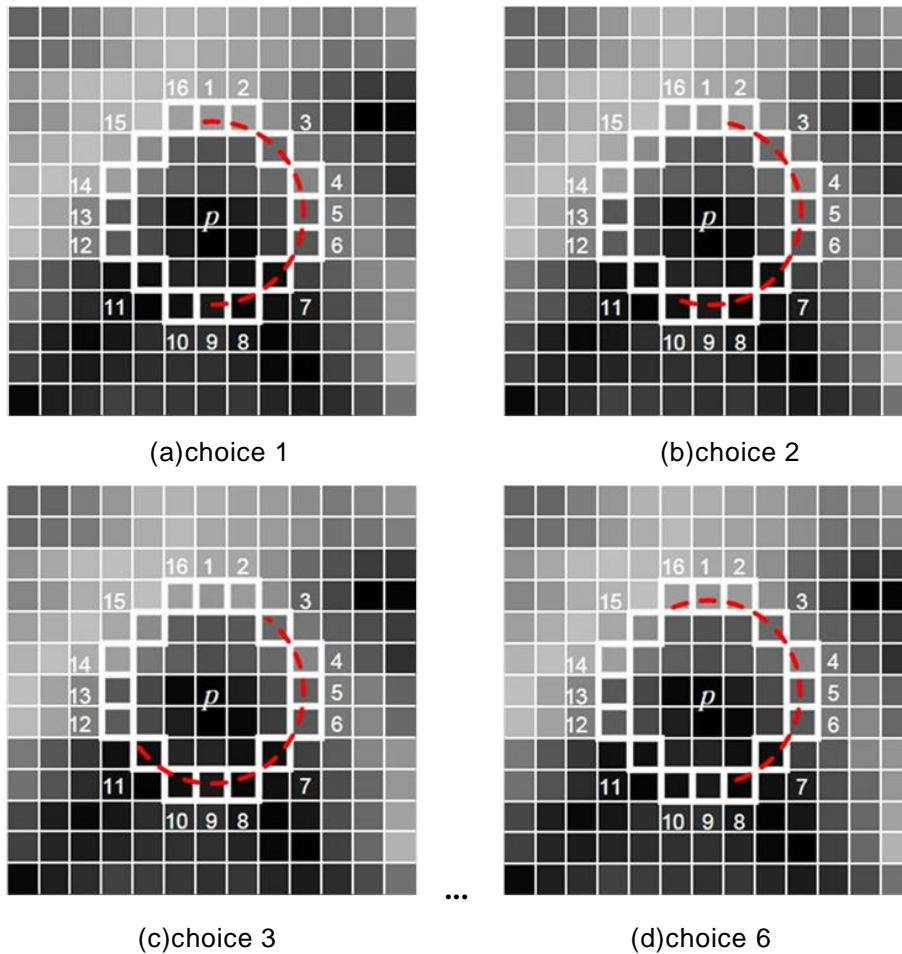
Figure 2. The Choice and Ordering of Nine Contiguous Pixels

(a)the pixel *p* on edge result   (b)the determine circle   (c)the detection

Figure 3. Skewed Edge Pseudo Corner

Sixteen pixels on the circle around the corner candidate *p* are divided into 4 groups. The pixels of 1, 5, 9, 13 is used to construct the first compass; The pixels of 2, 6, 10, 14 is used to construct the second compass; The pixels of 3, 7, 11, 15 is used to construct the third compass; The pixels of 4,8,12,16 is used to construct the four compass, as illustrated in Figure 4.

