IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)
e-ISSN: 2278-2834,p-ISSN: 2278-8735
PP 58-63
www.iosrjournals.org

A Fast Panorama Stitching Method of Image Sequence

A.Jenitta[1], G.Abinandhini[2], M.Geerthanadevi[3], M.Latha[4]
Idhaya Engineering College for Women, Chinnasalem.
jenittaiecw@gmail.com, abinandhinig6296@gmail.com

Abstract: *An image stitching application panorama gives serious distortion when compositing a long image sequence. To overcome the distortion, improved algorithm is proposed in this paper, including altering the way of selecting the reference image and putting forward a method that can compute the transformation matrix for any image of the sequence to align with the reference image in the same coordinate space. Additionally, the improved stitching method dynamically selects the next input image based on the number of SIFT matching points. Compared with the traditional stitching process, the improved method increases the number of matching feature points and reduces SIFT feature detection area of the reference image. The experimental results show that the improved method can not only accelerate the efficiency of image stitching processing, but also reduce the panoramic distortion errors, and finally we can obtain a pleasing panoramic result.*
Index Terms: *Image Stitching, Image alignment, SIFT, Wide baseline images, Image Registration.*

I. Introduction

Image Stitching is a process to combine a sequence of images together, mutually having overlapping areas, resulting into a seamless, smooth panoramic image [1]. The hand-held camera has limited resolution and small field-of-view, while the image stitching can get high-resolution and high-quality panorama by using hand-held equipment. Image stitching has become a hotspot in the field of computer vision, image processing, and computer graphics.

Image registration [2] is an important step in the image stitching process. The quality of image stitching greatly depends on the accuracy of image registration. According to the different methods for image registration, the image stitching algorithms are divided into two categories generally, region-related image registration [3] and feature-based image registration [4, 5]. Region-related image registration studies the relationship of the same dimension blocks between the input image and the reference image and computes their similarity degree. But when the image is rotated or resized, this method would not result in a desired result. While the textures are too strong or too weak, the result would also show enormous stitching errors. Feature-based image registration method uses mathematical models to find the abstract description features of the useful pixel information by comparing the description features to find the correspondence connection between the input image and the reference image. However, the traditional feature detection methods such as Harris corner and Susan operator do not have the invariance properties. So a stable feature detection method is requested for image stitching process. In 2004, Lowe proposed local scale-invariant image feature extraction algorithm (SIFT) [6], which received a good performance from different scale, different rotation direction, and perspective distortion images.

This paper uses the feature-based image registration method and selects scale-invariant SIFT features to implement panorama image stitching. The aim of image stitching is to transform multiple source images with areas overlapping each other to unify in the same coordinate system through transformation matrixes. Therefore, it is important to select a reference coordinate system. The traditional stitching process [7–9] constructs panoramic images from ordered image sequences, stitching step by step from left to right. The first image of the sequence is selected as the reference image. Subsequently, select the following stitching result as the next new reference image in the traditional stitching process. The traditional stitching process cumulates the matching errors of each stitching process in the reference image, which would be seriously distorted [10]; when the set of image sequences is large, it affects the quality of panoramic result. The improved method proposed in this paper first implements image registration for all adjacent images in the sequence and calculates the transformation matrix between the adjacent images and then took the middle image of the sequence as the reference image. According to the transformation matrixes of all adjacent images, the improved method can realize image anywhere in the sequence transforms to the coordinate space of the reference image. Therefore, all images in the sequence can be unified to the same coordinate system after undergoing all stitching processes. The experimental results show that the improved method reduces the distortion errors of panorama and saves the time of stitching process; moreover, it enhances the quality of the stitching result.

The rest of this paper is organized as follows. Section 2 describes the SIFT algorithm for extracting image features and the RANSAC algorithm for purifying the matching feature points; meanwhile it obtains the transformation matrix for the matching images. Section 3 describes the traditional image stitching process and Section 4 proposes the improved image stitching process. Section 5 shows the experimental results and quantitative analysis to evaluate the improved method. Section 6 acts as the conclusion of the whole paper.

