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Improvement in Image Alignment using Hybrid Warping Technique for Image Stitching

Omkar S. Vaidya[1], Dr. Sanjay T. Gandhe[2]

[1]Research Scholar, Sandip Institute of Technology and Research Centre, Nashik, India.
[2]Professor and Research Guide, Sandip Institute of Technology and Research Centre, Nashik, India.
Savitribai Phule Pune University, Pune, India.

Abstract

This research work is mainly focused to stitch two images of different view-scene which are captured at fixed view point having small overlap between them. To achieve accurate alignment while stitching the images, images must be properly registered and failure in it causes structural misalignments, ghosting effect and parallax error. To overcome above problem, Hybrid Warping technique is proposed which uses combination of local and global warping while registering pair of images. The two-dimension position dependent homography warp is used especially in overlapping region to achieve better image alignment. Similarly, mesh based projective warp viz. smoothened homography transform and similarity transform employed in non-overlapping source and target image respectively. The proposed warp is compared with well-known existing methods quantitatively and qualitatively. The experimental results showed that improvement in image alignment is achieved far better using Hybrid warping in all standard datasets.

Keywords: Hybrid warping, Image Alignment, Image Stitching, Moving direct linear transformation, Similarity transformation.

I. INTRODUCTION

There are abundant famous image stitching tools currently available in market such as Microsoft ICE, Hugin, Autostitch and many others. But, for complex datasets all above mentioned tools are unable to provide perfect solution. The success of image stitching lies in accurate image alignment which is rarely achieved by traditional 2-D geometrical transformation (global transforms). Therefore, several local warping models were introduced. But local warping does not solve issues like limited field of view, distortion and blurring in stitched image.

In this paper, Hybrid Warping technique is introduced to improve image alignment stage of image stitching. The proposed warp is combination of local warp based on moving direct linear transform and global warps like similarity plus smoothened homography transforms. Hybrid warping not only improve image alignment but also produce good looking panorama which is free from motion parallax, ghosting effect and seam line.

The paper is structured as follow: The developments of various local and global warping methods are reviewed in Section II. Section III explained proposed technique in detail. The experimentation is presented in Section IV. The quantitative and qualitative analysis over standard datasets is compared in Section V. In Section VI, paper is concluded.

II. REVIEW OF RELATED PAPERS

The tutorial on image stitching is presented in [1] by Szeliski. In this, basic concepts of image alignment and image stitching were discussed. It reviewed basic motion models, direct and feature based registration technique and blending algorithm. Chia-Yen Chen explained different image acquisitions method to obtain panoramic images [2]. Also, it compared registration based on similarity measures and merging based on linear distribution of intensity. Authors in [3] studied systematically pre-processing, post-processing of image stitching and gave idea about selection of appropriate algorithms in each stage of image stitching. The performance of single scale (viz. KLT and Harris) and multi-scale feature detectors and descriptors (viz. SIFT) are compared in [4].

W. Y. Lin et.al. were first to explore local warp called smoothly varying affine (SVA) which minimized registration errors and effectively handled parallax and occlusions [5]. J. Gao et.al. used dual homography warping (DHW) by assuming image has two planes viz. foreground and background in [6]. Authors used two homographies but not applicable to multiple images of randomly selected arbitrarily scenes. Authors in [7] used as projective as possible (APAP) local warp in overlapping region while image registration. It gives better alignment accuracy but use of projective transform in non-overlapping region produced non-uniform stretching which leads to shape distortion. The drawback of APAP is solved by employing shape preserving half projective (SPHP) warp [8]. It is combination of projective transformation in one half-space and preserving shape in other half space. But the parallax is still remains same in SPHP as it uses global homography in overlapping region.

Yu-Sheng Chen proposed global similarity prior term in addition with local warp model which is similar to APAP warp. The focal length and 3-D rotation is estimated to get naturalness of stitched image in [9]. Jing Li et. al. implemented Elastic Local Alignment (ELA) function that achieved accurate alignment and are parallax tolerant [10].

The framework of proposed warp in [10] is based on thin plate spline (TPS) model. The Bayesian refinement model used to detect and match features speedily. Nan Li proposed Quasi-homography warp that relies on global homography in [11]. This warp eliminates perspective and projective distortion through global consistent slope preservation and local consistent scale linearization respectively.

III. HYBRID WARPING TECHNIQUE

Initially, local warp is executed to determine corresponding points in overlapping images using moving direct linear transformation. After that for non-overlapping region of source image smoothened homography transformation is estimated. At the end, similarity transformation is employed over non-overlapping region of target image.

