International Journal of CAD/CAM Vol. 9, No. 1, pp. 37~46 (2009)

INTERNATIONAL JOURNAL OF CAD/CAM
www.ijcc.org

Feature Based Multi-Resolution Registration of Blurred Images for Image Mosaic

Xianyong Fang *[1], Bin Luo, Biao He, and Hao Wu
Key Lab. of Intelligent Computing and Signal Processing of MOE, Anhui University, China

Abstract – Existing methods for the registration of blurred images are efficient for the artificially blurred images or a planar registration, but not suitable for the naturally blurred images existing in the real image mosaic process. In this paper, we attempt to resolve this problem and propose a method for a distortion-free stitching of naturally blurred images for image mosaic. It adopts a multi-resolution and robust feature based inter-layer mosaic together. In each layer, Harris corner detector is chosen to effectively detect features and RANSAC is used to find reliable matches for further calibration as well as an initial homography as the initial motion of next layer. Simplex and subspace trust region methods are used consequently to estimate the stable focal length and rotation matrix through the transformation property of feature matches. In order to stitch multiple images together, an iterative registration strategy is also adopted to estimate the focal length of each image. Experimental results demonstrate the performance of the proposed method.

Keywords: **blurred image mosaic, multi-resolution stitching, feature detection and matching, non-linear optimization, iterative focal length estimation**

1. Introduction

Image mosaic has been intensively studied in recent years [18] and there are a lot of products commercially available now, such as MGI PhotoVista, Panorama Factory, QuickTIme VR, etc. Those products can help the user creating a mosaic very easily when clear images are photographed. But during the photographing process, the image can be blurred because of the accidently hand shaking. To our best knowledge, there are few papers on the mosaic of blurred images. But this type of images can be easily obtained during the tedious capturing process. Therefore it is very interesting if we can successfully register those images and then mosaic them. In this paper, we study the problem and propose a robust solution.

Image mosaic can be roughly divided into two methods [18], direct method and feature based method. Direct method stitches images by minimizing the intensity difference, while feature based method stitches images by detected features. Direct method can easily lead to local minimum. Feature based method is much more robust with robust feature detection and matching mechanism than direct method [5, 3]. Therefore we adopt the feature based method. In addition, to automatically register them, as [22], we propose a multi-resolution scheme. In such a scheme, a rough translation can be first obtained as the initial motion by some block matching algorithm (BMA) or phase correlation method on the coarsest layer. Then layer by layer registration of Gaussian pyramids is used to obtain a finally fine stitched output.

*Corresponding author:
Tel: +86-(0)136-7560 5091
E-mail: xianyong.fang@gmail.com

Our main contribution is a feature based registration method in each layer for blurred images. First blurring features are detected with Harris corner detector [9] and their matching positions are obtained by the initial motion obtained from the previous layer. Then those matching features are clarified with RANSAC [7] to remove outliers as well as rectify the initial motion for the next layer. With such robust feature matches, focal length and rotation angle are estimated under the transformation property of feature matches. Robust nonlinear optimization methods, simplex method and subspace trust region method, are used respectively to obtain the stable values. For multiple blurred images, an additional iterative strategy is used to estimate their focal lengths robustly so that they can be finely stitched together.

Two types of image pair are possible for blurred image registration. One type consists of a clear image and a blurred image and the other type consists of two blurred images. Our method treats them in the unified way, thanks to the feature based inter-layer registration method.

In the following, related work will be reviewed first in Section 2. Then the feature detection and matching scheme will be introduced in Section 3. The focal length and rotation estimation methods are introduced consequently in the next section. The experimental results are presented in Section 5 and the whole paper is summarized in Section 6.

2. Related work

Existing studies on the registration of blurred image can be divided into two categories. One type assumes the distribution of point spread function (PSF) [8, 14] and the other type does not assume such a distribution [19, 21, 15].

In the first type, Flusser et al. [8] proposed a rotation and blur invariant descriptor based on the properties of the invariant moment and the centrosymmetric PSF. Similar assumption of PSF is also used in [14] where Fourier-Mellin is used to calculate a rotation, scale and blur invariant descriptor. Real PSF is not simply centrosymmetric and therefore those studies are not robust with the blurred images naturally captured.

