Accurate and Robust Image Matching Method Based on an Improved FAST Algorithm

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Abstract. Image matching holds fundamental significance in varieties of applications in CV (computer vision)., demanding methods that strike a balance between speed and robustness. This paper introduces an image matching approach built upon an improved version of the FAST (Features from Accelerated Segment Test) algorithm. The primary objective is to enhance both the accuracy and robustness of image matching processes. The algorithm incorporates targeted modifications to the FAST algorithm, addressing its limitations while preserving its efficiency. In this improved algorithm, it introduces a two-layer adaptive threshold mechanism. The most suitable threshold is employed to detect optimal feature points, ensuring adaptive adjustments in different grayscale regions according to the current situation. Based on this algorithm, the accuracy of the image matching process has been improved. Moreover, the robustness of the image matching based on the improved algorithm performs better than the original FAST algorithm. The findings open new avenues for applications requiring real-time and accurate image matching techniques.

Keywords: corner detection, image matching, FAST algorithm

1 Introduction

In today's age of pervasive visual data, image matching holds pivotal significance across a multitude of applications, including facial recognition systems [1], autonomous vehicles [2], constructing 2D mosaics [3], motion analysis [4], etc. Among the methods used to implement image matching [5,6], corner detection stands out as a highly effective approach. Corners represent fundamental features within images. Nevertheless, achieving accurate and robust corner detection for image matching remains a challenge: conventional image matching methods relies on traditional corner detection algorithms, such as SUSAN, SIFT, and Harris [7-9].

To pursuit for enhanced image matching lies the FAST algorithm. FAST empowers numerous applications by swiftly detecting and characterizing features within images. Since its inception in 2005 by Rosten [10], built upon the SUSAN method. In 2010, Mair introduced AGAST features, which means combining the specific decision trees to find the best decision tree in an ECCV conference paper. [11].

Building upon traditional FAST corner detection, this paper introduces a two-layer adaptive threshold mechanism and refines corner assessment criteria to detect diverse

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corner types. This improved method is then applied to the image matching process. By comparing experimental outcomes, the efficacy of this enhanced algorithm is substantiated.

2 Methodology

2.1 The drawbacks of traditional FAST algorithm

The whole process can be divided into five steps: Read an image, pretreatment, corner detection, corner matching and image matching. In this article, the main enhancement is to improve the pretreatment and the corner matching steps.

The improvement strategies primarily encompass two approaches.

First, the effectiveness of FAST corner detection critically hinges on the threshold setting [12,13].

Fig. 1 displays a flower image detected by FAST under three distinct thresholds. From left to right, the thresholds are set to 30, 10, and 5, respectively. Drawbacks are obvious: With high threshold, the evident corners, such as leaves are unmarked. With a low threshold, every single change will be marked as corner.

Fig. 1. Performance of traditional FAST detection at different thresholds (Photo/Picture credit: Original)

Additionally, traditional FAST corner detection exhibits limitations in its approach: It primarily examines whether a candidate pixel's surrounding pixels include n contiguous points (typically 12) exceeding a certain threshold. This approach primarily targets L-shaped corners, potentially leading to the exclusion of other corner types and consequently missing out on various feature points.

2.2 FAST comer detection algorithm

Article [11] propose the FAST corner detection, the FAST corner detection algorithm is commonly used to identify feature points with significant local grayscale changes. It offers not only high-speed computation but also a high level of accuracy.

The detailed steps are as follows:

1. For the point under consideration, denoted as P, its grayscale value is represented as I(p).
2. Choose an appropriate empirical threshold 't'.
3. Create a discrete circle with a radius of 3 pixels around point 'P', resulting in 16 discrete points on the circle.

In a 16-pixel circular area with pixel values either consistently greater than I(p)+t or consistently smaller than I(p)-t, if there exist N (which is typically set to 9 or 12) continuous pixels then pixel 'p' is classified as a corner, as indicated in Equation (1).

$$state = \begin{cases} dark & I_{p\to x} \le I_p - t \\ same & I_p - t < I_{p\to x} \le I_p + t \\ bright & I_p + t \le I_{p\to x} \end{cases} \tag{1}$$

4. During practical implementation, optimizations are often applied. Only four positions (clockwise location 1, 9, 5, and 13) are typically checked on the circle.
5. Additionally, a non-maximum suppression step is often applied to remove feature points with lower response values within a region, ensuring that only the most significant corner points are retained.

2.3 Image matching using improved FAST corner detection algorithm with adaptive threshold.

Image pretreatment

The input image is converted to grayscale and subjected to Gaussian smoothing to mitigate noise influence. The 2-dimensional Gaussian kernel is represented by (2).