III.I Local Warping using Moving Direct Linear Transform (MDLT)

Assume that the source (I) and target image (I') are having certain overlapping between them. Now consider x and x' are matching points between I and I'. The transformation is given by the form x' = Hx. This form can be expressed in terms of vector cross product x'× Hx = 0. This form involves homogeneous vectors. If the i^{th} row of the matrix H is denoted by h^{iT}, then it can be written as:

$$Hx = \begin{bmatrix} h^{1T}x \\ h^{2T}x \\ h^{3T}x \end{bmatrix} \quad (1)$$

$x' = (x', y', w')^T$, the cross product is given in (2) as:

$$x' \times Hx = \begin{bmatrix} y'h^{3T}x - w'h^{2T}x \\ w'h^{1T}x - x'h^{3T}x \\ x'h^{2T}x - y'h^{1T}x \end{bmatrix} \quad (2)$$

As $h^{jT}x = x^T h^j$ for j=1,2,3. This gives set of 3 equations in entries of H. So, (2) can be written in (3) as:

$$\begin{bmatrix} 0^T & -w'x^T & y'x^T \\ w'x^T & 0^T & -x'x^T \\ -y'x^T & x'x^T & 0^T \end{bmatrix} \begin{bmatrix} h^1 \\ h^2 \\ h^3 \end{bmatrix} = 0_{3\times1} \quad (3)$$

Equation (3) is form of A.h=0, where A is 3×9 matrix and h has 9-vectors of matrix H.

$$h = \begin{bmatrix} h^1 \\ h^2 \\ h^3 \end{bmatrix}, \mathrm{H} = \begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix} \quad (4)$$

From (2), out of three equations only two of it is linearly independent [12]. According to DLT algorithm, matrix H is determined from h.

To align images, arbitrarily x pixel from image I is to be warped to position of x' in image I'. Feature point x is continuously moving in source image for finding its correspondence, similarly the warp H also moved. For this, location dependent homography is used by assigning weights to feature points. But some of weights assigned to feature points which are not belong to overlapping region, and hence small offset value is set to prevent the numerical issue [7].

The source image is divided into dense grid of 200 ×200 cells, and center of each cell is taken as x. It reduces effects of warp discontinuities. The grid size selection address the resolution of source image and increase chances of warping time for higher resolution.

III.II Global warping using Smoothened Homography

As discussed earlier in case of APAP, warp is stretched in non-overlapping region of source image using global projective warp. This resulted unnecessary extrapolation and produces projective distortion (i.e. enlarged size and stretched shapes). Such stitched result is deformed and look like unnatural. To resolve above issue, perspective distortion in non-overlapping area of source image is reduced by using smoothened homography transformation. But the thing is determination of boundary points from overlapping and non-overlapping region before applying smoothened homography is essential. The derivative of single point is calculated for differentiating the transformation. The normalized weighting function used in dual homography warp is used here by computing Euclidean distance from point x to all boundary points [6].

III.III Global warping using Similarity Transformation

Many well-known methods discussed earlier [8], [9], [11] used similarity transformation to achieve naturalness qualities of stitched image. The global similarity transformation S is estimated by minimizing (5).

$$J_A = \sum_{i=1}^{n_r} \| Sx - x' \|^2 \quad (5)$$

Where, n_r: refined point match and $S = \begin{bmatrix} \cos\theta & -\sin\theta & t_x \\ \sin\theta & \cos\theta & t_y \end{bmatrix}$.

Finally, combination of smoothened homography and similarity transformation is carried out as mentioned in ANAP warping [13].

$$H_x = \mu_h H + \mu_s H_s \quad (6)$$

Where, μ_h and μ_s are weighting coefficients and

$$H_s = \begin{bmatrix} \cos\theta & -\sin\theta & t_x \\ \sin\theta & \cos\theta & t_y \\ 0 & 0 & 1 \end{bmatrix} \quad (7)$$

Both values of weighting coefficients are in between 0 and 1 such that $\mu_h + \mu_s = 1$.

On the same line of (6), target image I' is also transformed as

$$H_{x'} = H_x . H^{-1} \quad (8)$$

The overlapping part between source and target image which were previously aligned by local warp may get disturbed. To repair the misalignment occurred, target image warp is transformed using global similarity transformation mentioned in (8).

