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# Feature Points Selection for Rectangle Panorama Stitching

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**Abstract.** Panoramic images can provide users with large view scene, which is widely used in various fields. Image stitching can combine images of adjacent views with small horizon field into a single image with large horizon. Currently stitching method can provide a rectangle panorama by cropped method to view or print. However, this method can occur shape distortion, and information loss. In this paper, we propose a novel feature points selection method to generate rectangle panorama image. First, to avoid local distortion in overlapping region, matched feature points are selected by feature cluster analysis. And then, depending on selected feature points, we establish mesh warping method to produce rectangle mesh. At last, bilinear interpolation algorithm is used to obtain the rectangle panorama image. Experimental results show that the proposed method can effectively stitch different view image to generate rectangle panorama without shape distortion.

**Keywords:** Image warping, Feature selection, Rectangle panorama

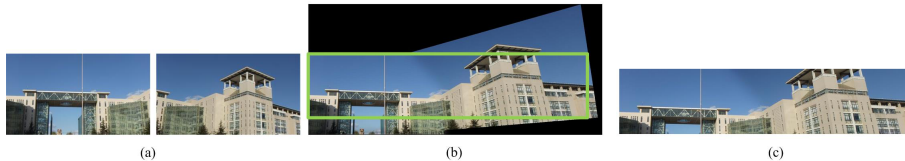
## 1 Introduction

With the development of virtual reality, an increasing quantity required for large view horizon image has been produced. However, due to the limitation of imaging equipment, it is difficult to capture a large view horizon image in a single camera shot. Therefore, a number of researchers on big view image generation has been proposed.

Image stitching can be used to stitch images of adjacent views with small angle view image into a single image with large horizon. Image stitching is typically implemented by using a parametric projective warping (e.g., cylindrical, spherical, or perspective) to bring images into alignment[1, 2]. Due to the casual camera moving, it is almost unavoidable that the stitched panoramic images

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**Fig. 1.** Result of traditional panorama stitching method. (a) input images, (b) stitched image by perspective transformation method, (c) cropped image.

exist misalignment or ghost[3–6], and exhibit irregular boundaries (Fig. 1(b)). To view, publish and print such panoramic images, the panorama with irregular boundaries can be cropped into a rectangular panorama image (Fig. 1(c)), where occur shape distortion and exist some information loss. In this paper, we study the issue of generating a rectangular panoramic image from the casual captured image, termed as rectangle panorama image.

To reduce shape distortion for image stitching, in recent years, similarity transformation has been introduced to reduce the distortions[7–12]. Chang et al.[7] proposed a shape-preserving half-projective (SPHP) warping for image stitching, which adopted projective transformation to align image, and similarity transformation to achieve gradually change from projective to similarity across the image. It can significantly reduce the distortions and preserve the image shape. But it may introduce structure deformations, such as line distortions, when the scene is dominated by line structures. Lin et al.[9] proposed an adaptive as-natural-as-possible (AANAP) warping, which linearizes the homography in the non-overlapping regions and combines these homographies with global similarity transformation by the direct and simple distance-based weight strategy to mitigate the perspective distortion. However, some distortions locally still exist when stitching images. Yu et.al[10]proposed a natural image stitching method with the global similarity prior, which constrains the warp of each image so that it resembles a similarity transformation as a whole. They adopt the local warp model and guides the warping of each image with a grid mesh. Xiang et al.[12] proposed a line-guided local warping with global similarity constraint method to reduce shape distortion for image stitching. Their method use corresponding line to guide the accurate alignment, while preserving image structures. To mitigate projective distortions in non-overlapping regions, they combine global similarity constraint with the projective warps via a weight strategy. However, these methods take a transition from perspective transformation to similarity transformation, which may occur image structure distortion, such as unnatural rotation of image.

Above methods can avoid shape distortion, however, to view, publish and print stitched images, the stitched image with irregular boundary need to change to become a rectangle panorama image. The naive cropping on image boundary has been proved inappropriate in boundary rectangle because of the loss of regional information and the reduction of the viewing frustum angle. There-

fore, there are a few rectangle panorama image [13–15]. He et al.[15] proposed a content-aware warping algorithm that generated rectangular images from stitched panoramic images. They adopt a seam carving technique[16] to re-fill irregular boundaries and establish correspondence relationship between the irregular panorama and a desired rectangular shape. At last, they use a content-aware warping to generate a rectangular panorama. These method can make finished stitched image to rectangle panorama image, i.e, the input of their method is stitched panorama image, and the output is rectangle panorama image. In contrast, our method can directly generate rectangle images from casual captured different view images.