(a)compass 1   (b)compass 2

(c)compass 3   (d)compass 4
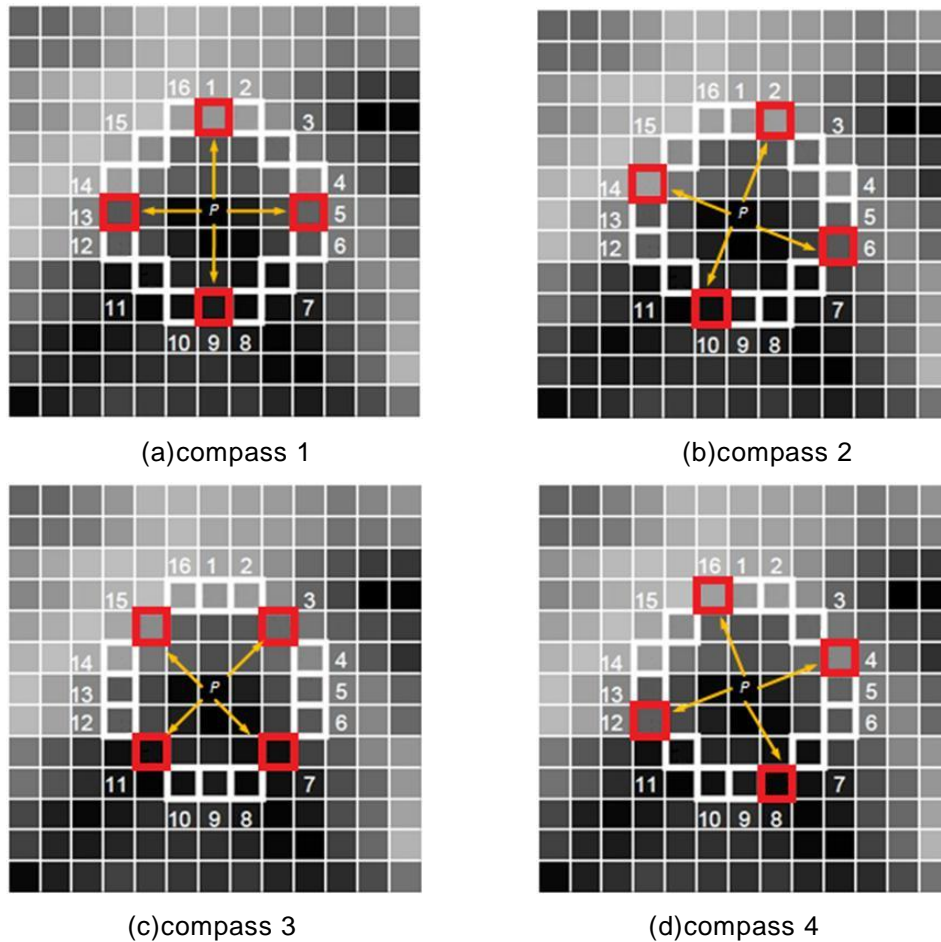
Figure 4. The Detecting Process for Compasses

Sixteen pixels on the circle are detected by four compasses (in Figure 4). The candidate pixel *p* is a corner if *CRF* is satisfied. The response function is defined as:

$$N = \sum_{x\forall(compass(i))} |I(x) - I(p)| > t \qquad (2)$$

Where, $I(x)$ is the intensity of the pixel on compass; $I(p)$ is the intensity of the candidate pixel p; t is the threshold; compass (i) is one of four compasses, $i \in \{1, \dots, 4\}$. The value of N can be computing by CRF. The candidate pixel is corner if $N > 3$.

2.2. The Adaptive Threshold

The choice of threshold t is critical in the process of corner computation. The threshold t shows the minimum contrast for detecting corner and the maximum limit value for reduction noise. Artificial threshold is needed to detect corner with the existing detection algorithms. If the threshold is too small, many pseudo corners are detected. If the threshold is too large, the number of corner satisfied CRF is too small. In order to enhance the adaptability of the algorithm, the threshold t is automatically selected by different image property.

In this paper, the intensity and contrast of the image is analyzed and the selection of threshold t is in accordance with absolute contrast. If the intensity of the image is well-distributed, the absolute contrast $\Delta I = I_{max} - I_{min}$. In order to accurately calculate absolute contrast ΔI, the mean value of n maximum and minimum intensities is calculated. In general, $n = 10$. If the value of the threshold t is 15% ~30% of ΔI, corner can be well extracted under different contrast. The function is defined as [12]:

$$t = \alpha \times (\frac{1}{n}\sum_{i=1}^{n} I_{i\,max} - \frac{1}{n}\sum_{i=1}^{n} I_{i\,min}) \qquad (3)$$

Where, $I_{i\,max}$ and $I_{i\,min}(i = 1, \dots, n)$ is n maximum and minimum intensities. α is $0.15 \sim 0.3$.

