

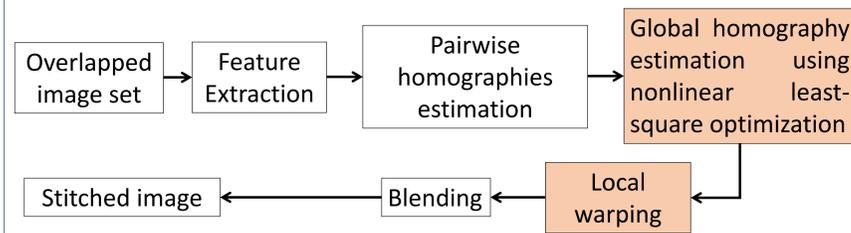
Introduction



Figure 1. Stitched image using DF-W [1] on rail data[2].

1. Homography estimation in SoA are based on linear algorithms, which ignore few parameters like lens distortion and leads to improper image stitching.
2. Homography based approaches in SoA miserably fails to handle parallax where the image is non-planar.

Proposed Flow



Contributed blocks are shown in color

Table 1. RMSE error comparison among APAP: as-projective-as-possible method[3]; DF-W: dual-feature method[1], MCC: multiple combined constraint method [2] and our proposed approach..

Data	APAP	DF-W	MCC	Proposed
temple	6.39	3.39	2.57	3.105
school	12.20	9.89	10.85	9.736
outdoor	11.90	9.52	6.75	7.433
rail	14.80	10.58	9.81	8.317
building	6.68	4.49	3.74	3.698
square	19.90	16.83	12.55	10.255
house	19.80	19.57	14.57	13.113
courtyard	38.30	36.23	29.17	30.258
villa	6.72	5.20	5.41	5.332
girl	5.20	4.81	5.05	4.726
park	11.07	8.18	5.85	7.528
road	2.28	4.59	1.67	1.917

Contact

[Arindam Saha]
[Embedded Systems and Robotics, TCS Research and Innovation]
[Kolkata, India]
[ari.saha@tcs.com]
[+91-9804499885]

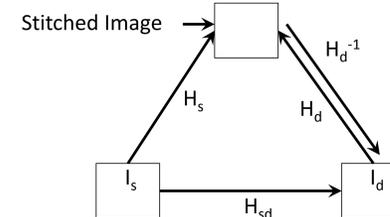
Proposed Method

SIFT point and edges points are used as feature points where edge points are tracked using bidirectional optical flow as described in [4].

We estimate all pairwise homographies using DLT with RANSAC.

Global Homography

$$C_w = \sum_{I_s, I_d \in \theta} \sum_{i \in \varphi} |(H_d^{-1} H_s) x_i - x'_i|^2 + \lambda * F_R(H_{sd}, (H_d^{-1} H_s))$$



Local Warping

$$C_L = C_D + \delta_1 C_P + \delta_2 C_G$$

Data Term

Align i-th feature point correspondence (x_i^{os} and x_i^{od}) with mid point x_i^m

$C_D = \sum_{i \in \varphi} |x_i^{os} - x_i^m|^2 + |x_i^{od} - x_i^m|^2$ where $x_i^o = \sum_{j=1}^9 \mathbf{w}_{i,j}^T P_{ij}^o$
It represent the i-th feature point with a bi-cubic interpolation of nine corner points enclosed in a 12x12 window region.

Photometric Term

Align image based on photometric correctness of sampled points and edge points.

$$C_P = \sum_k |I_s(x_k^o) - I_d(x_k)|^2$$

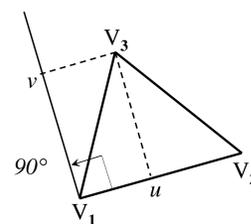
Geometric Term

Preserving geometric structure of a mesh using the equation

$$C_G = \sum_{\ell=1}^{\Delta_n} |V_3^o - (V_1^o + u(V_2^o - V_1^o) + v \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} (V_2^o - V_1^o))|^2$$