IV. EXPERIMENTATION

The implementation of the work is carried on Intel corei3 processor with 2 GHz CPU and 4 GB RAM and experimentation is carried in MATLAB R2017a. To test results, dataset available in [7] is used such as Railtracks, Temple, Garden, Chess Girl, Apartment, Couch and Rooftops. The comparative performance analysis is conducted including Hybrid warping (HW) with APAP [7], SPHP [8] and ELA [10].

Hybrid warping method is compared with well-known methods such as APAP, SPHP and ELA. The identification of correct match points between two images is key step to align accurate images especially for image stitching application. From pair of two images, keypoint features are detected using SIFT and computed matched points using RANSAC iterative algorithm. RANSAC fits inliers points and remove outliers while keypoint matching.

After this, individual warping technique is employed. The equirectangular projection is considered as a compositing surface. After successful registering images, around the overlapping regions the seam is visible. It highlights inconsistency in terms of structure and colour. To clear above problem linear blending method is applied which then obtained pleasant stitched result.

V. RESULTS AND DISCUSSIONS

V.I Quantitative Evaluation

Table 1 depicts the percentage matching rate on seven standard datasets. In experimentation, RANSAC threshold is kept as 0.1. The Hybrid warping method obtained highest number of correct matches as compared with other methods. The guided sampling function of RANSAC is implemented in case of Hybrid warping; while in case of APAP, random sampling function is incorporated. RANSAC with Homography model computed best inliers score in SPHP and ELA. It is considered that if amount of overlap between two images is more, then naturally it produces accurate and better stitched image. Even so with least overlap between source and target image (in case of Railtracks dataset), Hybrid warping method gives high percentage matching score. Also, the output result for the same is free from structural misalignments, parallax error and blurring (as shown in Fig. 2(f)).

The comparative analysis of stitching time at each stage among different methods is shown in Table 2. The average time consumption of APAP, SPHP and ELA is around 8-15 seconds and that of Hybrid warping is 15-20 seconds. This is because; the grid size in warping function for ELA, APAP and SPHP is taken as 100 × 100 cells while in case of Hybrid warping it is 200 × 200 cells. Also in case of Hybrid warping, the shifting of local warping to similarity transformation is done to mitigate problem of over fitting in non-overlapping area of target image. This additional stage increases warping processing time in Hybrid warping. The overall stitching processing time also depends on the size of image pair.

V.II Qualitative Evaluation

To evaluate experimental results, two image datasets viz. Temple and Railtracks are considered in this paper. The source and target image of Temple dataset is shown in Fig. 1 (a) and (b). The final stitched image by APAP, SPHP, ELA and Hybrid Warping method is shown in Fig. 1 (c), (d), (e) and (f) respectively.

From Fig. 1(c), structural misalignment is highlighted in red circles on ground plane of APAP based stitched image. Also, non-overlapping area of source image is stretched severely that deform the stitched result. In case of SPHP (Fig. 1 (d)), output image show unnatural rotation with parallax error as shown in red circle. ELA based stitched result also show perspective projection and hence buildings object highlighted are not parallel to temple object. Similarly, in overlapping area parallax error is seen. The Hybrid Warping stitched result is shown in Fig 1(f). In this case, overlapping region is properly aligned without any misalignment error. Also, source image is smoothened and minimize problem of perspective distortion. Overall stitched image looks pleasant and aesthetic.

Table 1. Comparison of Percentage Matching Rate on Different Database

Image Dataset	Size of Source & Target Image	No. of Features Extracted		% Overlap	No. of Features Matched				No. of Inliers				% Matching Rate			
		Target Image	Source Image		APAP	SPHP	ELA	HW	APAP	SPHP	ELA	HW	APAP	SPHP	ELA	HW
Temple	487 X 730	1462	1585	43.18	482	478	482	482	415	262	320	429	86.10	54.81	66.39	**89.00**
Railtracks	720 X 960	3200	2911	35.39	737	751	739	721	671	486	487	660	91.04	64.71	65.90	**91.54**
Rooftops	240 X 320	366	381	49.79	107	107	105	106	91	90	63	92	85.05	84.11	60.00	**86.79**
Garden	682 X 1024	2997	3259	53.42	1318	1323	1317	1317	1236	1199	1051	1237	93.78	90.63	79.80	**93.93**
Apartment	804 X 1071	3653	3227	40.75	1321	1322	1008	1320	1111	974	577	1112	84.10	73.68	57.24	**84.24**
Chess Girl	898 X 1197	3754	3867	73.86	847	825	597	810	731	489	366	713	86.30	59.27	61.31	**88.02**
Coach	898 X 1197	3641	3084	81.63	1115	1082	875	1093	973	600	548	957	87.26	55.45	62.63	**87.56**

