Novel SURF image mosaic method based on wavelet transform

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ABSTRACT

To tackle the issues of significant computational requirements and extended processing times inherent in traditional image mosaic algorithms, a novel SURF-based image mosaic method that employs wavelet transform is proposed in this paper. Firstly, the Haar wavelet image preprocessing method is adopted to obtain the second order decomposition and extract the low-frequency (LF) components of the image. Then the wavelet gradient vector is utilized to extract characteristic points in the overlap region of LF images. This allows for quick acquisition of transformation parameters for characteristic points in LF images, which can guide the selection of characteristic point extraction in high-frequency (HF) images. Based on this, an improved SURF image matching algorithm is proposed utilizing properties such as single direction matching and orientation coherence. This approach effectively eliminates mismatched point pairs, thereby improving accuracy and real-time performance of characteristic point matching. Finally, two experiments are conducted to confirm the practicality and usefulness of these proposed outcomes.
Keywords: Image stitching, wavelet transform, SURF, characteristic points matching

1. INTRODUCTION

Image stitching technology denotes to the utilization of numerous image fusion algorithms and image registration algorithms to stitch multiple images with imbrication areas into a single wide-field of view, seamless, high-resolution image, or active all-around image[1]. At present, image stitching technology has been applied widely to unmanned aerial vehicle (UAV) shadowing and exploration, virtual reality, space investigation, satellite remote detection, medicine, military and other fields[2], and many scholars at home and abroad have also conducted numerous investigate on this technology and achieved productive outcomes.

In 1999, Lowe et al.[1] introduced the scale-invariant characteristic transform (SIFT) algorithm, which is capable of effectively extracting image characteristic points. However, the algorithm generates a high number of subdimensions for characteristic description, impacting the real-time performance of image matching. Bay et al.[3] proposed the Speeded Up Robust Characteristics (SURF) algorithm, which addresses the limitations of the SIFT algorithm by utilizing the Hessian matrix to identify candidate points and implementing a non-maximal suppression strategy. Additionally, it effectively ensures the stability of image scale and affine transformation[4]. Based on this foundation, Hu et al.[5] proposed a rapid regional centroid image registration algorithm to address the intricate issue of utilizing the traditional Normalized Cross Correlation (NCC) image registration method. This algorithm seeks the best matching point instead of the usual upper left corner of the image and also enhances the real-time performance of image matching. In order to further enhance the speed of image registration, a new method for optimizing the rapid registration of SIFT images was proposed in Reference[6]. This method effectively reduces the number of characteristic points by utilizing the image downsampling preprocessing technique and improves the characteristic point matching rate by employing the extreme characteristic extraction method of the image coincident region. Xu et al.[7] utilized the enhanced Harris corner detection algorithm to extract scale-invariant corners, employed the Forstner operator concept for precise corner localization, and applied SIFT to describe the diagonal points of the operator in order to achieve rapid and stable image matching. Dai et al.[8] combined the Oriented Characteristics from Accelerated Segment Test and Rotated Binary Robust Independent Elementary Characteristics. Apart from the scale invariance of the traditional SURF algorithm, they proposed an image characteristic point matching based on improved ORB to effectively enhance the characteristic point matching rate in the image tile region. Liu et al.[9] proposed an image registration algorithm based on an improved wavelet transform and SIFT characteristics. The algorithm preprocesses the data and subsequent images through multi-resolution wavelet decomposition. It utilizes the SIFT algorithm to extract characteristic points from the LF components of the image, which contain a large amount of information. Furthermore, it employs the Random Sample Consensus (RANSAC)

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International Conference on Optics, Electronics, and Communication Engineering (OECE 2024), edited by Yang Yue, Proc. of SPIE Vol. 13395, 1339542 · © 2024 SPIE · 0277-786X · Published under a Creative Commons Attribution CC-BY 3.0 License · doi: 10.1117/12.3049845

algorithm and the Best Bin First (BBF) algorithm to test and search for characteristic point pairs. Zhan et al.[10] proposed an image matching method based on the scale-limited SURF algorithm, which effectively addresses the issue of high false matching rates in traditional SURF algorithms. It is achieved by employing the SURF algorithm and scale-limited processing to conduct coarse and fine matching of image characteristic points, as well as utilizing a sample statistical method to eliminate false matches.