In the second type, Vandewalle et al. [19] proposed a frequency method to register blurred image. Their registration is taken after a low-pass filter to remove those aliased high frequencies. Since the frequency method can lead to local optimums during registration, this method is not robust. Sroubek and Flusser [17] proposed a method to register and deblur images simultaneously. The problem is formulated as a maximum a posteriori estimator (MAP) and solved via an alternating minimization (AM) algorithm. The problem with this method is that it assumes the white Gaussian noise and a Gibbs prior distribution model. But real images are hard to comply with these models. This method is only applied to small translations. Similar statistical method is also proposed by Yuan et al. [21]. In this work, the statistical property of the blur kernel, sparseness, is used to find the best registration position through many trials. Many trials of different transformations increases the time consumed. This method is also only applied to small translations. Vandewalle et al. [19], Sroubek and Flusser [17], and Yuan et al. [21] all assume the planar model to register images. But this model can lead to distortions when it is applied to images for mosaic. These images are captured with an almost fixed optical center and only 3D calibration of rotation matrix can obtain the registration result without distortions.

To our best knowledge, there is only one study on the registration of blurred images in image mosaic [1]. It applies the idea of Vandewalle et al. [19] to realize registration. As we discussed before, this registration method is not robust.

In this paper, we propose a feature based registration method to robust register images in a multi-resolution way so that a distortion-free registration can be obtained for the mosaicking of images captured naturally. Our idea comes from Zhou [22] who proposed an interesting idea to stitch clear images. But there are four differences between ours and Zhou.

First, we use Harris corner detector to detect blurring features while Zhou uses Kitchen-Rosenfeld detector. According to the experiments of Kautsky et al. [10], Harris corner detector is better in feature detection of blurred images than Kitchen-Rosenfeld. In addition, Harris has been proved to be an effective feature detector for a clear image considering that there are also clear/blurred image pairs during registration.

Second, matching features are obtained by rectified motion (homography) from former layer in our method while Zhou simply uses the 3D motion of former layer. Since homography rectified by RANSAC has been a stable technique [6], this motion is better than the unstable 3D motion obtained from the optimization result of former layer.

The third difference is that we propose the simplex method and the subspace trust region method to get the focal length and rotation matrix while they use golden section search to get the focal length with unspecified rotation matrix estimation methods. The problem of golden section search is that there must be an initial range and thus the focal length of former layer is hard to be effectively utilized. Simplex, on the other hand, utilizes the focal length from former layer to find an optimized new focal length and thus more robust than golden section search, especially in the multi-resolution framework. Our proposed rotation matrix estimation method is also very robust as our experiments show later.

The last difference is that we propose an iterative estimation strategy to find the focal lengths of each image when more than 2 images are stitched together. In this strategy, we attempt to estimate the focal length of current image in current layer based on the focal length of its previous image in the same layer or pyramid. This strategy for the robust estimation of the focal lengths of multiple images when mosaicking together is also not described in Zhou's work.

We now discuss our feature based mosaic method inside each layer. For how to obtain the initial motion in the coarsest layer, users can refer to the BMA algorithm used in Zhou [22] or other similar techniques, such as phase correlation [2].

3. Feature detection and matching

Each image is decomposed into a L layer pyramid with the top layer indexed 0 as the coarsest layer. Assumed that the current layer is the cth layer and the corresponding images in the pyramids of the source image pair I_i and I_j are I_i^c and I_j^c, the features in I_i^c are detected first by the Harris detector. Then matching features in I_j^c are initialized by the motion obtained from the previous layer.

Matching features are refined based on illumination normalized BMA [22] to exactly locate each matching feature. For each matching features, first a source block sized 8×8 is defined for the feature in I_i^c with this feature as the block center, then a target block sized 16×16 is defined for the corresponding feature in I_i^c with that feature as the target block center. By translating the same sized block as the source block in the target block, the block matching algorithm refines the position of the matching feature in sub-pixel accuracy.

Outliers may exist because of the inaccurately initial motion obtained from previous layer or the incorrectly sub-pixel relocation. The illumination difference can also misguide the final pixel selected in the target block. Outliers lead to wrong estimated motion and thus further deteriorate the stability of the next layer.

An improved strategy based on RANSAC is adopted to solve the above problem. It will remove outliers and simultaneously obtain the globally correct projective motion (homography) based on the feature matches from the subpixel BMA. In our method, RANSAC implementation of [11] is adopted.

The matching features can be reliably detected in the next layer with the accurate motion from RANSAC. In the next section, we discuss the estimation of the focal length and rotation matrix in the current layer.

4. Focal length and rotation matrix estimation

Generally, we estimate the parameters of the current image based on its values from its previous image in the same layer or pyramid. The parameters from the previous image will ensure a fast and accurate convergence of the current image.

