A fast image stitching algorithm based on improved SURF

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***Abstract*—A fast image stitching algorithm based on improved speeded up robust feature (SURF) is proposed to overcome the real-time performance and robustness of the original SURF based stitching algorithms. The machine learning method is adopted to build a binary classifier, which identify the key feature points extracted by SURF and remove the non-key feature points. In addition, the RELIEF-F algorithm is used for dimension reduction and simplification of the improved SURF descriptor to achieve image registration. The threshold-based weighted fusion algorithm is used to achieve seamless image stitching. Finally, several experiments are conducted to verify the real-time performance and robustness of the improved algorithm.**

Key words: fast image stitching; SURF algorithm; machine learning; RELIEF-F algorithm; image fusion

I. INTRODUCTION

Image stitching refers to spatially registering or aligning image sequences with overlapping regions to produce a wide-angle panorama, Being a hot topic of image processing, image stitching technology has attracted great attention in relevant researches on a global scale [1].

Specifically, image stitching includes two steps, image registration and image fusion, of which the first step is the key part. Common image registration algorithms can be classified into two groups, i.e., domain-based registration and feature-based registration [2]. By comparison, the latter features low complexity and high robustness, thus has been used in wide applications in recent years.

Previously, Lowe et al. [3] proposed scale-invariant feature transform (SIFT) with scale and rotation invariance and no sensitivity to noise. However, SIFT has shortcomings of being sensitive to the changes in viewing angle and involving slow detection and registration. Alternatively, Bay et al. [4] proposed speeded up robust feature (SURF), which is greatly improved compared to SIFT in terms of repeatability, robustness, and computational speed. To date, SURF has been successfully applied to image retrieval, object recognition, image stitching and etc.

Many scholars have focused on the improvement of SURF, aiming to further improve the performance of the algorithm. Yang et al. [5] proposed a method combining SURF and SC-RANSAC, which achieves fast image registration. Shi et al. [6] reported on an image registration method combining SIFT and SURF, in which parallel computing is used to improve computational efficiency. Zhou et al. [7] optimized the parameter configuration of SURF from the perspectives of weight value of window filter, selection of subdomain around feature points, and sampling range of Haar wavelet transform in the subdomain, in order to maximize the advantages of the algorithm in applications with different emphases. Although the existing improved algorithm can reliably describe the corresponding

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relations between image sequences under different conditions, the robustness and real-time performance cannot meet the needs of practical applications.

To solve the above problems, this study presents a fast image stitching method based on improved SURF. The SURF algorithm is first improved based on machine learning, in order to identify key feature points and eliminate non-key feature points. Additionally, the RELIEF-F algorithm [8] is used for dimension reduction and simplification of the improved SURF descriptor, which is then used for training of the feature point classifier. Finally, the improved weighted fusion algorithm [9] is employed for image fusion, which effectively solves the problems of blurring and ghosting, achieving seamless image stitching.

II. PRINCIPLE OF SURF ALGORITHM

The two parts of SURF are feature point selection and description.

1) Feature point extraction: SURF chooses the Hessian matrix based detector. For a point on the input image I, the Hessian matrix in scale space σ is expressed as:

$$H(x,\sigma)=\begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{yx}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix}$$

The discriminant of Hessian matrix is then computed, and its negative or positive value is used to determine whether the point is an extreme point.

2) Feature point description: The SURF feature point descriptor first constructs a window region with a feature point as the center and then divides the window into 4 × 4 sub-window regions. From each sub-window, 5 × 5 sampling points are taken to calculate the Haar wavelet response in horizontal and vertical directions. The obtained wavelet coefficients are denoted as d_x and d_y. The wavelet coefficients of each sub-region are weighed using Gaussian function, generating $\sum d_x$, $\sum d_y$, $\sum |d_x|$, and $\sum |d_y|$ to form the four dimensions in the descriptor. Each of the 4 × 4 sub-window has a four-dimensional vector, and a 64-dimensional vector (4 × 4 × 4) is thus obtained, i.e., the SURF descriptor. The construction process of the descriptor is shown in Fig. 1.

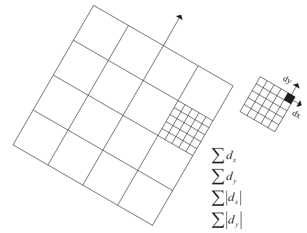


Fig. 1 The 64-dimentinoal descriptor generated by SURF

III. IMPROVED SURF BASED ON MACHINE LEARNING

The main idea of machine learning based feature point extraction [10] is to divide the SURF-extracted feature points into two classes: 1) key feature points, i.e., the key region of image feature recognition. For two images to be stitched, the corresponding relationship between key feature points is more important; and 2) non-key feature points, which have little effect on feature point registration and thus almost can be excluded from the registration process.

