A New Global Registration Algorithm for Image Mosaic

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Abstract: In this paper, we proposed a new bundle adjustment algorithm based on the distance minimization of feature matches, to eliminate the accumulated errors over a sequence for seamless mosaic. The new feature based image mosaic approach improved the stability of the global registration among images. Our experiments show that the new mosaic method is robust.

Key–Words: Feature based image mosaic, Bundle adjustment, Global registration

1 Introduction

Image mosaic tries to composite several narrow-angle images into a wide-angle image and is widely used in aerial and satellite photographing [1], virtual touring and exhibition [2-3], photo edition [4], etc. Szeliski [5] reviewed the principles and advances of image mosaic. As described in [5], there are two types of method: direct method and feature based method, and the latter becomes more robust than the former with the advances of feature detection.

Feature based methods [6-9] mosaic the images by first automatically detecting and matching the features in the source images, and then warping these images together. Normally it consists of three steps: feature detection and matching, local and global registration, and image composition. Feature detection and matching aims to detect features and then match them. Local and global registration starts from these feature matches, locally registers the neighboring images and then globally adjusts accumulated registration error so that multiple images can be finely registered. Image composition blends all images together into a final mosaic. For more details on the current state of feature based mosaic, please refer to [5]. Registration is still not finely solved with existing techniques and our focus in this paper is also on how to improve the stability of registration for feature based mosaic.

Many papers on wide baseline matching [10-12], object recognition [13-14] and image/video retrieval [15-17] consider how to improve the stability of feature matching. In these works, feature matching is improved by spatial consistency which means the match features of each feature and its every neighboring feature should have the same spatial arrangement. Sivic et al. [15] used each region match in the neighborhood of each feature match to vote this feature match. The sum of votes of the whole frame decides the rank of the frame and match without vote is rejected. Ferrari et al. [10, 16] iteratively applied a expansion and contraction scheme to add new matches and remove wrong matches while expansion is fulfilled based on the similarity of affine transformations between neighboring region matches and contraction is reached by the sidedness constraint which bases on the fact that, to a triple of region matches, the center of a first region should be on the same side of the directed line going from the center of a second region to the center of a third region. The median flow filter [18] is also used to remove wrong matches, which compares the length and anger of each match vector with the median length and anger of its several neighboring match vectors respectively and selects the one whose length and anger below the thresholds.

But on the image mosaic side, there are few researches considering eliminating wrong matches before robust registration. As far as we know, only Cho et al. [6] applied the median flow filter to remove wrong matches before registration for image mosaic.

For image mosaic, to locally register the neighboring images, 8-parameter homography can be applied to accurately model the mapping between views under general image condition. RANSAC [19] is a commonly accepted way to refine the homography between images [7-9] because RANSAC can return the final inliers when getting the final homography. Except RANSAC, LMedS (the Least Median of Squares)

[20] is also used for homography calculation, but it can not return the final inliers.

For global registration, bundle adjustment is a widely acceptable idea. While decomposing the projective transformation matrix into rotation angles and the focal length is very sensitive to image noise [7], the iterative registration methods [21-22] is complex and weak. Another more robust way is presented by Marzotto et al. [23] where the homography of each source image to the reference mosaic surface is adjusted by minimizing the total misalignment of a predefined set of m grid points on the mosaic. With the local registration strategy in the previous paragraph, the global registration can be build upon inliers and the homography between neighboring views. In this paper, a new bundle adjustment based on the feature matches is proposed so that the homographies between all images and the mosaic surface are adjusted by minmizing the distances of feature matches.

With above discussions, a new robust feature based image mosaic method can be proposed. First, features are localized with SIFT [24], described by PCA-SIFT [25] and matched with priority search in k-d tree structure [26]. Then the RANSAC homography algorithm is applied to locally register neighboring images and the bundle adjustment algorithm based on the distance minimization of feature matches is applied to globally register all the images together. After registration, image composition can be fulfilled by multi band blending [27], featuring algorithm [2] or gradient domain fusion [28] and then a final mosaic can be generated.

In the following paragraphs, the algorithm will be discussed in detail in the Section 2. Then experimental results will demonstrate the stability and efficiency of our method. The first step, feature detection and matching, and the last step, image composition, will not be discussed here and interested readers can refer to related papers.

2 RANSAC Homography for Local Registration

After feature detection and matching, the source images need to be registered together. RANSAC algorithm can be applied to get the homography of each image pair. Four initial putative feature matches are selected in the random selection step of each iteration in RANSAC [19], and a correct homography can be got after one iteration.