The literature above primarily focuses on researching and improving the extraction of image characteristic points, as well as enhancing the effect and efficiency of image matching. It has achieved certain results in this area. However, there is still room for improvement in the stitching effect to enhance real-time image stitching and the matching rate of characteristic points while ensuring high-quality image stitching. Therefore, this paper proposes a novel SURF image stitching method based on wavelet transform. This method utilizes the wavelet gradient vector to extract characteristic points in the overlapping region of the LF image through two-dimensional wavelet transform. This allows for obtaining transformation parameters of characteristic points in the LF image quickly, which guides the extraction of characteristic points in the HF image. Based upon this, an improved SURF image matching algorithm is proposed. Finally, two sets of experiments are conducted to verify the effectiveness of proposed method.

2. IMAGE PREPROCESSING AND CHARACTERISTIC POINT EXTRACTION AND MATCHING

The flowchart of the novel SURF image stitching method employing wavelet transform is presented in Figure 1. It primarily comprises three components: 1) Image preprocessing utilizing the Haar wavelet function, which involves the wavelet decomposition of the image to be registered for LF images acquisition. 2) Characteristic point extraction employing the wavelet gradient vector, where the overlapping region of the LF image is identified using the wavelet gradient vector. This facilitates obtaining transformation parameters for characteristic points within the LF image to guide characteristic point extraction from the HF image; and 3) Characteristic point matching employing the SURF algorithm, which leverages unidirectional matching and directional consistency constraints to effectively eliminate mismatched point pairs. This ultimately enhances both accuracy and real-time performance in characteristic point matching.

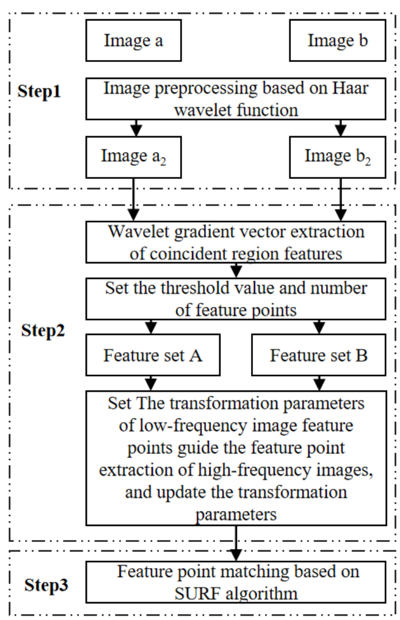


Figure 1. Flow diagram of improved algorithm.

2.1 Image preprocessing based on Haar wavelet function

The HF components in the image contain the effect of noise, and the multi-layer decomposition using wavelet transform can effectively remove the HF components, and the more wavelet decomposition layers, the better the effect of removing noise interference[11,12]. Therefore, the wavelet transform in this paper will be utilized to decompose and preprocess the images to be registered, so as to match the decomposed LF images. Given that the matching characteristic points in the decomposed LF image will decline, and if the image is matched after wavelet multi-layer decomposition, there may be too few matching characteristic points, or even unable to satisfy the normal matching requirements. Therefore, this paper proposes to use a two-layer Haar wavelet decomposition method for image preprocessing and then extract the matching characteristic points from the LF components.

The Haar wavelet function is the simplest and the first orthogonal wavelet basis function with tight support. It is defined as:

$$\psi_H = \begin{cases} 1, & 0 \le x < 1/2 \\ -1, & 1/2 \le x < 1 \\ 0, & else \end{cases} \tag{1}$$

The scale function is:

$$\phi = \begin{cases} 1, & 0 \le x \le 1 \\ 0, & else \end{cases} \tag{2}$$

The two-dimensional wavelet decay of the registered image $f(x, y)$ is carried out through the Haar wavelet function, and firstly, the x way of the registered image function is examined by $\psi_H(x)$ and $\phi(x)$ respectively, and $f(x, y)$ was disintegrated into two parts: low and high incidence. On this basis, an alike examination is done in the y way. The image $f(x, y)$ to be recorded is managed by $\phi(x)$ and $\phi(y)$ to obtain the image LL after the first layer of wavelet decay, and the other three images are LH, HL, and HH, respectively. The similar dispensation is done for LL in Figure 2 to gain image LL_1 after the second layer wavelet decay of the image $f(x, y)$ to be recorded, as shown in Figure 2.