4.1. Focal length

For the clarity of description, the camera coordinate is showed in Fig. 1(a).The coordinate of the image I is denoted as (O, X, Y) and the camera coordinate is denoted as (o, x, y). The optical axis passes the image center. Assuming the focal length is f, the pixel coordinates of 3D features A and B, A' and B', are (x_a, y_a, $-f$) and (x_b, y_b, $-f$) respectively and the angle between the feature vector $\overrightarrow{oA}$ and $\overrightarrow{oB}$ is θ. If A and B are imaged in several images, θ will keep the same value as Fig. 1(b) shows. In this figure, A and B are imaged in I_i^c and I_j^c as A_1, B_1, and A_2 and B_2 respectively. The focal lengths for each image are f_i and f_j with O_i and O_j being the corresponding image centers. The coordinates of A_1, B_1, and A_2 and B_2 can be written as (x_{a1}, y_{a1}, $-f_i$), (x_{b1}, y_{b1}, $-f_i$), (x_{a2}, y_{a2}, $-f_i$) and (x_{b2}, y_{b2}, $-f_i$). Taking the vector angles between $\overrightarrow{oA_1}$ and $\overrightarrow{oB_1}$ as $\theta_{A_1B_1}$, and between $\overrightarrow{oA_2}$ and $\overrightarrow{oB_2}$ as $\theta_{A_2B_2}$ yields

$$\theta_{A_1B_1} = \theta_{A_2B_2} \tag{1}$$

When there are N pairs of feature matches, $(N^2 - N)$ / 2number of angle pairs satisfying equation 1 can be obtained. In practice, a weighted minimization method is used where a weighted sum of the 2 vector pairs is added to accelerate the convergence speed:

$$E(f_i, f_j) = \sum_{k=0}^{(N^2-N)/2} w_k \left\| \theta_{i,c,k} - \theta_{j,c,k} \right\| \tag{2}$$

In above equation, $\theta_{i,c,k}$ and $\theta_{j,c,k}$ are No. k vector angles in I_i^c and I_j^c respectively. w_k is the sum of the lengths of the 2 feature vectors corresponding to $\theta_{i,c,k}$ and $\theta_{j,c,k}$.

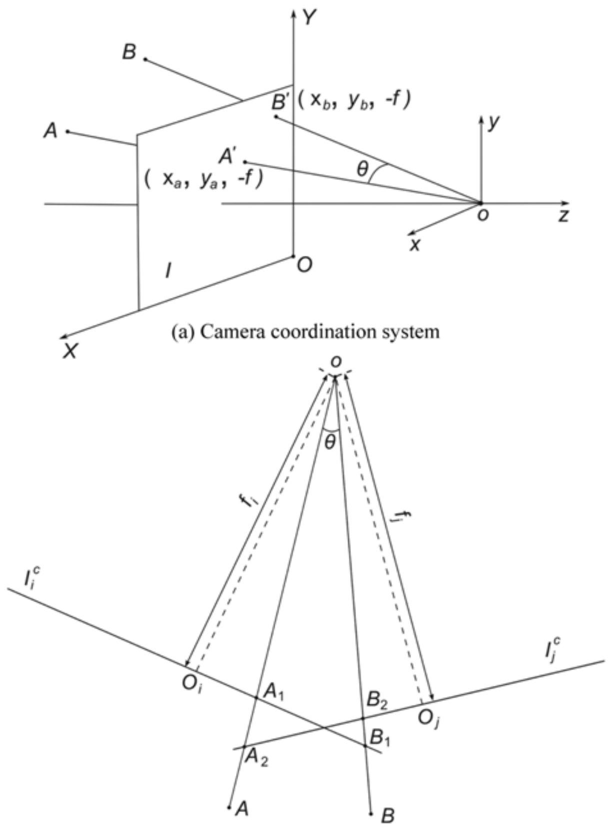
The focal lengths of the two images can be set to equal. This is because we can use the associative property of matrix multiplication to transfer the rotation equation 3 discussed later with the same unknown focal length f. Therefore, f_i and f_j in equation 2 turns to be one focal length f to estimate: For the coarsest layer, i. e., $c = 0$, f is estimated by golden section search with an initial search interval; for the non-coarsest layer, i. e., $c > 0$, f is estimated by simplex method with the initial value obtained from the previous layer. In practice, the initial search interval of focal length is set to be [0, 100max (image height, image width)].