Here a binary classifier is built to distinguish the above two classes of feature points. A set of feature points K is extracted from image I using the SURF algorithm; each feature point $k_i \in K$ can be described using a set of features F extracted from the feature image $Q_\omega^F(k_i)$ where k_i is the center and ω is the width. Additionally, each feature point is assigned with a marker according to the feature image using the classifier $Y(Q_\omega^F)\in L$, $L=\{-1,1\}$. When $Y(Q_\omega^F)=1$, k_i is considered to be a key feature point; when $Y(Q_\omega^F)=-1$, this feature point is discarded.

Next, we will further discuss some specific issues in the implementation of the proposed algorithm.

A. Removal of redundant information

When establishing a training dataset with feature points extracted from the image being proximal in spatial location, the feature image may contain redundant information, thereby reducing the efficiency of image registration. To avoid the redundancy, it is necessary to add distance constraints between the extracted feature points. Denote K_I as a set of feature points extracted from image I. For each feature point pair with the same mark (both marked as 1 or -1), k_1, $k_2 \in K_I$. The distance between the feature points is ensured to be greater than the critical value d, i.e., $dist(k_1, k_2) > d$, where $dist$ is a distance function, here referring to Euclidean distance; and d is set as 5 pixels.

B. Training dataset balancing

Feature point extraction using the above-mentioned method may cause imbalance in training dataset. That is, the number of non-key feature points far exceeds that of key feature points in the dataset. Classification based on imbalanced dataset can not achieve accurate classification result.

In order to solve this problem, sampling in the original data set is performed to establish a balanced training data set, and random sampling without replacement is used to train the classifier [11]. This method generates a smaller data set than the original one. Sampling without replacement can ensure the training objects are real instance, thus making the classifier more accurate.

C. SURF descriptor improvement and simplification

The SURF descriptor has 64 dimensions generated by computation of Haar wavelet response in 4 × 4 sub-regions with feature points as the center. Here we describe the feature points using the SURF descriptor with the following four attributes added: 1) the strength of feature points (positive value represent black point and negative value represent white point); 2) Gaussian model of extracted feature points; 3) trace of Gauss matrix used to discover feature points; and 4) direction of feature points. Finally, a 68-dimensional feature vector is obtained.

To further simplify the computation and remove redundancy, we use the RELIEF-F algorithm for dimension reduction and simplification of the 68-dimensional SURF descriptor into a 48-dimensional descriptor [8]. The simplified SURF descriptor is used to identify key feature points in the classification. The basic idea of RELIEF-F algorithm is to randomly select examples from the training data set, compute their neighborhood, as well as adjust feature vector to separate an example from different kinds of neighborhood elements and use it to train the feature point classifier.

IV. IMAGE FUSION

During the image acquisition process, there are differences in light intensity and shooting angle as well as errors in image registration. Although the conventional weighted average method can achieve smooth transition in the stitched region of the panorama, the phenomena of blurring and distortion may occur in the overlapping region. Additionally, it remains difficult to eliminate light differences and ghosting [12].

The improved algorithm applies threshold-based weighted smoothing [13], in which a threshold K is introduced. For the stitched image, difference between the pixel value and weighted average of the point before smoothing is first computed and compared with threshold K before assigning a value. This approach divides the overlapping region of the image into three parts which are blended separately.

The overlapping parts of two images to be stitched are set as I_1 and I_2, whose corresponding pixel values are $im1$ and $im2$, respectively; the weighted average is denoted as $Mean = d_1 \times im1 + d_2 \times im2$ ($0 \le d_1 \le 1$, and $d_1 + d_2 = 1$); $im3$ denotes the pixel value after smoothing, and the overlapping region is divided into three parts from left to right, i.e., L_1, L_2, and L_3.

In L_1: If $|im1 - Mean| < K$, $im3 = Mean$; otherwise, $im3 = im1$;

In L_2: if $|\max(im1, im2) - Mean| < K$, $im3 = Mean$; otherwise, $im3 = \max(im1, im2)$;

In L_3: if $|im2 - Mean| < K$ $im3 = Mean$; otherwise, $im3 = im2$.

V. EXPERIMENTAL RESULTS AND ANALYSIS

Experimental environment: Intel i5 quad-core processor, 3.1 GHz processor speed, 4 G memory, and Windows 7 operating system;

Software development platform: Visual Studio 2010 + OpenCV 2.4.3.