II. Related Works

A. SIFT Feature Extraction

Brown and Lowe proposed scale-invariant features extraction algorithm (SIFT) in 2004 and continuously proposed the image stitching process [9] based on SIFT algorithm in 2007.The SIFT algorithm detects the image features speedily and provides invariant property when the image is rotated, resized, or illuminated. The SIFT detection process is shown in Figure 1.

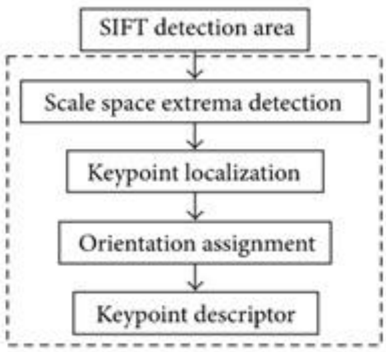

Fig 1. SIFT detection process

We search the extreme points in DOG space. Each sampling point is compared with the 8 neighborhood points of the same scale factor and 18 neighborhood points of the adjacent scale factors. The detected extreme points are chosen as the candidate key points. In order to improve the stability of the key points, correct the parameters of the DOG operator based on the Taylor formula to obtain the accurate position and scale factor. Meanwhile, eliminate the low contrast points and unstable points at the edge to enhance the stability of the matching points. Around the neighborhood of the key points, the gradient orientation of the pixels is counted by histogram and then distributes the maximum orientation of the histogram for the key points to provide the rotation-invariant characteristic.

B. RANSAC Algorithm

RANSAC (Random Sample Consensus) algorithm calculates the parameters of mathematical model based on random sampling, through continuously iterating new random combinations of sample data until a mathematical model that can explain or adapt to distribution of all data sets is found [12]. For each feature point of the image, search the matching points based on the minimum Euclidean distance using a k-d tree. The coordinate space mapping relationship between matching points is represented by the 3×3 transformation matrix. This paper is intended to use RANSAC algorithm to obtain the transformation matrix between the matching points and then make matching images mapped to the same coordinate space by the transformation matrixes information. In this paper, image sequences were shot by a hand-held camera along the same horizontal plane. So the transformation matrix is suitable for the affine matrix.

III. Traditional Stitching

After referring to the paper published by Xiong and Pulli [7] and Brown and Lowe [9], we summarize that the traditional stitching method is shown as in the following steps.

Algorithm 1

The traditional image stitching process:

Input. n ordered image sequence (S 0, S1,..., n−1) which mutually have overlapping areas

Output. A panoramic image.

Step 1: Select the first two images of the set S to calculate the SIFT feature points, respectively.

Step 2: Select the first image in the sequence S as the reference image and the second image as the new input image. Use KNN (K Nearest-Neighbors) algorithm [16] to search matching feature points between the new input image and the reference image in accordance with the minimum Euclidean distance.
Step 3: According to the matching feature points data set, use the RANSAC algorithm to calculate the affine matrix H, which can transform the new input image into the coordinate space of the reference image.
Step 4: Use the L-M algorithm to optimize the affine matrix H.
Step 5: Use the optimized H to transform the new input image.
Step 6: Search the optimal seam between the affine transformation result in step (5) and the reference image; then, along the seam to combine them together seamlessly, obtain the stitched result $imgResult$.
Step 7: Add the $imgResult$ into S to replace the input image and the reference image. In next stitching process the $imgResult$ is selected as the new reference image.
Step 8: Return to step (1) to continuously implement the next stitching process until there is only one image existing in the S, which is the panoramic result.

However, in traditional method, each time when an image stitching is completed, the dimension of reference image will continue to increase. The overlapping area between the new input image and the reference image accounts for smaller and smaller proportion comparing with the entire reference image area. Therefore, calculating SIFT feature points for the whole reference image will consume a lot of system resource and registration time. In addition, the approach of the traditional stitching algorithm to selecting the next input image is relatively single. Each time when the adjacent image is selected as the new input image, it does not give priority to the overlapping area size or the matching feature point number between new input image and the reference image. Meanwhile, if there are many matching errors in image registration process, the matching errors will be preserved and affect every subsequent registration process because the reference image is formed by the previous stitched results. Finally, the panoramic image will be seriously distorted.