2.3. Skewed edge pseudo corner elimination

According to the equation (2), there are two types of corner. 1)the real corner; 2) skewed edges pseudo corner, as illustrated in Figure 5.In Figure 5.(a), the pixel p is an corner, but in Figure 5.(b), the pixel p is a skewed edge point. In order to eliminate corners on skewed edges, there is a brief analysis for Figure 5.
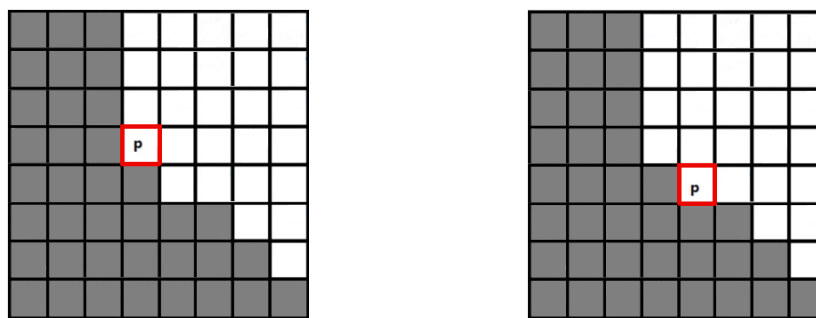
(a) the pixel p is a corner   (b)the pixel p is a skewed edge pseudo corner

Figure 5. Pseudo Corner Detection on Skewed Edges

In the process of corner detection, the corner is a pixel that has large contrast with other pixels in the neighborhood of the corner. In Figure 5.(a), the candidate pixel p is a corner, so there are large differences between the candidate pixel p and other pixels in the neighborhood of p. In Figure 5.(b), the candidate pixel p is on skewed edge. According to the spatial correlation, the intensity of the image is a

process of continuous change. If a pixel p is a skewed edge point, the intensity of the pixel p has little difference with other pixels in the neighborhood of p.

To avoid detecting corner on skewed edges, equation (4) is used to detect pixel p. According to the feature of corners, the values of a, a_1 and b, b_1 need to be examined to eliminate edge pixel. The test is started from one point on the circle and stopped when it return true. In this case p is not a corner [13], as illustrated in Figure 6.

$$\left| I(a) - I(a_1) \right| > t$$
$$\left| I(b) - I(b_1) \right| > t \tag{4}$$

If the equation (4) holds, the pixel p can be eliminated. The threshold t is the same as the equation (3).
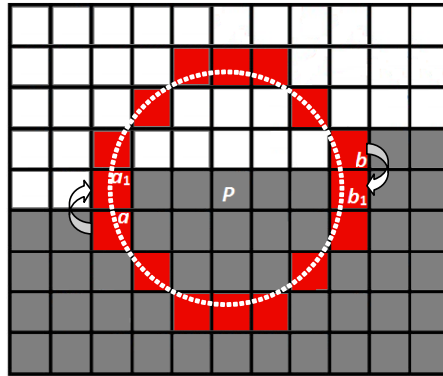

Figure 6. Test for a Point on Skewed Edges

2.3. Non-Maximum Suppression

Once edge and region responses are eliminated, we reject remaining multiple adjacent responses by keeping only points which have extremal value of Laplacian.

The Laplacian is approximated in a very simple manner [14], as illustrated in Figure 7:

$$LOG(p) = \sum (I(x) - I(p) + I(q)) \tag{5}$$

$$P_{\max} = \underset{ij \in S}{Max}(LOG(P_{ij})) \tag{6}$$

Where, x, q are two right opposite points on the 16-circle associated to the considered point p.
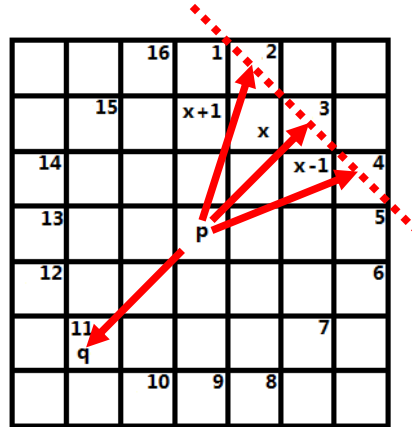
Figure 7. Laplace Extremum Calculation

3. Experimental Analysis

3.1. Robustness of Algorithm

In order to verify the algorithm robustness, the performance of corner detection is compared by repeatability, which means the higher of the repeatability, the better of the robustness. The repeatability can be defined as [15]:

$$r_s = \frac{N_c}{\min(N_1, N_2)} \qquad (6)$$

Where, N_1 is the number of corners in image1; N_2 is the number of corners in image2; N_c is the number of corresponded corners of image1 and image2 in the situation of image transformation.