Two sets of images were selected to display the performance of the proposed stitching algorithm. Fig. 2 shows the stitching process of the first set of experimental images, in which (a) and (b) are the captured original image to be stitched. The two images are of equal size with different light intensities and shooting angles. There is an overlapping region between the two images. Key feature point pairs were extracted from (a) and (b) using the improved algorithm, as shown in Fig. 2(c) and (d). A total of 13 key feature point pairs were obtained from the original images (extraction time, 3.58 s). Fig. 2 (e) illustrates the stitching result of the original images A and B, which was subjected to image fusion using the threshold-based weighted average (registration time, 0.63 s; fusion time, 0.17 s). The results demonstrate that the proposed algorithm yields good fusion efficiency, which has no obvious signs of stitching between images and effectively avoids blurring and distortion in the overlapping region.


(a)


(b)


(c)


(d)


(e)

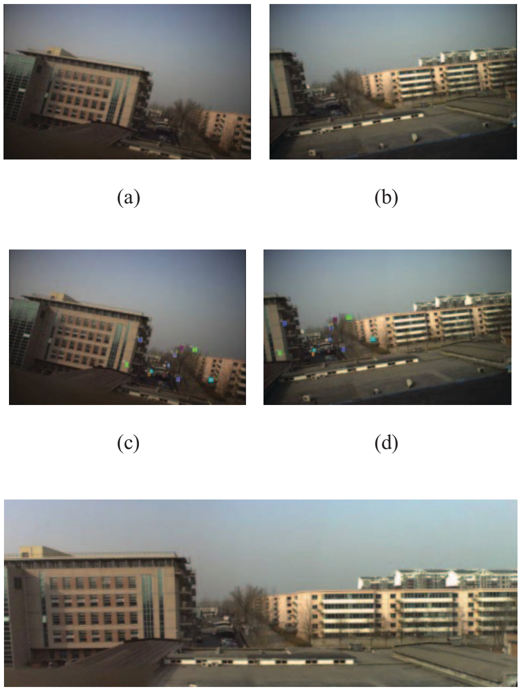
Fig. 2 Image stitching experiment I. (a)(b) The original images to be stitched, which are of equal size with different light intensities and shooting angles; (c)(d) key feature point pairs extracted from the original images using the improved algorithm; and (e) the resulting panorama.

The stitching process of the second set of experimental images is shown in Fig. 3, in which (a) and (b) are the captured original image to be stitched. There exist changing horizontal shift, rotation, scale, and light intensity in the two images, which are considered to be difficulties for stitching. Fig. 3(c) and (d) show the key feature point pairs extracted from the original images using the improved algorithm. The stitched image is given in Fig. 3 (e), which verifies that the proposed method achieves higher precision of seamless stitching and fusion for images with changing horizontal shift, rotation, scale, and light intensity, as well as possesses good robustness and adaptability.

In order to further verify the advantages of the proposed algorithm, a comparison of performance was made between the original SUIF and the improved algorithm (Table 1), and obtained different results regarding the time of feature point detection, number of feature point pairs, and time of image registration. Results show that the improved algorithm needs to identify key feature points using the classifier, thereby taking longer time than the original SUIF for feature point detection. However, the former extracts much less feature points than the latter, thereby reducing the registration time by approximately 2/3. Thus, the proposed algorithm has certain practical value by improving the efficiency of image registration and the speed of image stitching.

TABLE I PERFORMANCE COMPARISON BETWEEN SURF AND THE IMPROVED ALGORITHM

Algorithm	***Time of feature point detection (s)***	***Number of feature point pairs***	***Time of image registration (s)***
SURF	2.62	85	2.58
Improved algorithm	3.37	11	0.75



(a) (b) (c) (d) (e)

Fig. 3 Image stitching experiment II. (a)(b) The original images to be stitched, which have changing horizontal shift, rotation, scale, and light intensity; (c)(d) key feature point pairs extracted from the original images using the improved algorithm; and (e) the resulting panorama.

VI. CONCLUSIONS

A fast image stitching algorithm based on improved SURF is proposed. In this algorithm, a machine learning based binary classifier is first built to identify key and non-key feature points, in order to improve the original SURF. Additionally, the RELIEF-F algorithm is used for dimension reduction and simplification of the improved SURF descriptor, which is then used to train the feature point classifier and complete image registration. For image fusion, the threshold-based weighed fusion algorithm is used to achieve seamless image stitching. Experimental results demonstrate that the proposed algorithm has good stitching performance and fast computation speed, as well as good robustness for changing scale, rotation, and light intensity. Thus, it can meet the need of image stitching for practical application.

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