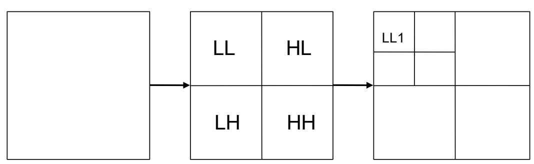


Figure 2. Diagram of wavelet decomposition.

2.2 Characteristic point extraction based on wavelet gradient vectors

The characteristic points of images are distributed in different scales. In order to solve the issue of the scale of the detection characteristic point, the SURF algorithm usages the Gaussian function to concept the line scale space, but there are fuzzy image outlines such as the linear scale space when detecting the characteristic point. Compared with the Gaussian function, the wavelet function has the compensations of choosing elasticity and tight support. In the wavelet transformation process, it may better retain different scale image characteristics, so start from the multi-scale performance angle of the wavelet transformation. The vector extracts the image characteristic point that does not change the scale and revolution[14].

After wavelet decomposition of the second layer of the obtained image $f(x, y)$ to be registered, the image LL_1 is set as image $g(x, y)$, and the characteristic points of the image coincidence region are extracted by the two-dimensional wavelet convert of the $g(x, y)$ image, that is, the characteristic points of the image are extracted by the wavelet mode maximum principle.

Based on the description of a two-dimensional wavelet function, it is evident that $t(x, y)$ represents a 2D smooth function. Given the impact of HF components in the image, directly identifying the inflection points of the smooth function $t(x, y)$ becomes more complex; therefore, we focus on determining the maximum value of the modulus of its first derivative.

Firstly, the partial offshoots of the variables in the function $t(x, y)$ are obtained, and the two-dimensional wavelet functions are obtained:

$$\psi^1(x,y)=\frac{dt(x,y)}{dx} \tag{3}$$

$$\psi^2(x,y)=\frac{dt(x,y)}{dy} \tag{4}$$

Subsequently, when functions $\psi^1(x,y)$ and $\psi^2(x,y)$ meet the criteria for two-dimensional wavelet transformation at scale 2^j, the corresponding wavelet generating functions can be derived as follows:

$$\psi_j^1(x,y)=\frac{1}{2^j}\psi^1(\frac{x}{2^j},\frac{y}{2^j}) \tag{5}$$

$$\psi_j^2(x,y)=\frac{1}{2^j}\psi^2(\frac{x}{2^j},\frac{y}{2^j}) \tag{6}$$

Subsequently, the convolution operation between equation (5), equation (6), and the image function $g(x,y)$ is performed. At scale 2^j, the two-dimensional wavelet transformation of an image $g(x,y)$ can be expressed as follows:

$$W_j^1 g(x,y)=g(x,y)*\psi_j^1(x,y) \tag{7}$$

$$W_j^2 g(x,y)=g(x,y)*\psi_j^2(x,y) \tag{8}$$

Through substituting equations (3) and (5) into equation (7), and (4) and (6) into equation (8), we get:

$$\begin{aligned} W_j^1 g(x,y) &= g(x,y)*\psi_j^1(x,y) \\ &= g(x,y)*(2^j\frac{dt_j}{dx})(x,y) \\ &= 2^j\frac{d}{dx}(g(x,y)*t_j)(x,y) \end{aligned} \tag{9}$$

$$\begin{aligned} W_j^2 g(x,y) &= g(x,y)*\psi_j^2(x,y) \\ &= g(x,y)*(2^j\frac{dt_j}{dy})(x,y) \\ &= 2^j\frac{d}{dy}(g(x,y)*t_j)(x,y) \end{aligned} \tag{10}$$

Thus:

$$\begin{aligned} \begin{bmatrix} W_j^1 g(x,y) \\ W_j^2 g(x,y) \end{bmatrix} &= 2^j \begin{bmatrix} \frac{d}{dx}(g(x,y)*t_j)(x,y) \\ \frac{d}{dy}(g(x,y)*t_j)(x,y) \end{bmatrix} \\ &= 2^j\nabla(g(x,y)*t_j)(x,y) \end{aligned} \tag{11}$$

Where: $\nabla(g(x,y)*t_j)(x,y)$ is the gradient vector.