Four kinds of image transformation are experimented: rotation transformation, viewpoint transformation, illumination transformation, scale change. Figure 8 ~ Figure 11, respectively, shows comparison experiment between ATCD and FAST based on Mikolajczyk05 [16] standard images set. Table.2 ~ Table.5,respectively, shows the number of detection and repeatability of ATCD and FAST algorithms.

As can be seen from Figure 8 ~ Figure 11, ATCD algorithm achieved good performance compared with FAST algorithm. Pseudo response on skewed edges is eliminated. The detected corners are uniformly distributed and accurately located.

As can be seen from Table.1 ~ Table. 4, the number of corners detected by ATCD is less than FAST. In this way, ATCD can raise the efficiency of the applications like image matching.

Figure 8 is a contrast experiment of illumination change. Table 1 shows a result of repetition rate of illumination change. Brightness transform can be expressed by the linear transfromation of pixel intensity ($aI(x) + b$). ATCD and FAST algorithm are not involved the second derivative in the process of detecting corners, so detection result has little influence on illumination change. In Table 1, the repetition rate of ATCD is superior to the FAST, because the pseudo corners on skewed edges with FAST are more than ATCD and there are some corners are clustering together.

Figure 9 is a contrast experiment of scale change. Table 2 shows a result of repetition rate of scale change. There are low repetition rate both ATCD and FAST, because image scales are not construsted both ATCD and FAST.

Figure 10 is a contrast experiment of rotation transformation. Table 3 shows a result of repetition rate of rotation transformation. Due to the characteristics of isotropy of detection circle both ATCD and FAST, detection results have little

influence on rotation transformation. ATCD and FAST algotirhm both have a good performace on minor scale change and the repetition rates are both more than 50%.

Figure 11 is a contrast experiment of viewpoint transformation. Table 4 shows a result of repetition rate of viewpoint transformation. In the process of viewpoint transfromation, two algorithms are not ideal and the stability of corners are poor. After the change of viewpoint, scale changes magnified the effect of viewpoint transformation and lead to poor results.

(a)ATCD   (b)FAST
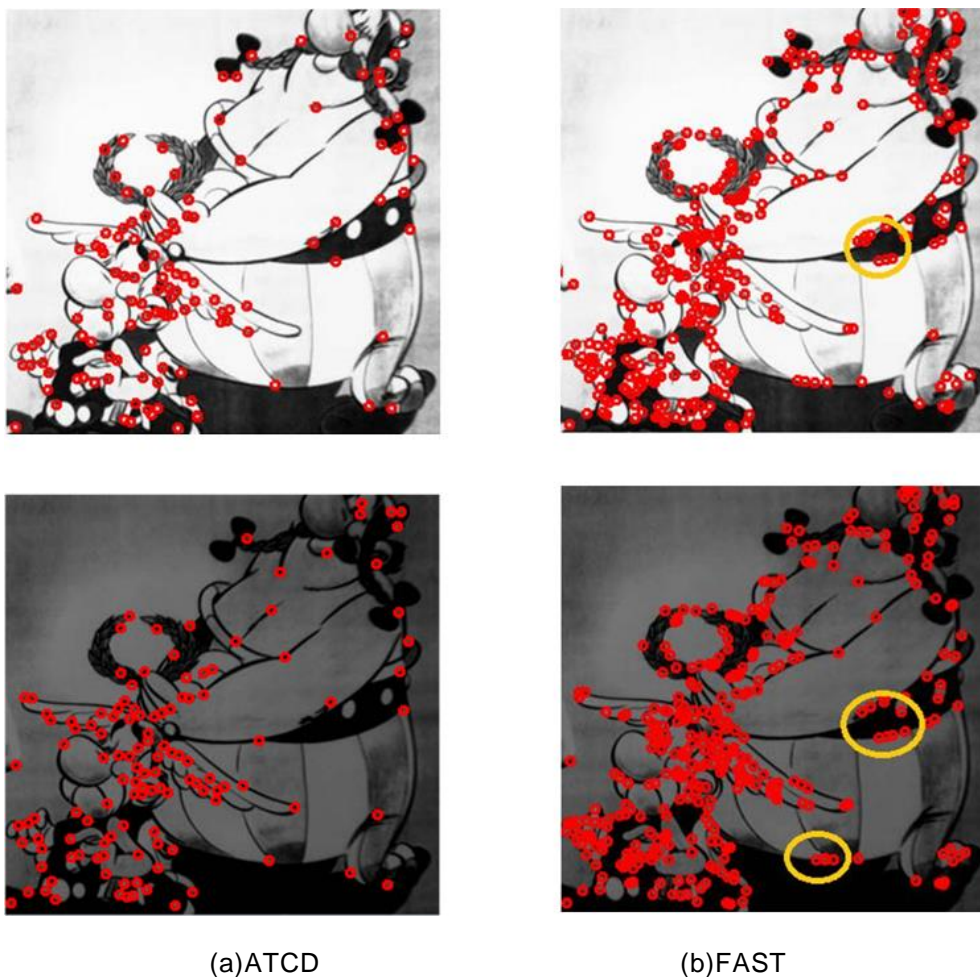
Figure 8. Comparison of ATCD and FAST with Illumination Change

