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# **Parallax-Tolerant Image Stitching for Outdoor Scenes**

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Abstract. Image stitching aims to obtain a natural panorama without ghosts. This paper proposes a panoramic image stitching method for outdoor scenes. This method gets the new homography matrix by analyzing the spatial distribution of the feature points of the outdoor scene image, and then combines with the local registration to achieve precise registration. In order to generate a more natural panorama, this paper also combines the result of registration with local similarity transformation and seam-cutting processing. Finally, the experimental results show that the proposed method obtains better performance than other methods in image stitching of outdoor scenes.

#### 1. Introduction

Image stitching technology has been a research hotspot in computer vision[1] and virtual reality[2], especially the parallax-tolerant stitching. Parallax images are widely used in applications of multimedia technology such as surveillance[3], immersive communication[4] and virtual reality[5]. In order to obtain high-resolution panoramic images in these scenes, it is necessary to stitch images with parallax. The traditional method usually estimates the optimal global transformation from the input images, for example, the AutoStitch[2] proposed by Brown. But this method is only suitable for ideal cases, that is, the camera translation is negligible [6] or the scene is near planar. However, for general cases, for example, the input images with parallax or scene is not near planar, such as figure 1, the result of AutoStitch has ghosts.

In order to stitch parallax images, some methods[7-9] use grid optimization to process parallax images. These methods first use the global homography, and then use local registration. Zaragoza et al. [7] proposed the as-projective-as-possible (APAP) warp algorithm, which uses the local homography matrix of each grid to optimize the alignment of the image. However, the homography model may cause projection distortion in non-overlapping regions. In order to solve this problem, Chang et al. [8] introduced global similarity transformation, and proposed the Shape-Preserving Half-Projective (SPHP) warp algorithm, which provides a more natural result by gradually transitioning non-overlapping regions to global similarity transformation. Li et al. [9] also studied the non-rigid deformation method, which represented the entire image plane deformation function in a grid form, and proposed a method to remove mismatched data to improved the accuracy of the matching data. But for parallax images in outdoor scenes, these methods can not obtain high-resolution panoramic images.

In order to solve the above problems, this paper proposes a global homography estimation method for outdoor scenes by analyzing the distribution of feature points, and then combines with local registration to obtain an excellent registration effect. At the same time, global similarity transformation and seam-cutting method are used in the post-processing of registration to get a more natural and seamless stitching result.

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#### 2. Method

The registration includes global registration and local registration. The traditional method is to estimate a global homography to minimize the cumulative sum of square errors of all feature points. However, as shown in figure 2, Because of the uneven distribution of feature points, the global homography has more registration deviations in the areas with sparse feature points, and without feature points. Local registration cannot solve the registration problem in the areas with sparse feature points, and without feature points, and without feature points. Therefore, we consider improving the feature point selection, so that the global homography has a better registration in the areas with sparse feature points and without feature points.



Figure 2. Distribution of feature points, the feature point set  $P_1$  is marked in blue.

# 2.1. Feature point selection based on spatial distribution characteristics

Before using the spatial distribution to select the feature points, the SIFT[10] algorithm is used to extract the feature points, then this paper uses the RANSAC algorithm [11] and the Bayesian Refinement of Feature Matches [9] to remove the mismatched feature points, then get the feature point set  $P_1$ . To fully guarantee the accuracy of the feature points. The feature point selection based on spatial distribution is as follows:

(1) This paper first calculates the average distance between each feature point and other points in the vertical direction. The average distance calculation is as follows:

$$l_{ij_y} = \frac{1}{n-1} \sum_{j=0}^{n-1} (p_i - p_j)$$
(1)

In which,  $l_{ij_y}$  represents the average distance between the first feature point and other points in the vertical direction,  $p_i$  represents the feature point, and  $p_i$  represents other feature points except for  $p_i$ .

(2) Construct a set  $L_{ij}$ , contains every  $l_{ij}$ , and sort to get the set.

(3) In the set, select the largest  $\alpha$  ( $\alpha$  is a constant) present of  $l_{ij_y}$ , and sample the remaining (1- $\alpha$ ) present of  $l_{ij_y}$ , and set the sampling frequency to  $\mu$  ( $\mu$  is a constant) to get the new set  $L_{ij_y}$ . Here we set  $\alpha = 20$  and  $\mu = 1/4$ . the set  $L_{ij_y}$  to the corresponding point to obtain the point set  $P_2$  which is selected from  $P_1$ .