4.2. Rotation

The principle of the rotation matrix estimation is also demonstrated in Fig. 1(b). Let I_i^c rotates a 9-parameter R to get I_j^c, for matching features A_1 and A_2, the relationship between $\overrightarrow{oA_1}$ and $\overrightarrow{oA_2}$ is

$$\begin{bmatrix} x_{a1} \\ y_{a1} \\ -f_i \end{bmatrix} = R \begin{bmatrix} x_{a2} \\ y_{a2} \\ -f_j \end{bmatrix}, \quad R = \begin{bmatrix} r_{11} r_{12} r_{13} \\ r_{21} r_{22} r_{23} \\ r_{31} r_{32} r_{33} \end{bmatrix} \tag{3}$$

Equation 3 holds for B_1 and B_2 as well as other feature matches. Therefore, similar to the focal length estimation



(b) The photographing process for mosaic

Fig. 1. Principle of focal length and rotation estimation.

method, this estimation can be written as a least squares problem with all feature matches considered together. But this time the weight used in equation 2 is not considered because it will add the sensitivity of the iterative solution. Therefore assumed that $M_{i,j}$ is the total number of feature matches between I_i^c and I_j^c and the No. k corresponding features are $p_{i,c,k}$ and $p_{j,c,k}$ the following non-linear minimization equation is applied to find the rotation between I_i^c and I_j^c:

$$E(R) = \sum_{k=0} \| norm(p_{i,c,k}) - norm(Rp_{j,c,k}) \| \quad (4)$$

Function $norm(v)$ is used to normalize the vector v. Equation 4 can then be solved by the subspace trust-region method [4].

To apply the subspace trust region method, a good initial value of rotation is very important to ensure the convergence. We apply the singular value decomposition (SVD) [20] to get it. For feature pairs $p_{i,c,k}$ and $p_{j,c,k}$ let $S = \sum p_{j,c,k}^T \, p_{i,c,k}$, the SVD of S is:

$$S = UAV^T$$

Thus the initial rotation matrix R is given by:

$$R = UV^T \quad (5)$$

For the coarsest layer, i. e., $c = 0$, the initial rotation can be obtained by Equation 5. For the non-coarsest layers, i. e., $c > 0$, their rotation matrices are computed with the initial value obtained from the previous layer.

4.3. Iterative focal length estimation

In former two sub-sections, our focus is on the registration of only two images. When there are more than two images, there may be big variations of focal lengths among those images and former focal length estimation method relying on the assumption of equal focal length will be hard to stitch them together. Therefore, we propose the following strategy to estimate the focal lengths of all images in each layer so that the focal length of each non-first-two image is computed robustly.

- If $c = L$ (top layer) I_i and I_j and are the first 2 images, golden section search is applied to get the equal focal lengths of both images, f_i^c and f_j^c;
- If $c = L$ (top layer) I_i and I_j and are not the first 2 images, simplex method [12] is applied to get the focal length of f_j^c with the known f_i^c;
- If $c < L$ (non-top layer) I_i and I_j and are the first 2 images, simplex method is applied to get their focal lengths whose initial values are set to be $2f_i^{c-1}$ and $2f_j^{c-1}$ respectively;
- If $c < L$ (non-top layer) I_i and I_j and are not the first 2 images, simplex method is applied to get f_j^c with its initial focal length set to be $2f_j^{c-1}$.

The above iteration method can lead to error accumulation when more and more images are processed. Therefore, an additional error rectification step is needed to avoid such a problem. One possible rectification method is to assign the focal length of the current image to be the average focal length of all previous images in the same layer since the focal length of each image in the same layer normally changes little. But this method can easily lead to wrong rotation matrix in the subsequent rotation estimation step considering the uncontrollable variations of focal lengths among multiple images. Instead, we take another robust way which uses the golden section search to refine the focal length of the problem image. It is initialized with a range without using its iterative value obtained from the previous layer. This proposed rectification step drops the average focal length and relies on its own feature matches and the robust focal length of its matching image.

With above strategy of focal length estimation of multiple images, the proposed rotation estimation method can be applied to the stitching of multiple images so that camera parameters of each image can be obtained finely.

5. Experimental results

In our test, all photographs are captured with a hand-held camera Cannon IXUS 860 IS. The blurring effect is obtained by shaking hand during capturing. Each image is decomposed till its size is smaller than 50

(a) The source images sized 640x480

Fig. 2. Continued.

(b) The obtained feature matches in the bottom layer before applying RANSAC. There are 157 matches.

(c) The obtained feature matches in the bottom layer before after RANSAC. There are 95 matches.