In accordance with equation (11), the binary wavelet coefficients $W_j^1 g(x,y)$ and $W_j^2 g(x,y)$ exhibit a direct proportionality to the partial derivatives of the image $g(x,y)$ smoothed by $t_j(x,y)$ along the X-axis and Y-axis directions, respectively, at scale 2^j.

Then the extraction steps of characteristic points are as follows:

Step 1: At scale 2^j, the modulus and Angle of the binary wavelet transform of image $g(x,y)$ are:

$$M_j g(x,y) = \sqrt{\left|W_j^1 g(x,y)\right|^2 + \left|W_j^2 g(x,y)\right|^2} \tag{12}$$

$$A_j g(x,y) = \arg(W_j^1 g(x,y)) + i(W_j^2 g(x,y)) \tag{13}$$

The local non-maximum values are suppressed based on the wavelet gradient vector, whereby the gradient value is compared against the nearby 8 points. If the present point possesses the largest gradient value, it is classified as an undetermined characteristic point; otherwise, it will be excluded from the characteristic point detection algorithm[15].

Step 2: If the gray value of the undetermined characteristic point exceeds the defined threshold value λ, it is classified as a applicant characteristic point; otherwise, points with gray values below the threshold λ are eliminated.

Step 3: If the quantity of applicant characteristic points exceeds the defined threshold value μ, the candidate characteristic points with higher gray value are selected as image characteristic points. If the quantity of applicant characteristic points is lower than the set threshold value μ, the candidate characteristic points are considered image characteristic points.

Step 4: By using the transform parameters of the characteristic points extracted from the LF image to director the characteristic points extracted from the HF image, and update the transform parameters.

2.3 Characteristic point matching based on SURF algorithm

In the procedure of characteristic point registration, in order to advance the correctness of image characteristic point registration, the improved image matching algorithm of SURF is adopted in this paper to determine the consistent matching relationship between characteristic points of the image to be registered through the registration method combining unidirectional and directionality constraints[16]. First of all, one-way matching is achieved on the matched image, and then the alteration in the way of the characteristic vector between each matching point pair is intended. When the difference is within a certain threshold range, the characteristic point matching is measured effective. Otherwise, other incompatible point couples are eliminated to recover the positive correctness of image characteristic point corresponding. The specific realization process is as follows.

Firstly, the alteration between each matching point and the key way of the characteristic vector was calculated:

$$H_i = H1_i - H2_i \tag{14}$$

$H1$ is the key way Angle of characteristic vector a of the image to be matched, $H2$ is the key way Angle of characteristic vector b of the image to be matched, and $i = 1,2,...n$, n is the logarithm of all matching points.

Secondly, the alteration of all matching point pairs was calculated to produce histogram, with 10º as 1 pillar, with a total of 36 columns.

Finally, the Angle conforming to the peak value in the histogram is calculated as the standard deviation value of the successful matching point pairs, and the matching point pairs within 10º degrees of the peak are retained, and other matching point pairs are eliminated.

3. EXPERIMENTAL VALIDATION

By using the programming software Matlab7.0 to confirm the possibility of the projected improved algorithm, two sets of experiments are now used to perform the splicing simulation experiment. Experiment 1 usages the images with Angle difference captured by the camera from two angles as the images to be matched, experiment 2 uses the images without Angle difference as the matched images. Traditional SURF algorithm, Reference[5] method, and this paper's method were accustomed to excerpt and competition characteristic points respectively, and the experimental results were compared.

Experiment 1:

The original image to be spliced is presented in Figure 3, where the scope of the captured image is 760×1280, and the images with dissimilar viewing angles taken by the camera from two angles to be matched are shown in Figures 3(a) and 3(b) correspondingly. In the experiment, the gray value threshold of characteristic points is set to 50, and the upper limit of characteristic points is 100. The result of characteristic point detection in the image coincidence area is exposed in Figure 4.