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \tag{2}$$

Initial Pixel Filtering

To enhance the efficiency of feature point detection, an adaptive threshold T1 suited for scale-space is employed as in Equation (3).

$$T_1 = \frac{1}{16 * 16} \sum (I(x_i) - \tilde{I})^2 \tilde{I} \tag{3}$$

This threshold initially filters pixel points, leveraging variance. High variance areas have larger thresholds post-adaptive adjustment. A pixel with M surrounding pixels differing from the center above the threshold meets the requirement.

Threshold adjustment

For the candidate points obtained in the second step, calculate the absolute differences in grayscale values between 16 pixels within a circular area of the candidate point and the center pixel as Equation (4).

$$D_X = |I_x - I_0| \tag{4}$$

Summarize all the results to obtain the maximum and minimum absolute differences in grayscale values, denoted asD_{max}andD_{min}. Based on the value of D_x, calculate its distribution score.

$$S = \begin{cases} 0 & D_{min} \le D_x \le \dfrac{2 * D_{min} + D_{max}}{3} \\ 0.5 & \dfrac{2 * D_{min} + D_{max}}{3} < D_x \le \dfrac{D_{min} + 2 * D_{max}}{3} \\ 1 & \dfrac{D_{min} + 2 * D_{max}}{3} < D_x \le D_{max} \end{cases} \tag{5}$$

Sum up all the 16 distribute points, adjust the threshold according to S as (6).

$$T_2 = \frac{\mathrm{S} * D_{max}}{16} \tag{6}$$

As in Equation (7), To minimize minor noise influence, set a lower limit for post-processed threshold (5 in this paper's experiment), and use latest threshold for corner detection and subsequent image matching.

$$T_2' = \mathrm{ma\,x}(T_2, Lowerlimit) \tag{7}$$

Corner detection of different types of corners

To detect the multiple types of corners, the rules are set as follows:

1. When points around the candidate point satisfying Equation 1 are less than 8, implying complex grayscale variations nearby, the point is discarded as a corner.

2. If over 12 consecutive points around the candidate point satisfy Equation 1 (traditional FAST logic), the point is recognized as an L-shaped corner.

3. If neither of the above conditions is met, grayscale variations of surrounding points are assessed. If two adjacent points—one satisfying Equation 1 and the other not—are identified, this signifies one transition. For an even number of transitions (4 for X-shaped, 6 for Y-shaped corners), the candidate point is recognized as an X or Y-shaped corner.

Non-Maximum Suppression

During the process, multiple detected corner points might aggregate around the same corner. To mitigate this, non-maximum suppression is implemented on detections, diminishing the prominence of clustered edges and feature points.

Image matching

For distinct images, the set of detected corner points includes usable and duplicate corners. Measurement criteria are as follows: a corner is considered usable if it appears in the first image and has a high likelihood of appearing in the second image, signifying matching potential. A corner is deemed a duplicate if an identical corner's physical location is identified in both images and correctly matched. The rate of duplicate corners is defined as number of corners repeated divided by usable.

In the matching process, after the detection, all the corners are located in the image. Since the corners are currently represented as individual pixels, SIFT descriptors are employed to create descriptors for each corner, highlighting their distinctive features. The nearest neighbor approach (KNN) is then used to match the corner points with their closest counterparts in the other image [14].

3 Experiment and Result

3.1 Detection result comparison

Experiments were conducted using an image of a flower with its leaves, after using four algorithms: Harris, SUSAN, traditional FAST and improved FAST to detect the flower picture, the result is as shown in Fig. 2.

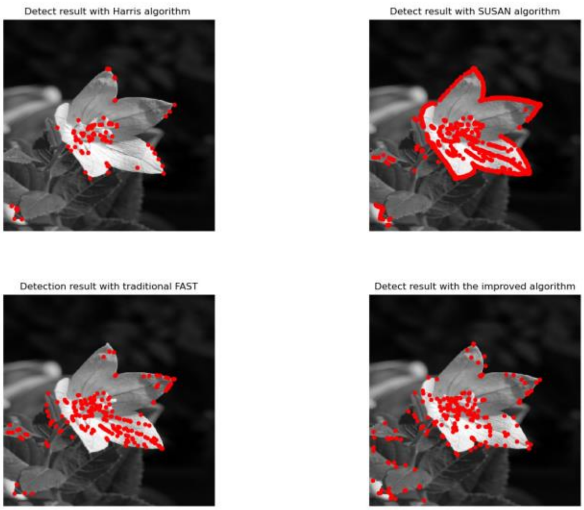

Fig. 2. Detection result with four algorithms (Photo/Picture credit: Original)

Comparing the performance of these four corner detection algorithms, the results reveal distinct patterns. SUSAN detects 725 corners, Harris detects 87, FAST detects 309, and the improved FAST detects 25. Harris excels at pinpointing vital corners. However, false detections and missed detections in areas like the leaves persists. In SUSAN, its accuracy is compromised by edges. Nearly all the flower's edges and the veins are falsely labeled as corners. Missed detections occurs too. Only few leaves are detected. As for FAST, its lack of robustness is evident: the petal's veins are prone to numerous false detections. Moreover, crucial corners on the petal and the leaf behind it remain undetected.