Fig. 2. Example registration of a clear image and a blurred image.

pixels during the pyramid construction.

Fig. 2 shows the registration result of one clear image and one blurred image of Fig. 2(a). We can find there are serious blurring effects in the right source image. But the Harris features in the left image and their matching features in the right image can be robustly located. The reliable feature matches are then refined by RANSAC. Table 1 lists the feature matches obtained before and after applying the RANSAC. We can find that around 50% features are removed; otherwise it would seriously degrade the registration quality. Fig. 2(b) and Fig. 2(c) show an example of the feature matches removed by RANSAC in the bottom layer. Among 157 initial feature matches, only 95 matches are in accordance with the homography transformation between the two input source images according to RANSAC.

Table 1. The feature matches before and after applying the RANSAC for the image pair of Fig. 2(a)

layer index	1	2	3	4	5
feature matches (before applying the RANSAC)	15	21	48	90	157
feature matches (after applying the RANSAC)	15	10	23	49	95

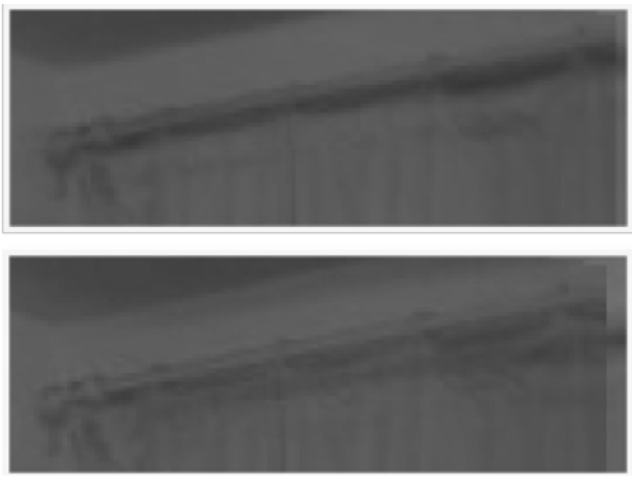
Fig. 3 gives the registration result of Fig. 2(a). They are finely stitched by equally weighted average of both

(a) The source images

Fig. 3. Continued.

(b) The registration result of the Panorama Factory

Fig. 3. The registration result of the images in Fig. 2(a) and its comparison with the Panorama Factory. A yellow rectangle and a green rectangle in each result are singled out to demonstrate the advantage of our idea. We also cut two rectangles (showed in Fig. 3) from each stitching result, as showed in the Fig. 4. In Fig. 4(a), our method has no ghosting while the Panorama Factory obtains significant ghostings around the curtain. In Fig. 4(b), there are also slight ghostings around the newspaper by the Panorama Factory while there is no visible ghosting existed by our method.