Table 2. Comparison of Stitching Processing Time on Different Database

Image Dataset	Feature Detection & Matching Time (sec)				Outlier Removal Time (sec)				Warping Processing Time (sec)				Blending Processing Time (sec)				Overall Stitching Processing Time (sec)			
	APAP	SPHP	ELA	HW	APAP	SPHP	ELA	HW	APAP	SPHP	ELA	HW	APAP	SPHP	ELA	HW	APAP	SPHP	ELA	HW
Temple	1.48	1.92	1.49	1.52	2.33	2.54	0.08	0.67	4	4.83	0.69	12.57	0.21	1.32	2.42	0.21	8.02	10.61	4.68	14.97
Railtracks	3.37	3.54	3.14	3.31	3.79	2.05	0.19	0.71	5.22	6.44	0.86	14.86	0.36	0.97	5.83	0.35	12.74	13	10.02	19.23
Rooftops	0.28	0.29	0.36	0.36	0.86	0.69	0.02	0.50	2.71	2.08	0.33	8.01	0.05	0.71	1.27	0.05	3.9	3.77	1.98	8.92
Garden	3.8	3.64	3.5	3.58	6.09	2.94	0.47	0.80	6.52	5.09	0.96	19.31	0.29	0.84	4.89	0.28	16.7	12.51	9.82	23.97
Apartment	4.28	4.14	2.68	4.21	5.49	2.87	0.37	0.79	6.48	6.85	1.34	17.66	0.33	0.81	7.1	0.3	16.58	14.67	11.49	22.96
Chess Girl	5.08	4.42	2.86	4.97	3.88	2.09	0.17	5.23	5.46	3.11	1.22	16	0.31	0.69	6.14	0.32	14.73	10.31	10.39	26.52
Coach	4.76	4.1	2.39	4.34	4.89	2.45	0.25	6.3	6.06	3.86	1.11	17.99	0.28	0.7	6.42	0.27	15.99	11.11	10.17	28.9

Another challenging example is Railtracks dataset as shown in Fig. 2 (a) and (b). From Fig. 2 (c), it is seen that Railtracks which is closed to scene is suffering from slight misalignments.

Also, the traction object in overlapping region shows blurring. SPHP result shown in Fig. 2 (d) has severe misalignments and ghosting effect highlighted in red circle. The overall projection is not uniform since right side part of stitched image is not parallel with left side traction objects. Image stitching results by ELA method shown in Fig. 2 (e) and Hybrid warping method in Fig. 2 (f) improve image alignment stage of Railtracks dataset. In case of ELA based image stitching, highlighted red box suffer from structure deformation. Hybrid warping based image stitching gives consistent view within overlapping and non-overlapping part.

Similarly in all other datasets, Hybrid Warping based stitched image shows excellent image alignment accuracy as compared with other warps. The combination of local and global warp helped to obtain uniform transformation without any unnecessary rotation and excessive extrapolation.

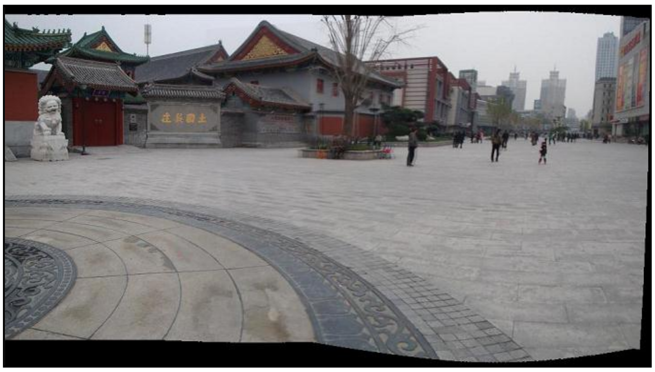
(a) Target Image

(b) Source Image

(c) APAP based Stitched Result

(d) SPHP based Stitched Result

(e) ELA based Stitched Image



(f) Hybrid Warping based Stitched Image

Fig. 1. (a), (b) Temple Dataset, (c), (d), (e), (f) comparison with different warping methods.