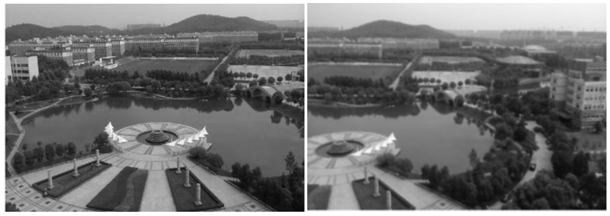
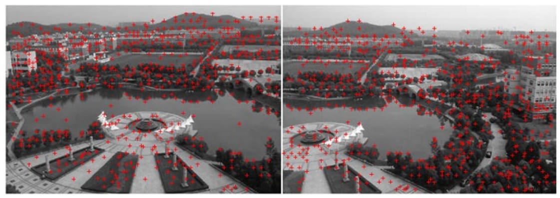
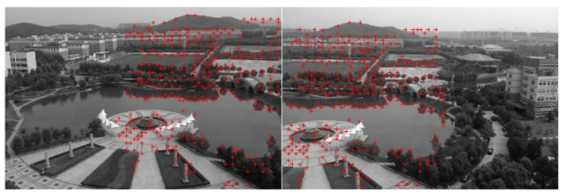


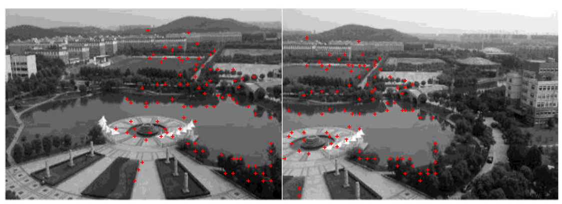
Figure 3. The matching image. (a): Picture of left camera lens; (b): Picture of right camera lens.



(a) Characteristic point extraction of traditional SURF algorithm.



(b) Characteristic point extraction of Reference[5].



(c) Characteristic point extraction of our method.

Figure 4. Image of characteristic point extraction.

After the improved image matching algorithm of SURF, the experimental renderings obtained by the proposed method were compared with those obtained by traditional SURF algorithm and Reference[5], as exposed in Figure 5.

(a) (b) (c)

Figure 5. (a): Mosaic effect of traditional SURF algorithm; (b): Mosaic effect of Reference[5]; (c): Mosaic effect of our method.

As can be seen from the above comparison table of the stitching effect diagram and the image stitching parameters, the comparison chart of the stitching effect of the image with viewing angle difference is shown in Figure 5, and the image stitching effect of the proposed method is better than that of the traditional SURF algorithm and the image stitching method of Reference5. From Table 1, compared with the traditional SURF algorithm, the matching rate increases from

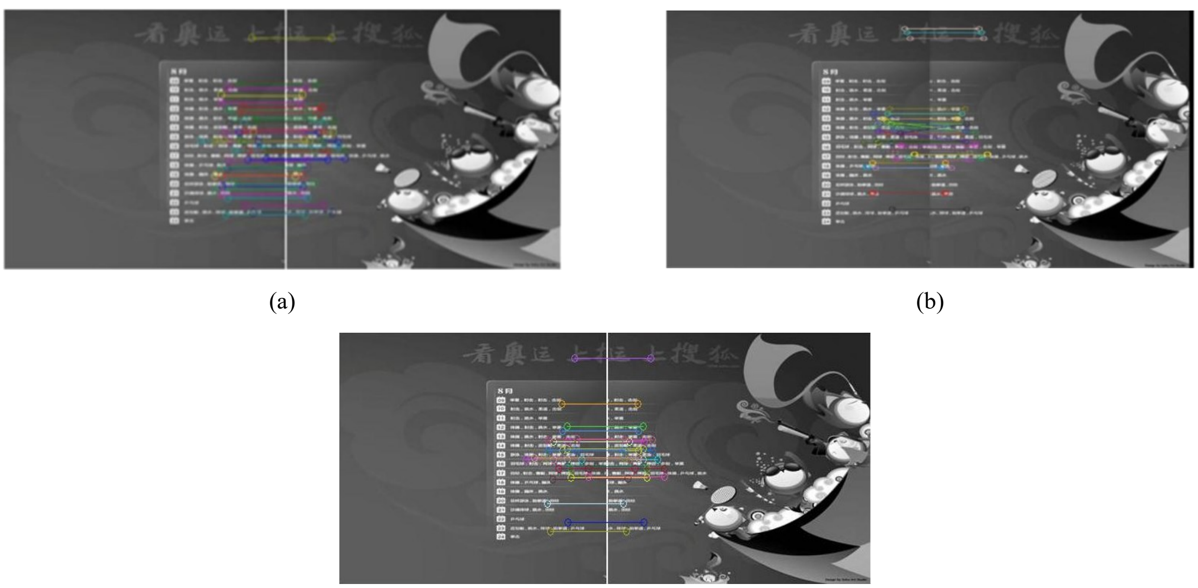
12.6% to 28.7%, the time for extracting characteristic points decreases from 26.07s to 2.72s, and the image stitching time decreases from 33.26s to 13.86s, and compared with the method in Reference[5], the matching rate increases from 9.1% to 28.7%. The time of extracting characteristic points declines from 5.39s to 2.72s, and the image stitching time decreases from 19.92s to 13.86s.