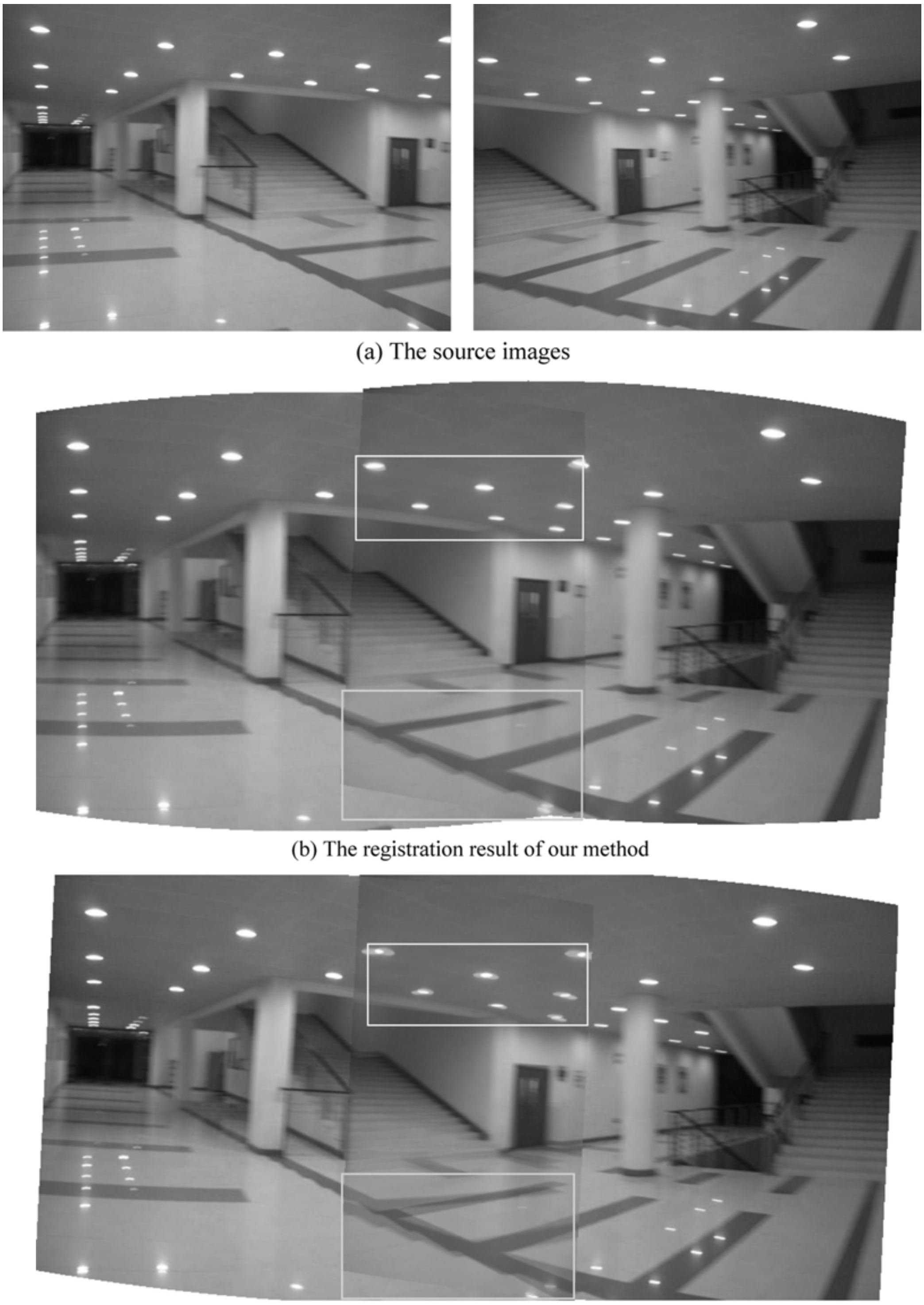
(a) The yellow rectangles denoted Fig. 3(a) (up) and Fig. 3(b) (down)

(b) The green rectangles denoted in Fig. 3(a) (left) and Fig. 3(b) (right)

Fig. 4. The details in the rectangles of Fig. 3. There is almost no visible ghosting in our method while there are significant ghostings around the curtain and the newspaper in the result of the Panorama Factory.

images in the overlapping area. We also test these two images with the latest version of the Panorama Factory [16], as showed in Fig. 3(b). The overlapping area is generated in the same way as Fig. 3(a). Checking these two registration results clearly, we can find our method obtaining better result with less ghostings than the Panorama Factory.

Our method is also applied to the registration of two blurred images. Fig. 5 shows such an example. Although there are heavy blur and noise with flat textures in both images of Fig. 5(a), their Harris features can also be detected and matched after RNASAC.



(a) The source images

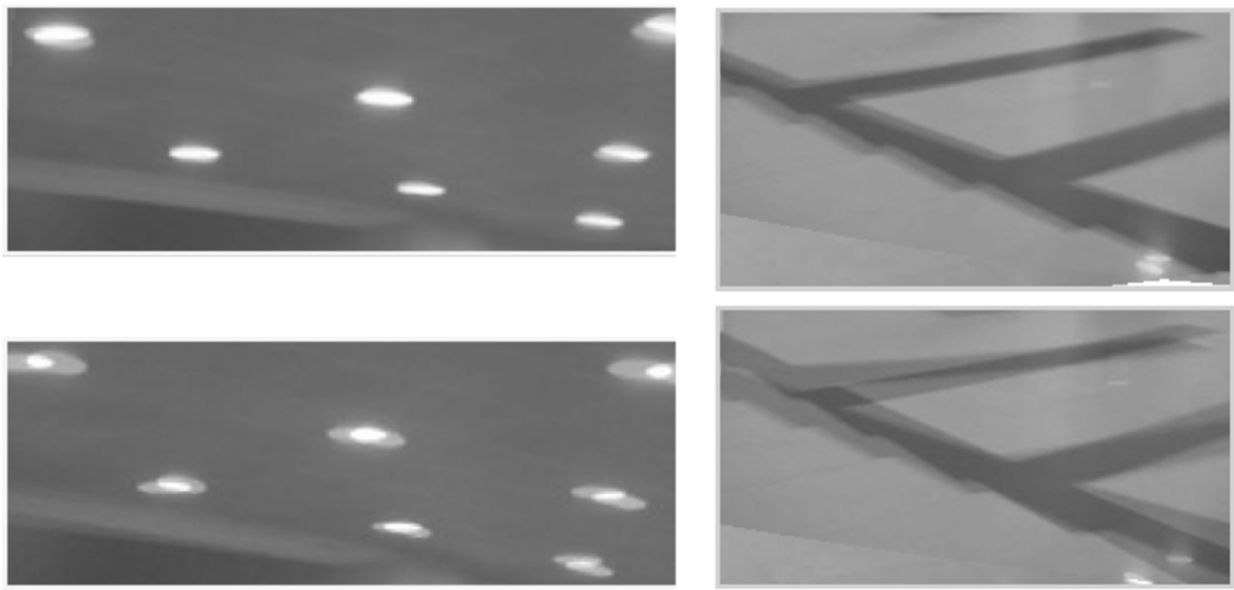
(b) The registration result of our method