In contrast, the improved algorithm not only detects redundant corners on the flower, but also accurately identifies leaf corners without any shifting. Compared to SUSAN, it effectively mitigates false detections. In comparison to Harris, it exhibits fewer instances of missed detection, demonstrated by its ability to detect leaf corners.

In summary, the improved algorithm displays significant superiority in terms of both the quantity of accurate detections and the distribution of corners.

3.2 Robust Test

To verify the improved algorithm's advantage of robustness, five units of Gaussian white noise are introduced to the image, then a detection is conducted.

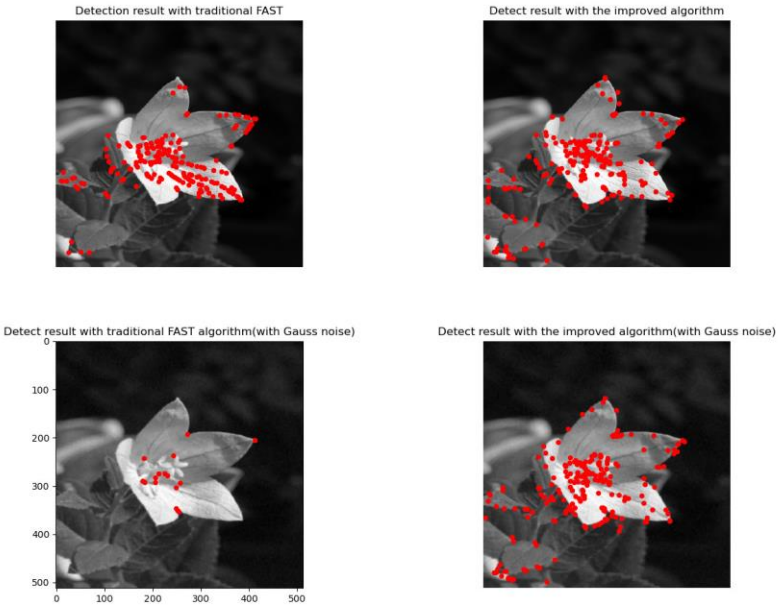

Fig. 3. Result comparison of the detection (with Gaussian noise) (Photo/Picture credit: Original)

Table 1. Statics of the Gaussian Noise added to the image

	Number	Number with noise	False detection (by noise)	Missed detection (by noise)
FAST	309	42	3	266
Improved FAST	253	214	18	57

As is shown in Fig. 3 and Table 1, The detection result remains stable with Gaussian noise added. In addition, only the location of a bit corners detected shifts. Also, the shift range is not significant. In the improved algorithm, A detection rate of 7.4% is observed among the corners identified in the original image, which is a great improvement compared with the 12.6% of the traditional FAST algorithm, proves that the improved algorithm demonstrates strong robustness.

Furthermore, an image of the real-life scenario (an office full of objects) is detected, aiming to take a further test of the robustness.

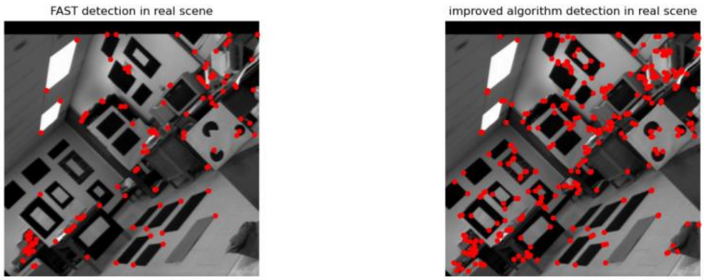

Fig. 4. Comparison of the detection result in real-life scene (Photo/Picture credit: Original)

As is shown in Fig 4, in a real-life detection, the improved algorithm has the ability to detect almost all of the corners. While the traditional FAST only detects part of them, leading to lots of missed detection. The result proves the robustness of the improved algorithm in a real-life scene.

3.3 Matching result comparison

Two images of a box (324*223 pixels) and the box in a scene shown are taken into match with Harris, traditional FAST and improved FAST algorithms, The first image (a box) is approximately fully contained within the second image (a scene with the box in it). the result is as shown in Fig. 5.

Fig. 5. Matching result with Harris, traditional FAST, improved FAST (from top to bottom) (Photo/Picture credit: Original)

Table 2. Statics of the image matching result

	Corners usable	Corners repeated	Corners mismatched
Harris	530	7	2
Traditional FAST	1621	9	9
Improved FAST	501	15	11

Fig. 5 shows the matching result by different algorithms and the Table 2 is the statics. It is obvious that compared to traditional FAST and Harris detection algorithms, under the same matching algorithm conditions, the improved FAST corner detection yields a greater number of matches. With the KNN feature point matching approach, the improved method detects a greater number of usable feature points. Moreover, it results in a larger quantity of matched corner points. This proves that the method holds significant advantages in both feature extraction and corner point repeatability.