Table 1. Repetition Rate of Illumination Change

	Corner number (up)	Corner number (down)	Points repetition rate
ATCD	166	129	50.86%
FAST	311	299	42.81%

(a)ATCD	(b)FAST
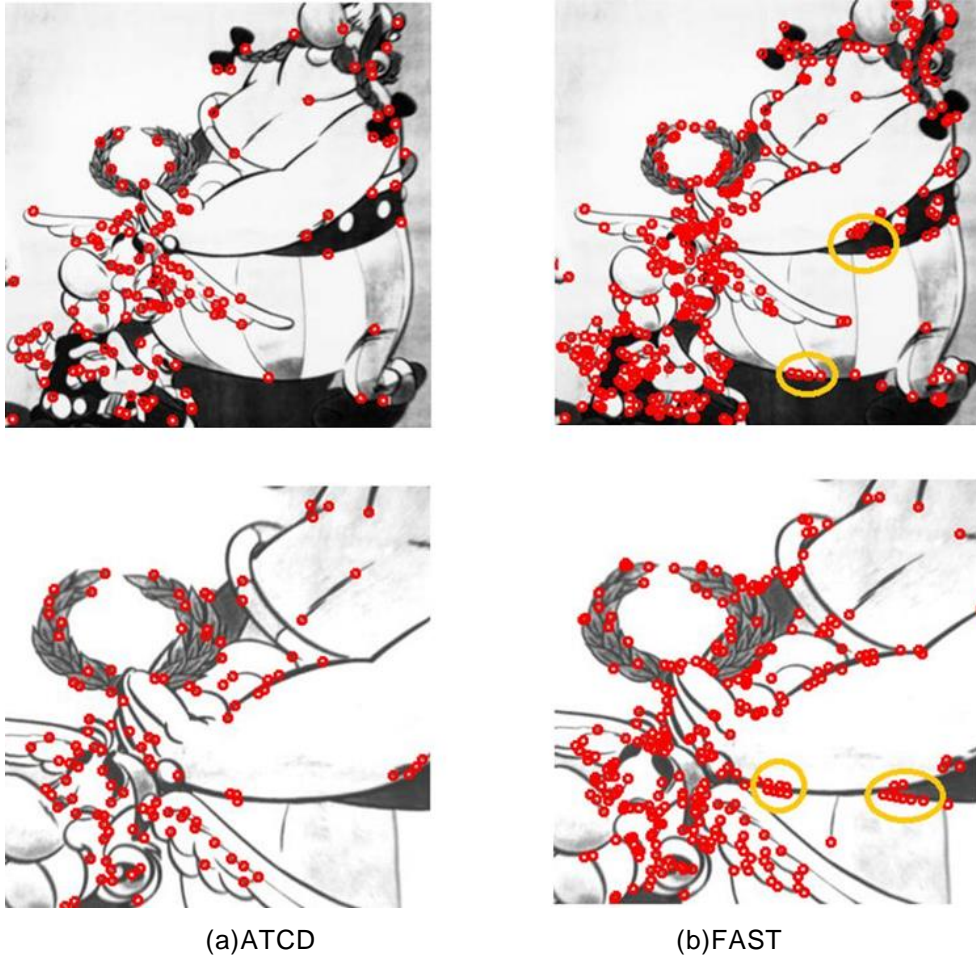
Figure 9. Comparison of ATCD and FAST with Scale Change