(c) The registration result of the Panorama Factory

Fig. 5. The example registration of two blurred images and its comparison with the Panorama Factory. There are also two rectangles specified in the same way as the rectangles of Fig. 3 for the performance comparison.

Fig. 5(b) and Fig. 5(c) show the registration results of our method and the Panorama Factory for the images in Fig. 5(a) respectively. The overlapping areas are generated in the same way of Fig. 3. The minor ghosting of our method is acceptable since these ghostings may be removed completely with some blending or deblurring method, such as [13]. But there are serious ghostings in Fig. 5(c) which are hard to be removed because of the wrong registration. As Fig. 3, there are also 2 rectangles cut out from each result for a comparison of our blurred image mosaic method with the Panorama Factory. The enlarged views in Fig. 6 show that there are serious ghostings in the floor and the ceil lights for the Panorama Factory. These figures prove that our method is robust and can obtain a much better registration result of blurred images than the Panorama Factory.

Fig. 7 shows the registration result of 6 blurred images with our proposed iterative strategy. We can find that there are quite different blurring effects among these 6 source images (Fig. 7(a)). They also have different focal lengths. But they can still be finely registered finally (Fig. 7(b)), thanks to our iterative focal length



(a) The yellow rectangles denoted in Fig. 5(b)(up) and Fig. 5(c)(down) (b) The green rectangles denoted in Fig. 5(b) (up) and Fig. 5(c)(down)

Fig. 6. The details in the rectangles of Fig. 5. There are serious ghostings inside both areas (floor and head lights) for Panorama Factory. Our method obtains a better result than the Panorama Factory.

(a) The 6 blurred source images indexed as 1 to 6 from left to right

(b) The stitched result of Figure 7(a) obtained by the iterative registration strategy

Fig. 7. Registration of 6 blurred images.

estimation method. Table 2 shows the focal length of each image obtained with our iterative estimation strategy.

6. Conclusion

A robust scheme to register blurred images for mosaic is proposed in this paper. It performs registration in a multi-resolution way with a feature based method applied to each layer. In the feature based method, Harris features and its matching features are detected first. Then the focal lengths and the rotation matrix are calibrated with the transformation properties of feature matches through a robust non-linear optimization strategy. An iterative strategy is also proposed to stitch multiple images together. In comparison with existing registration method for blurred images, our method has no assumed imaging model and registers naturally blurred images in 3D space through camera calibration without the distortion problem of planar registration. Experimental results demonstrate that the efficiency of our method.

Acknowledgements

The work is under the co-support of the National Nature Science Foundation of China (60772122) and the Science Fund for Higher Education of Anhui Province (KJ2007B005).

References

[1] Boutellier, J., and Silvn, O. (2006) Panoramas from partially blurred video. In Proceedings of International Workshop on Intelligent Computing in Pattern Analysis/Synthesis (IWICPAS 2006), vol. 4153, pp. 300-307.

[2] Brown, L. G. (1992) A survey of image registration techniques. *ACM Computing Surveys* 24, 4, 325-376.

[3] Brown, M., and Lowe, D. G. (2007) Automatic panoramic image stitching using invariant features. *International Journal of Computer Vision* 74, 1, 59-73.

[4] Coleman, T. F., and Li, Y. (1996) An interior trust region approach for nonlinear minimization subject to bounds. *SIAM Journal on Optimization* 6, 418-445.

[5] Fang, X., Pan, Z., He, G., and Li, L. (2006) A new method of feature based image mosaic. International *Journal of Image and Graphics* 6, 3, 497-510.