IV. Proposed System

In the image stitching process, as we know, the accuracy of image registration decides the quality of the panoramic image, and the affine transformation matrix is the final result, which is what we wanted by image registration. So it is important to obtain a precise transformation matrix as shown in Fig 2.

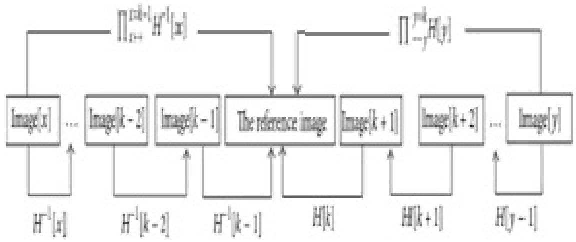

Fig 2. The process of calculating affine transformation matrix for arbitrary image.

A. Algorithm 2

The improved image stitching process:

***Input*:** n ordered image sequence ($S0$, $S1$,..., $Sn-1$) which mutually have overlapping areas.

***Output*:** A panoramic image.

Step 1: Do image registrations for all adjacent images.

(i) Assume the adjacent images are Si and $Si1$, $i \in [1, n-1]$, use KNN algorithm to search matching SIFT feature points between Si and $Si1$ in accordance with the minimum Euclidean distance, and then preserve the matching feature points data and the matching points number separately by using the arrays $featureLis\ t$ and $numList$.

(ii) According to the matching feature points data set $featureLis\ t$, compute the affine matrix that can be transformed from the coordinate space of the image $S\ i{-}1$ to the coordinate space of the image $S\ i$ and then preserve the affine matrix in the array $HList$.

(iii) Return to step (i) to complete the image registrations for the next adjacent images.

Step 2: k represents the middle index of the set S. Take $S\ k$ as the reference image. According to the array $numList$, select the image which has larger matching points number with Sk as the next new input image.

Step 3: According to the index of the new input image and the array $HList$, calculate the affine matrix$H$ between the new input image and the reference image based on formula (9).
Step 4: Use the L-M algorithm to optimize the affine matrix H.
Step 5: Use the optimized H to transform the new input image.
Step 6: Search the optimal seam between the affine transformation result in step (5) and the reference image; then along the seam combine them together seamlessly and obtain the stitched result $imgResult$.
Step 7: Add the $imgResult$ into S to replace the input image and the reference image. Therefore, the stitched result $imgResult$ becomes the new middle image of the sequence S.
Step 8: Return to step (2) to continuously implement the next stitching process until there is only one image existing in S, which is the panoramic result.

B. Block Diagram

The purpose of the ASIFT is to improve the corner detection method, which cannot solve the shortcoming of scale invariability. With this method, all calculation is established within the scale space, with three categorization procedures are detecting extreme value within the scale space, Direction assignment, Partial image descriptor. Using the scale space we find implication of simulating the change in distance, allowing single image file to be transformed into more identifiable data which can be used to find stronger features. have the function of Gaussian scale space, with scale space function L as follows:

$$L(u,v,\sigma) * I(u,v)$$

$$G(u,v,\sigma) = \frac{1}{2\pi\sigma^2} e^{-(u^2+v^2)/2\sigma^2}$$

(1)

where, * is convolution, l(u,v) is the image input, is a parameter of Gaussian function, the larger this value, the more fuzzy the image will become. u is the horizontal more fuzzy the image will become. u is the horizontal coordinate and v is the vertical coordinate of the image. To construct a dimensional space, the method of realization is Difference of Gaussian Filter (DoG). The main concept is that using two different variances of the Gaussian Filter to process the original image, resulting in two images with different level of fuzziness. The block diagram of ASIFT shown in figure 3.