Because in outdoor scenes, the uneven distribution of feature points is mainly reflected in the vertical direction, and the sparser the distribution of feature points, the greater the average distance the points have. Therefore, get the set by calculating the average distance of points in the vertical direction and selecting the point with the largest average distance. At the same time, some feature points with a small average distance are retained to ensure the robustness. Through this selection, the feature points used for global homography, the ratio of feature points between dense and sparse areas is changed from 1:4 to 1:1. The selection based on spatial distribution makes the global homography more focused on the registration with sparse feature point distribution. As shown in figure 3, the point set  $P_2$  is marked in red.



Figure 3. The point set  $P_2$  which is marked in red.

# 2.2. Global homography estimation and local registration

We estimate the global homography by giving matched points  $p_i = (x_p, y_p)$ ,  $q_i = (x_q, y_q)$  in the point set  $P_2$ , and the global transformation between  $I_p$  and  $I_q$  can be estimated by minimizing the cumulative sum of square errors, the formula is as follows:

$$\hat{h} = \arg_{h} \min \sum_{i=1}^{n} |a_{i}h|_{2}^{2} = \arg_{h} \min |Ah|_{2}^{2}, s.t. |h|_{2} = 1$$
(2)

 $\hat{h}$  is an estimated global homography, the degree of freedom is limited to 8 by  $|h|_2 = 1$ ,  $|\cdot|$  means Euclidean distance, and the matrix A represents the matched points  $p_i = (x_p, y_p)$ ,  $q_i = (x_q, y_q)$  in the point set  $P_2$ . Then, the local registration method can refer to the Li et al. algorithm[9].

#### 2.3. Image post-processing

As shown in figure 4, since the projection transformation will cause relatively large distortion in the non-overlapping area, it is combined with the global similarity transformation to make the stitching more natural, and then using the seam-cutting method to get a natural panoramic image.

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Figure 4. Image post-processing.

(a) the result after local registration, (b) the result after combined with global similarity transformation, and (c) the result after seam-cutting processing.

#### 3. Experiment



Figure 5. Comparison of different methods.

We compares our algorithm with APAP[7], SPHP[8]methods, as shown in the figure 5. To be fair, our results have not undergone image post-processing. It is implemented by MATLAB on the Windows operating system, which runs on the Intel I7 8500U processor and 8GB memory host. As shown in the figure 6, we compare results of our method after seam-cutting processing with results of Autostitch, the ghosts are disappeared in our result.

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Figure 6. Comparison of Autostitch and our method.

This paper conducted a lot of tests on the data set [7-8] and the root mean square error (RMSE) is used as the index of registration accuracy. The calculation formula of the RMSE is as follows:

$$RMSE(\Delta I_{1}, \Delta I_{2}) = \sqrt{\frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (gray(\Delta I_{1})_{ij} - gray(\Delta I_{2})_{ij})^{2}}$$
(3)

 $gray(\Delta I_1)_{ii}$  and  $gray(\Delta I_2)_{ii}$  are the gray value of the overlapping area of the images.

database	RSME	removal		
	name	APAP	SPHP	OURS
outdoor images	airport	13.28	14.43	10.72
	high bridge	6.37	11.39	4.53
	gym	6.91	7.06	4.12
	east area	6.57	10.26	5.32
	temple[7]	7.24	10.54	6.50
	bridge[7]	11.54	13.54	10.98
	park[7]	14.05	21.27	7.39
	railtracks[7]	15.18	17.81	10.11
	building[8]	17.48	17.89	13.95
indoor images	laboratory	5.32	13.95	6.57
	2nd floor	7.04	13.90	6.45
	6th floor	11.44	18.66	10.49
	window[8]	16.61	21.06	14.97

 Table 1 RMSE of different objects indoor and outdoor

As shown in table 1, after doing a large number of tests on the data set, it is proved that our algorithm is better than other algorithms in images for outdoor scenes. In order to prove the robustness of this method, we also tested images for indoor scenes, the test results of this method are better in most images than other methods other than the images of laboratory. The reason may be the distribution of feature points is more uniform in the images of laboratory, and the APAP algorithm [7] performs better in images with uniform feature distribution.

### 4. Conclusion

This paper proposes a feature point selection based on spatial distribution, then by using it with global homography and local registration, obtains better stitching results in most images for outdoor scenes. We also obtained a natural, accurate and seamless panorama by combining with global similarity transformation and seam-cutting processing. However, for outdoor scenes, especially scenes with artificial buildings, line features are also very important features. Our future work will focus on how to use line features to solve image stitching in outdoor scenes.

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