Where a vertex is linearly dependent on other two vertex of the triangle

$$V_3 = V_1 + u(V_2 - V_1) + v \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} (V_2 - V_1)$$



Result

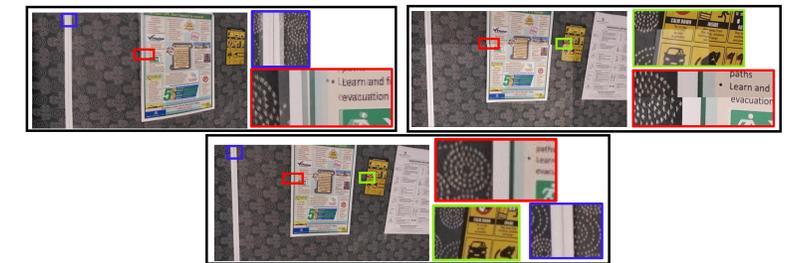


Figure 2. First Row Left: Stitched blended image with only global homography using inlier point correspondences. There are highest alignment error; First Row Right: Stitched image with data term and photometric term using noisy point correspondence; The stitched image is without blend to show the misalignment. Second Row: Stitched image with all proposed constraints.

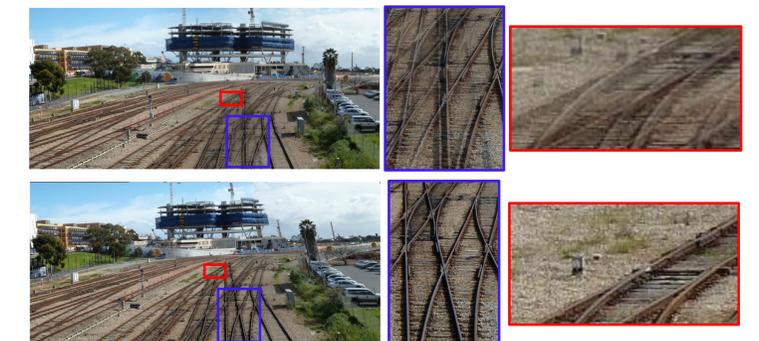


Figure 3. First Row: Stitched image using DF-W [1] where misalignment presents in rail tracks. Second Row: Stitched image using our proposed approach where rail tracks are perfectly aligned.

Discussion

- Table 1 presents the RMSE comparison among SoA and our proposed methods.
- Dual feature method performs better homography estimation than a single point feature.
- Our proposed approach uses only point features for global homography estimation where feature points are included from both edges and SIFT matching that yields better homography estimation.
- Homography estimation using only SIFT point correspondences is erroneous on edges due to lack of matched features in those areas. The result improves significantly by adding more matched point features on edges and overlapping boundaries.
- Local warping produces the best alignment.

Conclusions

We present a novel image stitching approach where images are initially aligned using a global homography estimation and further rectify misalignments using a multi-constrained local warping approach. We use photometric as well as geometric constraints in local warping to achieve a smooth structure-preserving stitching among overlapping images. Evaluation of our proposed approach on different open datasets shows better accuracy than state-of-the-art methods.

References

1. S. Li, L. Yuan, J. Sun and L. Quan, "Dual-feature warping-based motion model estimation," in IEEE International Conference on Computer Vision (ICCV), 2015, pp. 4283-4291
2. K. Chen, J. Tu, B. Xiang, L. Li and J. Yao, "Multiple combined constraints for image stitching," in IEEE International Conference on Image Processing (ICIP), 2018, pp. 1253-1257
3. J. Zaragoza, T. Chin, M. S. Brown and Suter D., "As-projective-as-possible image stitching with moving dlt," in IEEE Conference on Computer Vision and Pattern Recognition, 2013, pp. 2339-2346
4. S. Maity, A. Saha and B. Bhowmick, "Edge slam: Edge points based monocular visual slam," in The IEEE International Conference on Computer Vision (ICCV) Workshops, Oct 2017