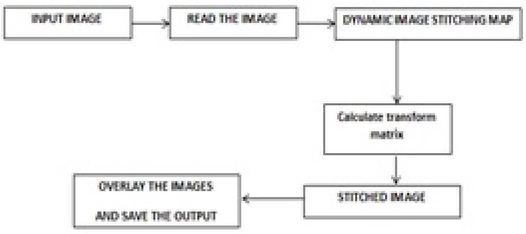

Fig 3. Block diagram of ASIFT

In the process of image connection, one image is firstly stabilized, using geometric transformation matrix to transform and adjust another image through horizontal moving, rotating, enlarging or reducing, so as to find the best position of connection for the stitching of the first image, in order to construct the mathematical relationship of the pixel coordinates between images. Transformation can be distinguished as affine transformation and transmission conversion. This study uses affine transformation as the model for the transformation of pixel coordinate between the images. Affine transformation model is a two-dimensional matrix A with 6 unknown parameters, as shown by equation 6, where the corresponding relationship of the pixel coordinates of the left and right images are presented by equation 2. In order to figure out the 6 unknown parameters [7], an equation with even number n is required, as shown by equation 3. To construct such equation, it is required that the point pairs obtained earlier are used, with at least 3 sets are input (n>=3). When the system is over-determined, a method resolving the Eigen value should be used to figure out the minimum error. If the point pairs found are incorrect, then the quality of matching would be poor.

Overlapping segmentation method First image one and image two divided into four equal parts ABCD to do cutting, extracted from BC to do stitching, reducing to find the feature points of time. BC was sutured to the use of images to Figure A Figure BC Figure C Figure do then, greatly improve the operating speed. ‘’ Imwrite ’’ command is used for save the panorama image. A SIFT match overlapping segmentation method time test as shown in figure 4.

$$A = \begin{bmatrix} m_0 & m_1 & m_2 \\ m_3 & m_4 & m_5 \\ 0 & 0 & 0 \end{bmatrix} \quad (2)$$

$$x_i{}' = m_0 x_i + m_1 y_i + m_2 \quad \textbf{(3)}$$

$$y_i{}' = m_3 x_i + m_4 y_i + m_5 \quad \textbf{(4)}$$

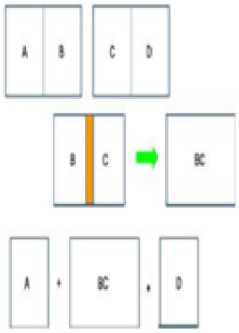

Fig 4. A SIFT match overlapping segmentation method time test.

By the experiment can be seen ASIFT with overlapping cutting to do the stitching time can be reduced to about 0.2 to 0.3 seconds than the SIFT algorithm significantly reduces the computation time.

V. Experimentation And Results

The stitching process can significantly improve the panorama distortions, obtaining high-resolution and high-quality panorama.

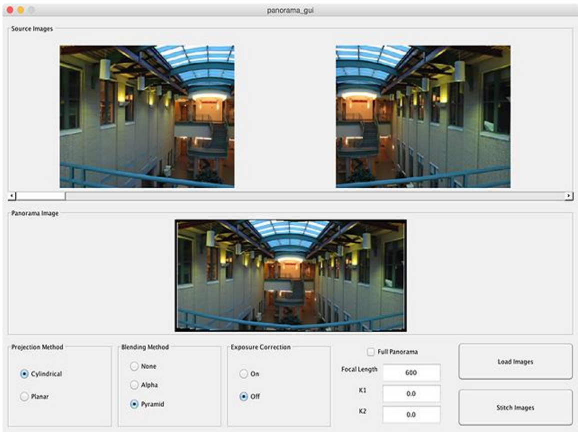

Fig 5. Screenshot of proposed system

First, we have to click the load image and then two source images are placed in the top of the GUI separately. After that click the stitch image, we get high quality panoramic image placed in the bottom of the GUI as shown in fig 5.

VI. Conclusion

This paper increases the number of the matching SIFT feature points by improving the traditional method, reducing the unnecessary SIFT detection area in the reference area as well. In addition, the improved method accelerates the panoramic stitching time efficiency and obtains a high-resolution, high-quality panorama image. Compared with the traditional method, the improved method proposed in this paper starts stitching from the middle position of the image sequence. The middle image is taken as the reference image. Then, we obtain the affine matrix for any image in the sequence to the reference image according to the statistics information of all affine transformation matrixes between the adjacent images. Meanwhile, the improved method dynamically selects the next new input image to join the stitching process based on the number of statistical matching points of the adjacent images. The experimental results verify that the improved stitching process can accelerate time efficiency and reduce the distortion of the panorama image.