[6] Fang, X., Pan, Z., Luo, B., Wu, F., and Guo, S. (2008) Robust image mosaic with ransac and bundle adjustment. *Journal of Computational Information Systems* 4, 4, 1613-1619.

[7] Fischler, M. A., and Bolles, R. C. (1987) Random sample consensus: a paradigm for model fitting with applications to image analysis and automated cartography. *Readings in computer vision: issues, problems, principles, and paradigms*, 726–740, Morgan Kaufmann Publishers Inc.

[8] Flusser, J., Boldys, J., and Zitov, B. (2003) Moment forms invariant to rotation and blur in arbitrary number of dimensions. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 25, 2, 234-246.

[9] Harris, C., and Stephens, M. (1988) A combined corner and edge detection. In Proceedings of The Fourth Alvey Vision Conference, pp. 147-151.

[10] Kautsky, J., ´a, B. Z., Flusser, J., and Peters, G. (1998) Feature point detection in blurred images. In International conference of Image and Vision Computing (IVCNZ'98), pp. 103-108.

[11] Kovesi, P. D. MATLAB and Octave functions for computer vision and image processing. School of Computer Science & Software Engineering, The University of Western Australia. Available from: <http://www.csse.uwa.edu.au/~pk/research/matlabfns/>.

[12] Lagarias, J. C., Reeds, J. A., Wright, M. H., and Wright, P. E. (1998) Convergence properties of the nelder-mead simplex method in low dimensions. *SIAM J. on Optimization* 9, 1, 112-147.

[13] Levin, A., Zomet, A., Peleg, S., and Weiss, Y. (2004) Seamless image stitching in the gradient domain. In 8th European Conference on Computer Vision (ECCV 2004), T. Pajdla and J. Matas, Eds., vol. 3024 of Lecture Notes in Computer Science, Springer, pp. 377-389.

[14] Ojansivu, V., and Heikkil¨a, J. (2007) Blur invariant registration of rotated, scaled and shifted images. In The 2007 European Signal Processing Conference, pp. 1755-1759.

[15] Rav-Acha, A., Engel, G., and Peleg, S. (2008) Minimal aspect distortion (mad) mosaicing of long scenes. *International Journal of Computer Vision* 78, 2-3, 187-206.

[16] Smoky City Design, L. The panorama factory v5.2. http://www.panoramafactory.com.

[17] Sroubek, F., and Flusser, J. (2004) Registration and fusion of blurred images. *Lecture Notes in Computer Science* 2004, 3211, 122-129.

[18] Szeliski, R. (2006) Image alignment and stitching: a tutorial. *Foundations and Trends in Computer Graphics and Computer Vision* 2, 1, 1-104.

[19] Vandewalle, P., S¨usstrunk, S., and Vetterli, M. (2006) A frequency domain approach to registration of aliased images with application to superresolution. *EURASIP Journal on Applied Signal Processing* 2006, 1, 233-233.

[20] Wang, C., and Mahadevan, S. (2008) Manifold alignment using procrustes analysis. In ICML '08: Proceedings of the 25th international conference on Machine learning, ACM, pp. 1120-1127.

[21] Yuan, L., Sun, J., Quan, L., and Shum, H.-Y. (2007) Blurred/non-blurred image alignment using sparseness prior. In IEEE 11th International Conference on Computer Vision (ICCV 2007), IEEE, pp. 1-8.

[22] Zhou, L. (2004) Image matching using resolution pyramids with geometric constraints. Patent number US 6785427.

Xianyong Fang received M. Eng. from Hefei University of Technology in 2002 and Ph. D. degree from Zhejiang University in 2005. He worked as a Postdoc in LIMSI-CNRS from 2007 to 2008. He is an associate professor of Anhui University and his research interests focus on image/video processing related graphics and vision topics.

Biao He received his B. S. degree from Anhui Normal University in 2008. He is a master student of the School of Computer Science and Technology at Anhui University. His research interests are computer vision and image processing.

Xianyong Fang

Biao He

Bin Luo received his Ph. D. from York University in 2002. He is a member of BMVA, IEEE and ACM. He is the chair of IEEE Hefei Section. He is also the professor and the dean of the School of Computer Science and Technology at Anhui University. His research interests are image processing and pattern recognition.

Hao Wu received her B. S. degree from Huaibei Coal Industry Teachers' College in 2008. She is a master student of the School of Computer Science and Technology at Anhui University. Her research interests are computer vision and image processing.

Bin Luo

Hao Wu