3 Bundle Adjustments for Global Registration

With the ransac algorithm, the pair wise homography of all input images can be got. To register all these images together, we must adjust all these calculated homographies together. Or there will be accumulated errors if simply selecting one reference image (the image selected as the mosaic surface) and warping all others to this reference image. So a bundle adjustment algorithm based on the minimization of the distances of feature matches is proposed to remove the accumulation of errors.

The reference image should be defined first before applying the bundle adjustment. In our current implementation, the middle image is selected as the reference image so that all images are trying to warp to the center and thus will have less accumulated errors than selecting other images. The best match image of each image should also be selected before applying bundle adjustment. In our current implementation, it is the image which has the maximum number of inliers with this image and which is processed earlier than this image.

The homography of each image to the mosaic surface should also be initialized and it can calculated in a recursive way. If the best match image of Image I_a is I_b, the homography of I_b to mosaic surface is H_b and the homography of I_a to I_b is H_{ab}, then the homography of I_a to the mosaic surface, H_a, is then calculated by

$$H_a = H_{ab} \cdot H_b \tag{1}$$

After above preparations, the bundle adjuster processed each source image one by one. For the current processing image I_n:

- Update the homographies of all existing images to their best match images under the following criterion of distance minimization of feature matches:

$$e = \sum_{i=1}^{n} \sum_{j \in L(i)} \sum_{k \in F(i,j)} f^2(r_{ij}^k) \tag{2}$$

$L(i)$ is the set of images overlapping with I_a. $F(i, j)$are the inliers between I_i and I_j. $f(x) = x$ and r_{ij} is calculated by warping the feature point in I_i with H_i and H_j :

$$r_{ij}^k = \left\| x_j^k - H_j^{-1} H_i x_i^k \right\| \tag{3}$$

Figure 1 explains Equation(3). For matching features x_i and x_j which are in I_i and I_j respectively, x_i is warped to the mosaic surface first and then warped to the image surface of I_j . After this two warps, we can get $x_i^{'}$ and r which equals to $x_j - x_i^{'}$ or $x_j - H_j^{-1} H_i x_i$.

- Update the homography of each existing image to the mosaic surface with the homography of it to its best match image. For example, assuming the updated homography of I_a to its best match image I_b is $H_{ab}^{'}$, then $H_{ab}^{'} \cdot H_b$.
- If not converge, go to step 1; else, end.

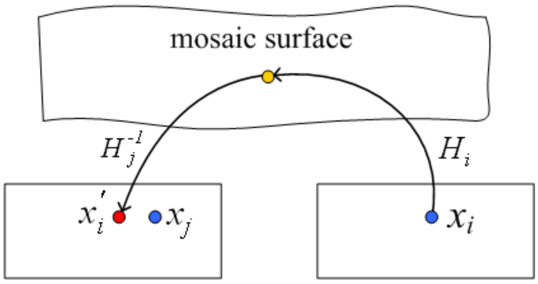

Figure 1: Distance minimization of feature matches.

The bundle adjuster is implemented by L-M algorithm and the derivatives can be computed by the chain rule.

4 Experiments

Figure 2,3,4 show the bundle adjustment results with four source images. These images are composed finally by featuring algorithm. In figure 2, there is no bundle adjustment. Ghosting is existed in the image. Figure 3 shows the bundle adjustment result if we do not update the homography of each image with its best match image but the homography of each image to the mosaic surface. Still there is ghosting existed although less than Figure 2. Figure 4 shows the mosaic after fully applying the bundle adjustment algorithm and there is no ghosting.

Figure 2: Mosaic without bundle adjustment.

Figure 5 shows another example of our mosaic method where nine images are finely mosaiced with the featuring algorithm after applying bundle adjustment to these images.

Figure 3: Mosaic after partially applying the bundle adjustment.

Figure 4: Mosaic after fully applying the bundle adjustment.

5 Conclusion

In this paper, we put forward a robust feature based image mosaic method. First features are detected with SIFT, described by PCA-SIFT and matched with priority search. Then images are locally registered with the RANSAC homography algorithm. Finally the images are fused to be one image with a blending method. In the new bundle adjustment algorithm, the homographies of all images to the mosaic surface are updated by the distance minimization of feature matches. Experiments show that our feature based image mosaic method is highly effective.

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Figure 5: Example bundle adjustment with 9 Images.

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