References

[1]. H.-K. Kim, K.-W. Lee, J.-Y. Jung, S.-W. Jung, and S.-J. Ko, "A content-aware image stitching algorithm for mobile multimedia devices," *IEEE Transactions on Consumer Electronics*, vol. 57,no.4, pp. 1875–1882, 2011.

[2]. Z. Song, S. Zhou, and J.Guan, "Anovel image registration algorithm for remote sensing under affine transformation," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 52, no. 8, pp. 4895–4912, 2014.

[3]. R.-F. Chang, K.-C. Chang-Chien, E. Takada et al., "Rapid image stitching and computer-aided detection for multipass automated breast ultrasound," *Medical Physics*, vol. 37, no. 5, pp. 2063–2073, 2010.

[4]. X. Qiu, S. Liu, and F. Liu, "An adaptive kernel-based target tracking method based on multiple features fusion," *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 7, no. 1, pp. 91–97, 2012.

[5]. V. C. S. Chew and F.-L. Lian, "Panorama stitching using overlap area weighted image plane projection and dynamic programming for visual localization," in *Proceedings of the IEEE/ ASME International Conference on Advanced Intelligent Mechatronics (AIM '12)*, pp. 250–255, July 2012.

[6]. D. G. Lowe, "Distinctive image features from scale-invariant keypoints," *International Journal of ComputerVision*, vol. 60,no. 2, pp. 91–110, 2004.

[7]. Y. Xiong and K. Pulli, "Fast panorama stitching for high-quality panoramic images on mobile phones," *IEEE Transactions on Consumer Electronics*, vol. 56, no. 2, pp. 298–306, 2010.

[8]. S. Ha, H. Koo, S. Lee, N. Cho, and S. Kim, "Panorama mosaic optimization for mobile camera systems," *IEEE Transactions on Consumer Electronics*, vol. 53, no. 4, pp. 1217–1225, 2007.

[9]. M. Brown and D. G. Lowe, "Automatic panoramic image stitching using invariant features," *International Journal of Computer Vision*, vol. 74, no. 1, pp. 59–73, 2007.

[10]. I. K. Hyung, S. K. Beom, and I. C. Nam, "A new method to find an optimal warping function in image stitching," in *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP '09)*, pp. 1289–1292, IEEE, Taipei, Taiwan, April 2009.

[11]. M. S. Bascil and F. Temurtas, "A study on hepatitis disease diagnosis using multilayer neural network with Levenberg Marquardt training algorithm," *Journal of Medical Systems*, vol. 35, no. 3, pp. 433–436, 2011.

[12]. Y. S.Kim, M. Ghergherehchi, S. Y.Kim, andH.Afarideh, "RANdom sample consensus (RANSAC) algorithm for enhancing overlapped etched track counting," *IET Image Processing*, vol. 9, no. 2, pp. 97–106, 2015.

[13]. J. Bentolila and J. M. Francos, "Homography and fundamental matrix estimation from region matches using an affine error metric," *Journal ofMathematical Imaging and Vision*, vol. 49,no. 2, pp. 481–491, 2014.

[14]. H. Pang, D. Chen, M. Pan et al., "Improvement of magnetometer calibration using Levenberg-Marquardt algorithm," *IEEE Transactions on Electrical and Electronic Engineering*, vol. 9, no. 3, pp. 324–328, 2014.

[15]. F.Hampel, C.Hennig, and E. Ronchetti, "Asmoothing principle for the Huber and other location M-estimators," *Computational Statistics & Data Analysis*, vol. 55, no. 1, pp. 324–337, 2011.

[16]. Z. Al Aghbari and A. Al-Hamadi, "Efficient KNN search by linear projection of image clusters," *International Journal of Intelligent Systems*, vol. 26, no. 9, pp. 844–865, 2011