Table 1. Comparison parameters of image stitching.

Method	Image stitching parameters			
	The number of characteristic points to be extracted	The number of matching characteristic points	The time at which the characteristic points were extracted (s)	Image stitching time (s)
Tradition SURF	997	126	26.07	33.26
Reference[5]	320	29	5.39	19.92
Novel SURF	94	27	2.72	13.86

Experiment 2:

The ash value threshold of the characteristic point in the experiment is set to 50, and the upper limit of the number of characteristic points is 100, and the image characteristic point matching results are shown in Figure 6.



(a) (b) (c)

Figure 6. (a): Matching results of traditional SURF algorithm; (b): Matching results of Reference[5]; (c): Matching results of our algorithm.

After the image matching improvement algorithm of SURF, the experimental results obtained by the method in this paper were compared with the experimental results obtained by traditional SURF algorithm and method in Reference[5] of Figure 7.

(a) (b) (c)

Figure 7. (a): Mosaic effect of traditional SURF algorithm; (b): Mosaic effect of Reference[5]; (c): Mosaic effect of our algorithm.

As can be seen from the above comparison table of the stitching effect and the image stitching parameters, the comparison chart of the image stitching effect without viewing angle difference is shown in Figure 7, and the image stitching result of the proposed method is basically the same as that of the outdated SURF algorithm. However, from Table 2, likened with the outdated SURF algorithm, the matching degree increases from 30.8% to 37.8%, the time for extracting characteristic points decreases from 7.78 seconds to 2.31 seconds, and the image stitching time decreases from 17.03 seconds to 11.65 seconds, and compared with Reference[5] method, the matching rate increases from 32.9% to 37.8%. The time of extracting characteristic points declines from 4.86 seconds to 2.31 seconds, and the image stitching time decreases from 14.91 seconds to 11.65 seconds.

Table 2. Comparison parameters of image stitching.

Method	**Image stitching parameters**			
	The number of characteristic points to be extracted	**The number of matching characteristic points**	**The time at which the characteristic points were extracted(s)**	**Image stitching time(s)**
Tradition SURF	146	45	7.78	17.03
Reference[5]	97	32	4.86	14.91
Novel SURF	66	25	2.31	11.65

4. CONCLUSION

Utilizing the traditional SURF image stitching algorithm, this study presents a novel SURF image stitching method employing wavelet transform. The LF component gained through second-order decomposition is derived by preprocessing the image with the Haar wavelet function. The wavelet gradient vector is employed to excerpt characteristic points in the overlapping regions of the LF images, while gray value and quantity threshold limits are implemented to decrease both the amount of characteristic point pairs and abstraction time. Experimental results demonstrate that, compared to Reference[5] and the traditional SURF algorithm, the proposed method not only ensures effective image stitching but also enhances characteristic point extraction and matching performance.

ACKNOWLEDGMENTS

The authors would like to thank anonymous reviewers and the editor for their valuable comments and helpful suggestions. This work was supported by the financial supports of Anhui University Natural Science Research Project (Grant NO.2022AH052353, Grant NO.2023AH052694).

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