Table 2. Repetition Rate of Scale Change

|	Corner number (up)	Corner number (down)	Points repetition rate
ATCD	166	121	17.91%
FAST	311	241	14.97%

<center>(a)ATCD   (b)FAST</center>
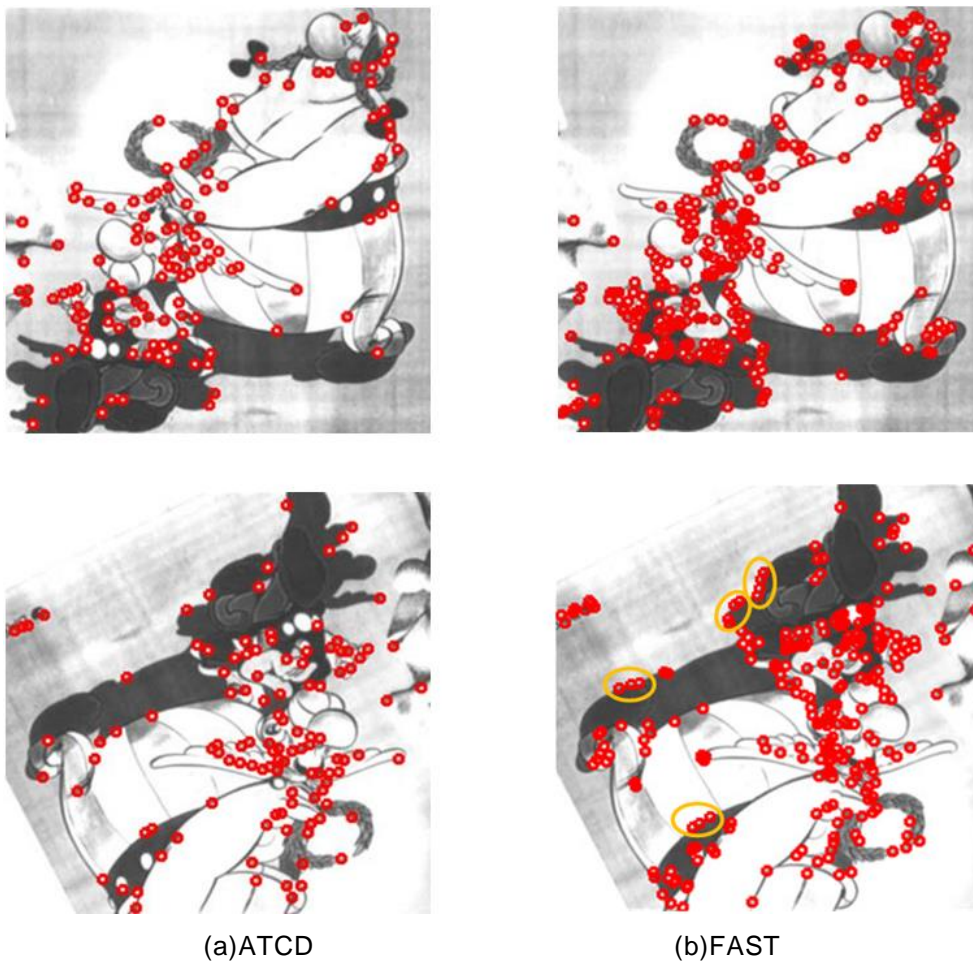
Figure 10. Comparison of ATCD and FAST with Rotation Transformation

Table 3. Repetition Rate of Rotation Transformation

	Corner number (up)	Corner number (down)	Points repetition rate
ATCD	123	114	53.51%
FAST	311	248	54.75%