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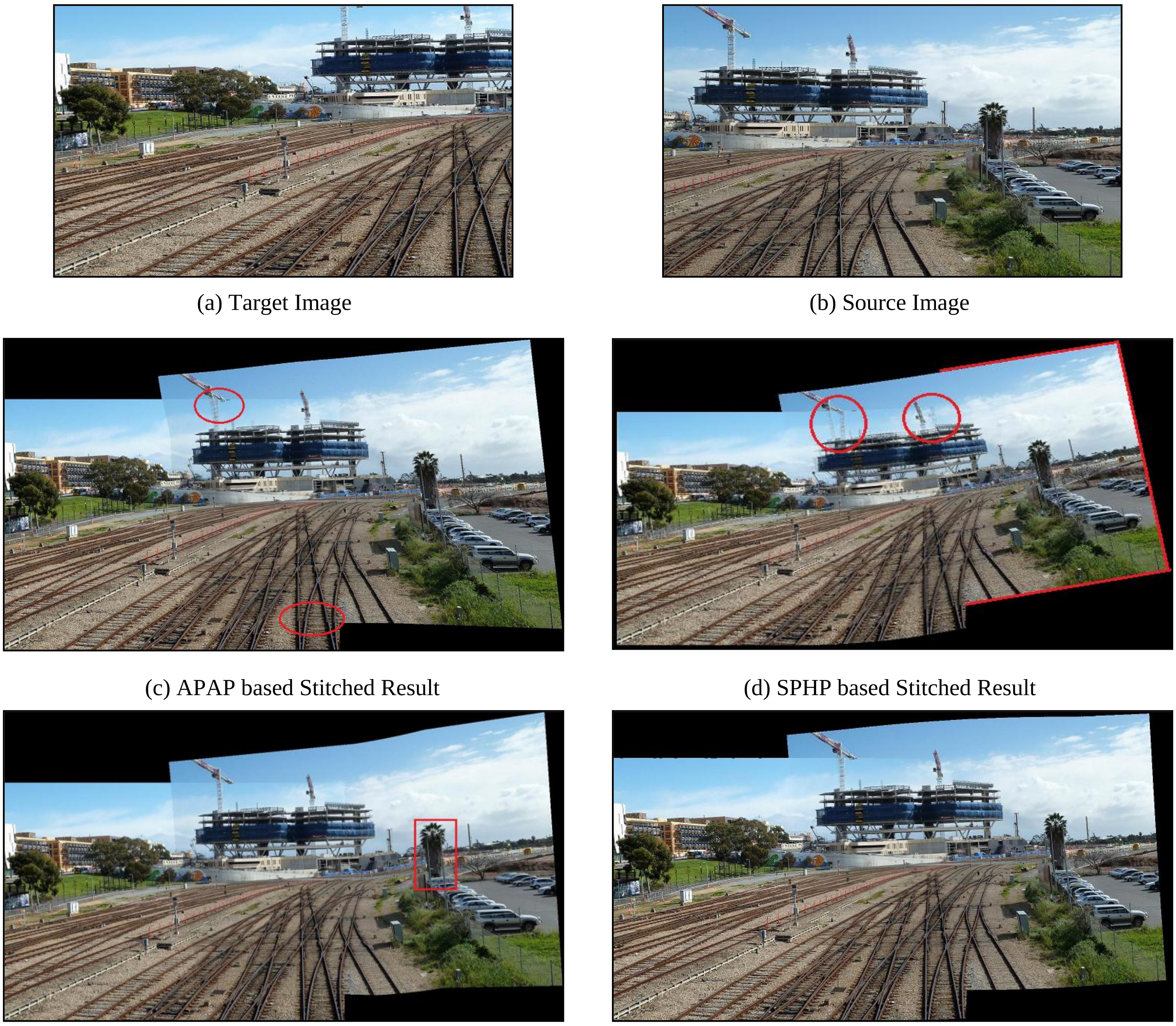

(a) Target Image (b) Source Image

(c) APAP based Stitched Result (d) SPHP based Stitched Result

(e) ELA based Stitched Image (f) Hybrid Warping based Stitched Image

Fig. 2. (a), (b) Railtracks Dataset, (c), (d), (e), (f) comparison with different warping methods.

VI. CONCLUSION

The mathematical modelling of Hybrid Warping technique to align image pair for image stitching is proposed in this paper. The local warping based on moving direct linear transformation is implemented in overlapping region while smoothened homography transform and similarity transform is applied in non-overlapping regions. The proposed method is compared with existing methods. From quantitative analysis, proposed method finds highest number of true matches and gives greater percentage of feature matching score. Qualitative results show that Hybrid Warping stitched image is free from any type of structural deformations, parallax error and ghosting artefacts. Also, output results preserve original perspective and remove visible seams, unnatural rotation, and shape/area distortion. The proposed warp takes slightly more time to stitch two images as compared with other methods.

Further research work includes stitching of multiple images to produce seamless panoramic view.

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