This paper proposes a feature points selection method for rectangle panorama image, which take Ransac method and clustering method to prune mismatched feature points, and use mesh warping method to generate a rectangle panorama image. Our method takes into account the flexibility for alignment, shape distortion, and information loss, in order to generate a rectangle panorama.

## 2 The proposed method for rectangle panorama

In this section, we introduce the proposed feature points method for rectangle panorama image method in detail. First, matched feature points are detected by Sift feature points, and then, use Ransac method and clustering method to prune feature points, last, we propose shape-optimization warping method to generate a rectangle panorama image.

### 2.1 Feature points selection

In this section, we align the input image by MDLT method[4] and avoid shape distortion. Image alignment based on feature points need first to find the matched feature points (generally SIFT feature points[18]). And the random sample consensus (RANSAC[1]) was used to eliminate outliers. Although, these feature points after RANSAC selection are almost matched points, there occur shape distortion on local region if these points include individual points in non-salient region.

Few feature points located in extrapolation non-salient region can cause image local distortion. We eliminate these points in overlapping region. First, we take take clustering method[19] to classify feature points after RANSAC method, and then eliminate such class with lower number. Feature points information is consisted of position, and its salient value[5], can be denoted as:

$$\begin{aligned} s_i &= (f_{ix}, f_{iy}, f_{is-v}) \\ S &= \{s_1, \dots, s_n\} \end{aligned} \quad (1)$$

We can classify the sample S with clustering method [19], and select feature points.

## 2.2 Shape-preserving warping

The image warping problem is formulated as a grid cell warping problem. We take MDLT to these mesh grid vertices in image overlapping. Since, the vertices is in the overlapping, not is in extrapolation region, the weight is  $w_{k,i,j} = \exp(-\|v_{i,j} - f_k\|^2/\sigma^2)$ . Assume the vertices after MDLT in overlapping region are  $v_{i,j,o}$ . Depend on the vertices in overlapping region, we can calculate these vertices in non-overlapping region. Here, we take our proposed DW method in our previous paper. The idea is that change gradually inclination angle of line by iterative method. That is the horizontal line converges to zero asymptotically, and the inclination angle of vertical line converges to 90 degree asymptotically. Assume the number of vertices is  $m \times n$ , the  $\Delta\theta_{x,i}$  and  $\Delta\theta_{y,i}$  denote the derivative angle at horizontal and vertical line,  $k$  and  $b$  denote the parameters of line. The iteration step, which is used to obtained new vertices, is shown in the following.

**Table 1.** Iteration process of derivative warping.

Input: Vertices in overlapping region, $v_{i,j,o}$
Output: Vertices in non-overlapping region, $v_{i,j,no}$
Initial: $v_{i,1,no}(x) = v_{i,end,o}(x)$ , $v_{i,1,no}(y) = v_{i,end,o}(y)$
1. Start $i, j$
2. If $N \leq n_1$
3. Calculating $\theta_{x,i,j-1}$ , $k_{x,i,j-1}$ , $b_{x,i,j-1}$ to obtain $y = k_{x,i,j-1}x + b_{x,i,j-1}$
Calculating $\theta_{y,i-1,j}$ , $k_{y,i-1,j}$ , $b_{y,i-1,j}$ to obtain $x = k_{y,i-1,j}y + b_{y,i-1,j}$ ;
4. Calculating intersection $v_{i,j,no}(x)$ , $v_{i,j,no}(y)$ ;
Else
5. $\theta_{x,i,j-1} = 0$ , Calculating $k_{x,i,j-1}$ , $b_{x,i,j-1}$ to obtain $y = k_{x,i,j-1}x + b_{x,i,j-1}$
$\theta_{y,i-1,j} = 0$ , Calculating $k_{y,i-1,j}$ , $b_{y,i-1,j}$ to obtain $x = k_{y,i-1,j}y + b_{y,i-1,j}$ ;
6. Calculating intersection $v_{i,j,no}(x)$ , $v_{i,j,no}(y)$ ;
7. $N = N + 1$ ; Until $i = m$ , $j = n$ ;
End

To generate rectangle panorama image, the mesh need to warp by solving an energy minimization framework based on defined energy terms including boundary term and mesh grid deformation term. The energy terms are described in detail below.