Table 4. Repetition Rate of Viewpoint Transformation

	Corner number (up)	Corner number (down)	Points repetition rate
ATCD	53	75	24.98%
FAST	119	139	21.56%

(a)ATCD   (b)FAST
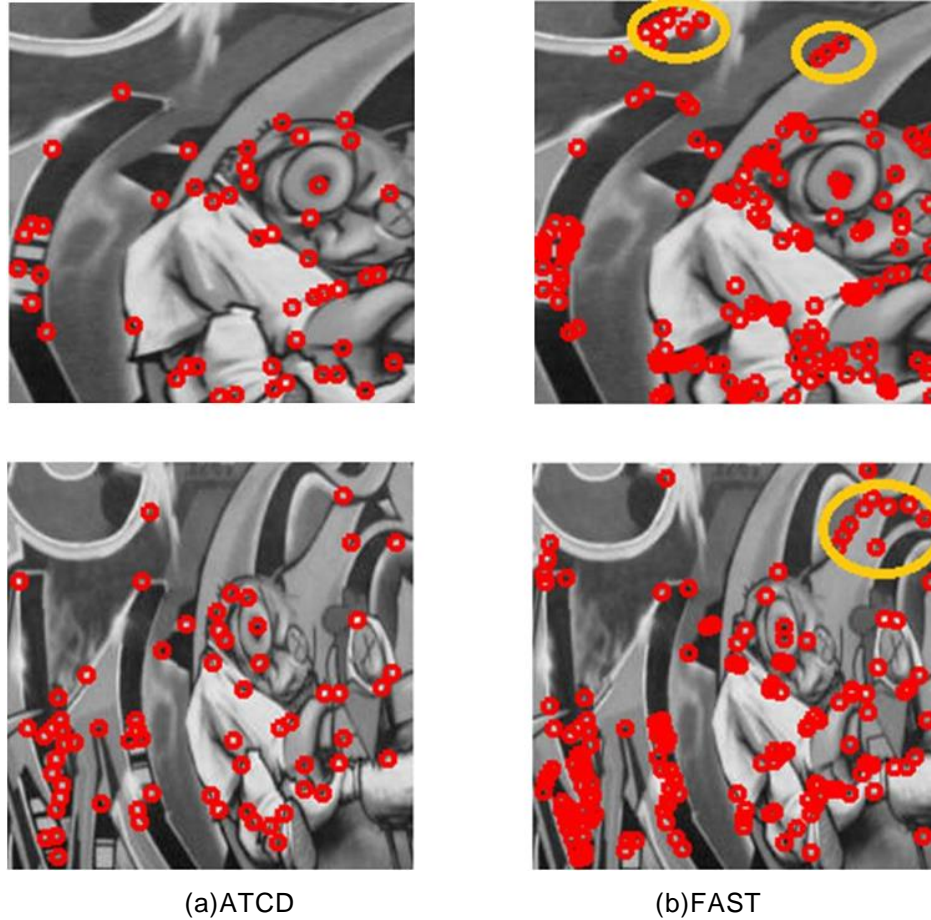
Figure 11. Comparison of ATCD and FAST with Viewpoint Transformation

3.2. Efficiency of Algorithm

In case of limited computational resources, corner detection algorithm only fast enough can be used in practical applications. For respectively testing the computation speed of ATCD and FAST algorithm, experiments were carried out based on multiple images with size of 320×278, 480×640, 694×1066, and 2056×2452.Average running time is shown in Table 5.

As shown in Table 5, ATCD algorithm not only improves the performance of the FAST algorithm but also keeps the advantage of time efficiency.

Table 5. Comparison of Algorithm Efficiency

Times (ms)	Image size (pixel $\times$ pixel)				
	320×278	480×640	694×1066	1200×1600	2056×2452
FAST	6.87	24.98	51.96	143.1	248.6
ATCD	6.98	24.86	53.47	142.8	250.1

4. Conclusion

Aiming at the weakness of the FAST algorithm, compass detection algorithm based on image corner detection is proposed. Comparative experiments between FAST and the proposed algorithm are carried out with respect to validity, robustness and efficiency. The

results show that the detected corners by the proposed algorithm are accurately located and well-distributed.

Acknowledgements

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