4 Conclusion

In this paper, an accurate and robust image matching method based on an improved FAST algorithm is proposed. By incorporating a two-layer adaptive threshold mechanism and modifying the corner judging template in image matching process, the algorithm can detect various types of corners, resulting in enhanced robustness and accuracy.

The superiority of the improved algorithm over traditional FAST and Harris detection methods is proved by the experiment results. The improved algorithm outperforms in both the quantity as well as distribution of identified corners. Furthermore, the algorithm's robustness was verified through experiments involving Gaussian noise and real-life scenarios, where it consistently maintained its accuracy in corner detection.

By adopting the improved FAST algorithm, the matching process benefits from an increased number of usable feature points and better repeatability of corner points. This signifies its potential for applications requiring real-time and accurate image matching techniques.

However, constrained by the pixel-centric underlying logic, the algorithm remains confined to a single-scale space, inevitably leading to susceptibility in complex corner scenarios and significantly impacting the detection outcomes.

Although deep learning methods of computer vision develops prosperously, many engineering fields still tend to traditional algorithms. Research in traditional algorithms remains meaningful. The image matching method based on improved FAST algorithm paves the way for numerous avenues of research and development in the field computer vision.

Reference

1. Arulkumar, V., Prakash, S. J., Subramanian, E. K., Thangadurai, N.: An Intelligent Face Detection by Corner Detection using Special Morphological Masking System and Fast

Algorithm. In: 2nd International Conference on Smart Electronics and Communication (ICOSEC), pp. 1556-1561. IEEE, Tiruchirappalli (2021).
2. Liu, J., Park, J.M.: "Seeing is not always believing": detecting perception error attacks against autonomous vehicles. IEEE Transactions on Dependable and Secure Computing 18(5), 2209-2223. (2021)
3. Zoghlami, I., Faugeras, O., Deriche, R.: Using geometric corners to build a 2D mosaic from a set of images. In: Proceedings of IEEE computer society conference on computer vision and pattern recognition (CVPR), pp. 420-425. IEEE, San Juan(1997).
4. Zhang, Z.: Research on vision based satellite motion analysis pose measurement and capture position detection. Harbin Institute of Technology, MA thesis (2020).
5. Hassaballah, M., Abdelmgeid, A.A., Alshazly, H.A.: Image features detection, description and matching. In: Awad, A., Hassaballah, M. (eds) Image Feature Detectors and Descriptors. Studies in Computational Intelligence, vol 630, pp 11–45. Springer, Cham. (2016).
6. Bansal, M., Kumar, M., Kumar, M., Kumar, K.: An efficient technique for object recognition using Shi-Tomasi corner detection algorithm. Soft Comput 25, 4423–4432 (2021).
7. Smith, S.M., Brady, J.M.: Susan - a new approach to low level image processing. International Journal of Computer Vision 23, 45–78 (1997)
8. Ng, P. C., Henikoff, S.: SIFT: Predicting amino acid changes that affect protein function. Nucleic acids research 31(13), 3812-3814 (2003).
9. Harris, C., Stephens, M.: A combined corner and edge detection. In: Proceedings of The Fourth Alvey Vision Conference, pp. 147–151 (1988).
10. Rosten, E., Drummond, T.: Fusing points and lines for high performance tracking. In: Tenth IEEE International Conference on Computer Vision (ICCV'05) Volume 1 Vol. 2, pp. 1508-1515. IEEE, Beijing (2005).
11. Mair, E., Hager, G.D., Burschka, D., Suppa, M., Hirzinger, G.: Adaptive and generic corner detection based on the accelerated segment test. In: Daniilidis, K., Maragos, P., Paragios, N. (eds.) ECCV 2010. LNCS, vol. 6312, pp. 183–196. Springer, Heidelberg (2010).
12. Willis, A., Sui, Y.: An algebraic model for fast corner detection. In: IEEE 12th International Conference on Computer Vision(ICCV'09), pp. 2296-2302. IEEE, Kyoto (2009).
13. Nasser, E. F.: Improvement of corner detection algorithms (Harris, FAST and SUSAN) based on reduction of features space and complexity time. In: Engineering & Technology Journal, 35(2 Part B), 112-118 (2017).
14. Liu, S., Liang, X., Liu, L., Shen, X., Yang, J., Xu, C. Lin, L., Cao X., Yan, S.: Matching-cnn meets knn: Quasi-parametric human parsing. In: Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR), pp. 1419-1427. IEEE, Boston (2015).