(a) Boundary term: The boundary term is used to ensure the rectangle panorama. First, we calculate the boundary value of shape-preserving stitched image. Suppose the left boundary value is  $w_l$ , the right boundary value is  $w_r$ , the top boundary value is  $h_t$ , the bottom boundary is  $h_b$ . The boundary term is defined as:

$$\begin{aligned}
 E_b = & \sum_{i=1}^m (v'_{i,1}(x) - w_l)^2 + \sum_{i=1}^m (v'_{i,n}(x) - w_r)^2 \\
 & + \sum_{j=1}^n (v'_{1,j}(y) - h_t)^2 + \sum_{j=1}^n (v'_{m,j}(y) - h_b)^2
 \end{aligned} \tag{2}$$

(b) Mesh grid deformation term: The mesh deformation of the image needs to be constrained, when the boundary changes. Since humans see a photo, they often are interested in the objects near the center of the image [5], we hope the mesh grid line around the center position keep the original size, more change happened in boundary position of image. The boundary term is defined as:

$$E_{q(i,j)} = \sum_{v_{i,j} \in q(i,j)} \|(v'_{i,j} - v'_{i,j-1}) - (v_{i,j} - v_{i,j-1})\|^2 \quad (3)$$

The all quad deformation term is:

$$E_Q = \sum_{i=1}^m \sum_{j=1}^n a_{i,j} E_{q(i,j)} \quad (4)$$

$$a_{i,j} = \exp(-\|v_{i,j}(x) - c_x\|^2 / \sigma_x^2 \cdot \|v_{i,j}(y) - c_y\|^2 / \sigma_y^2)$$

Here,  $c_x, c_y$  denotes the central pixel position of image.  $\sigma_x, \sigma_y$  is the horizontal variance, vertical variance.

The total energy function is

$$E = E_b + E_Q \quad (5)$$

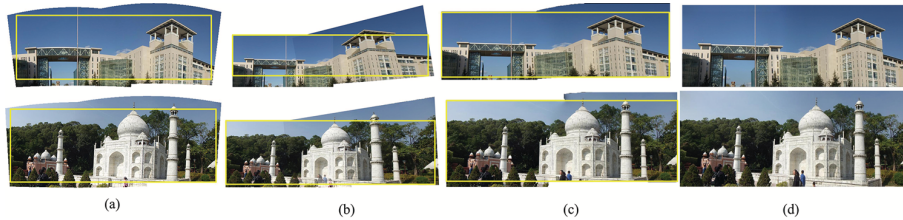
Since the energy  $E$  is a quadratic function of  $v'_{i,j}$ , the minimization problem is solved via a sparse linear solver.

Once the output meshes are obtained by the Eq.5, bilinear interpolation algorithm[20] is used to obtain the final rectangle panorama image.

### 3 Experimental results

In order to verify the effectiveness of proposed method, experiments are performed on casual captured different view images in this section, and generation panorama results are compared with other three stitching methods, i.e., cylindrical panorama by Photoshop CS6, APAP method[4], and DW method[17]. The comparison results are shown in the Fig. 2. In addition, we show more results of proposed method. APAP warp employs local projective warps to make image accurate alignment. DW method uses derivative warping transformation to avoid shape distortion.

Fig. 2(a) show a cylindrical panorama. There are some shape distortions, information loss after cropping image. As shown in Fig.2(b), the APAP could well align input image with ghost, while they could not produce a good panorama image due to the lack of shape constraints. Since APAP extrapolate local projective warps into the non-overlapping regions, which are severely stretched and non-uniformly enlarged. As shown in Fig. 2(c), DW method can reduce shape distortion using derivative warping transformation, while there are occur information loss after cropping image. In contrast, the proposed method can avoid local distortion by feature selection, in addition, the proposed method guarantees image alignment and reduces shape distortion in a combination of MDLT and derivative warping method, and reduce information loss using a quadratic mesh



**Fig. 2.** Comparison results among different panorama stitching approaches. (a) cylindrical panorama by photoshop, (b) APAP method, (c) DW method, (d) the proposed method.

grid optimization. The proposed method (see Fig.2(d)) can generate rectangle panorama without ghost, shape distortion and information loss.

## 4 Conclusion

This paper proposes a novel shape-optimization based on feature selection for rectangle panorama image. First, the matched feature points is selected to avoid the local distortion in alignment. And then, we use shape-optimization mesh warping method to generate rectangle panorama image. At last, bilinear interpolation algorithm is used to obtain the rectangle panorama image. Experimental results show the effectiveness of the proposed method, which can stitch different view image to generate rectangle panorama without ghost, shape distortion and information loss.

## References

1. R. Szeliski, “Image alignment and stitching: a tutorial landsat ” *Foundations and trends in computer graphics and vision* , vol. 2, no. 1, pp. 1–104, 2006.
2. L. Zelnik-Manor, G. Peters, P. Perona , “ Squaring the circle in panoramas,” *In Proc. ICCV.*, pp. 1292–1299, 2005.
3. W. Y. Lin, S. Liu, Y. Mastsushita *et al.*,” Smoothly varying affine stitching,” *In Proc. CVPR.*, pp. 345–352, 2011.
4. J. Zaragoza, T. J. Chin, and Q. H. Tran, “ As-projective-as-possible image stitching with moving DLT,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 36, no. 7, pp. 1285–1298, 2014.
5. S. Goferman, L. Zelnik-Manor, and A. Tal, “ Context-aware saliency detection,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 34, no. 10, pp. 1915–1926, 2012.
6. F. Zhang, F. Liu, “ Parallax-tolerant image stitching,” *In Proc. CVPR* , pp. 3262–3269, 2014.
7. C. H. Chang, Y. Sato, Y. Y. Chuang, “ Shape-preserving half-projective warps for image stitching,” *In Proc. CVPR.*, pp. 3254–3261, 2014.
8. Q. Chai, S. Liu, “ Shape-optimizing hybrid warping for image stitching,” *In Proc. ICIP.*, pp. 1–6, 2016.

9. C. Lin, S. Pankanti, K. N. Ramamurthy, A. Y. Aravkin, “ Adaptive as-natural-as-possible image stitching,” *In Proc. CVPR.*, pp. 1155–1163, 2015.
10. Y. Lu, Z. Z. Hua, K. Gao, T. F. Xu, “ Multi-Perspective Image Stitching and Regularization via Hybrid Structure Warping,” *Computing in Science Engineering.*, vol. 20, no. 2, pp. 10–23, 2018.
11. Y. S. Chen, Y. Y. Chuang, “ Natural Image Stitching with Global Similarity Prior,” *In Proc. ECCV.*, pp. 186–201, 2016.
12. T. Z. Xiang, G. S. Xia, X. Bai *et al.*, “ Image stitching by line-guided local warping with global similarity constraint,” *Computer Vision and Pattern Recognition*, arXiv:1702.07935, 2017.
13. C. Barnes, E. Shechtman, A. Finkelstein, D. B. Goldman, “ Patch-match: A randomized correspondence algorithm for structural image editing,” *ACM Trans. Graph.*, vol. 28, no. 3, pp. 1–8, 2012.
14. J. Kopf, W. Kienzle, S. Drucker, S. B. Kang, “ Quality prediction for image completion,” *ACM Trans. Graph.*, vol. 31, no. 6, pp. 1–8, 2012.
15. K. He, H. Chang, J. Sun., “ Rectangling panoramic images via warping,” *ACM Trans. Graph.*, vol. 32, no. 4, pp. 1–9, 2013.
16. S. Avidan, A. Shamir, “ Seam Carving for Content-Aware Image Resizing,” *ACM Trans. Graph.*, vol. 26, no. 3, pp. 1–10, 2007.
17. W. Q. Yan, C. P. Hou, “ Reducing perspective distortion for stereoscopic image stitching,” *In Proc. IEEE ICME. workshop*, pp. 1–6, 2016.
18. D. G. Lowe, “ Distinctive image features from scale-invariant keypoints,” *Int. J. Comput. Vis.*, vol. 60, no. 2, pp. 91–110, 2004.
19. Q. He, X. Jin, C. Du, F. Zhuang, Z. S. “ Clustering in extreme learning machine feature space,” *Neurocomputing*, vol. 128, pp. 88–95, 2014.
20. P. S. Heckbert, “Fundamentals of texture mapping and image warping,” *M.S. thesis, Dept. Elect. Eng. Comput. Sci., Univ. California, Berkeley*, Berkeley, CA, USA, 1989.