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Low-rank registration of images captured under unknown, varying lighting

SSVM 2021
May 17-19 2021
Cabourg (COVID -> online)

Introduction

Photometric stereo infers a surface geometry from images captured with a fixed camera, but varying lighting [1]. Slightly misaligned images result in blurry 3D-reconstructions (Fig. 1), and hallucinated geometry (Fig. 2). To prevent this, the image sequence can be registered prior to 3D-reconstruction.

Even on quasi-planar scenes, registration remains arduous due to lighting variations, which may induce cast-shadows or specularities. We propose an open-source [5] robust affine registration technique for images captured under unknown, varying lighting, based on low-rank approximation and convex relaxation.

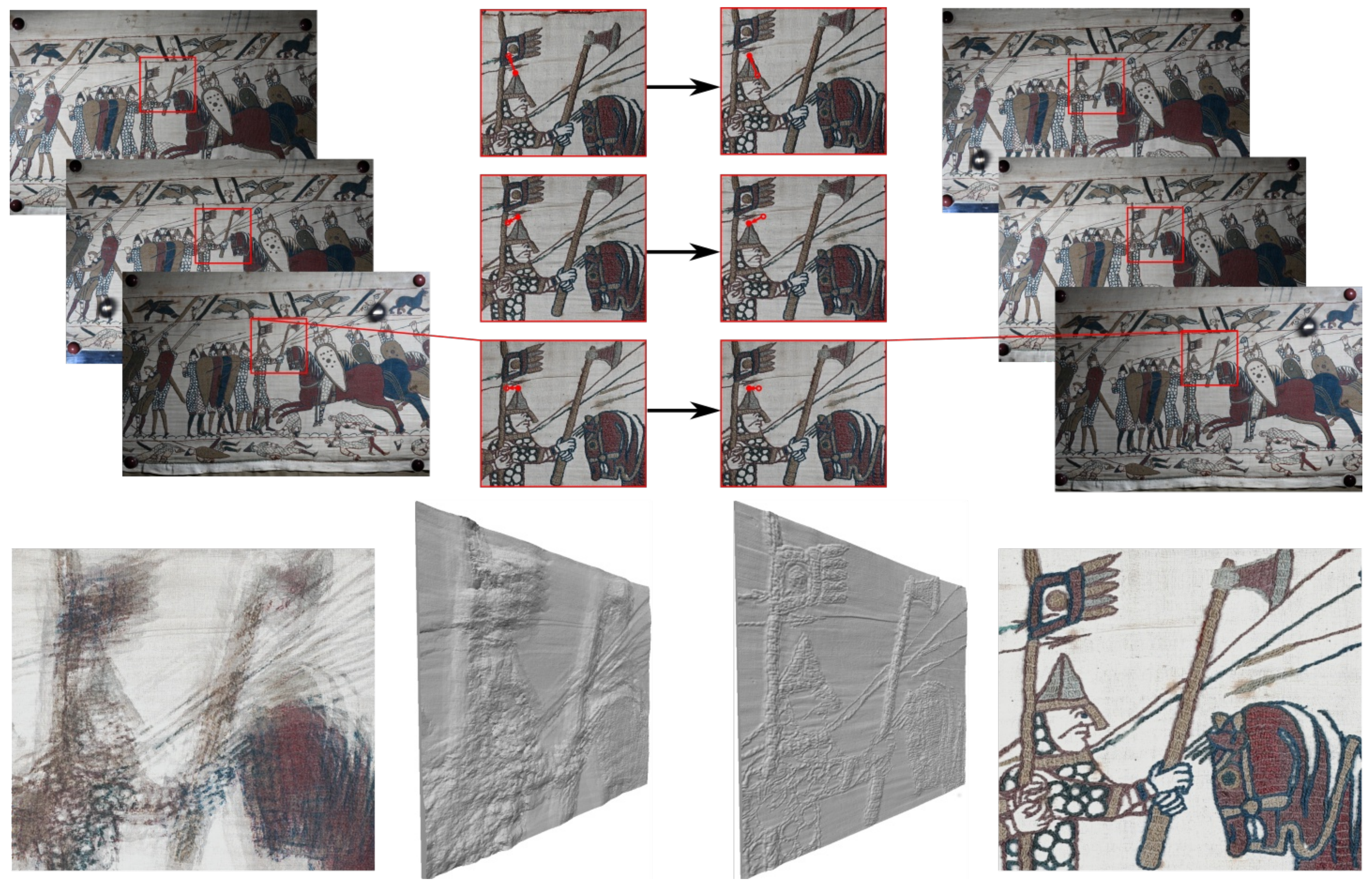


Fig 1. Bayeux Tapestry 3D-reconstruction from unregistered (left) and registered (right) images.

Low-rank registration

$$\min_{\theta \in \mathbb{R}^{mp}} \quad \operatorname{rank}\left(\operatorname{Mat}(W(u;\theta))\right) \qquad (1)$$

Where $W(u;\theta)$ is a warp transformation of the data matrix u parameterized by θ.

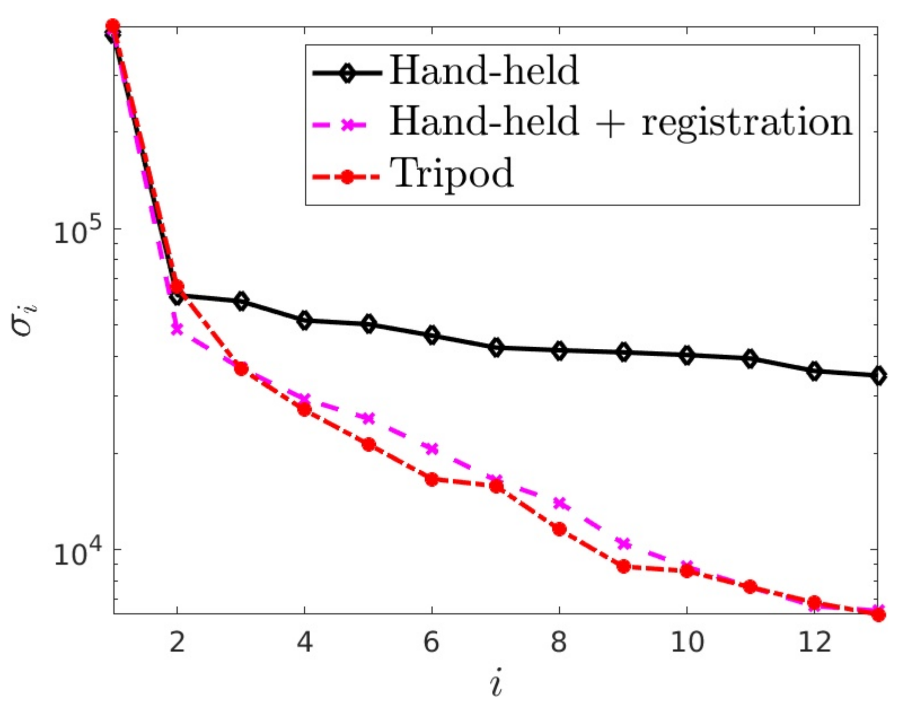


Fig 3. Singular values of the observation matrix for the data in Fig. 1.

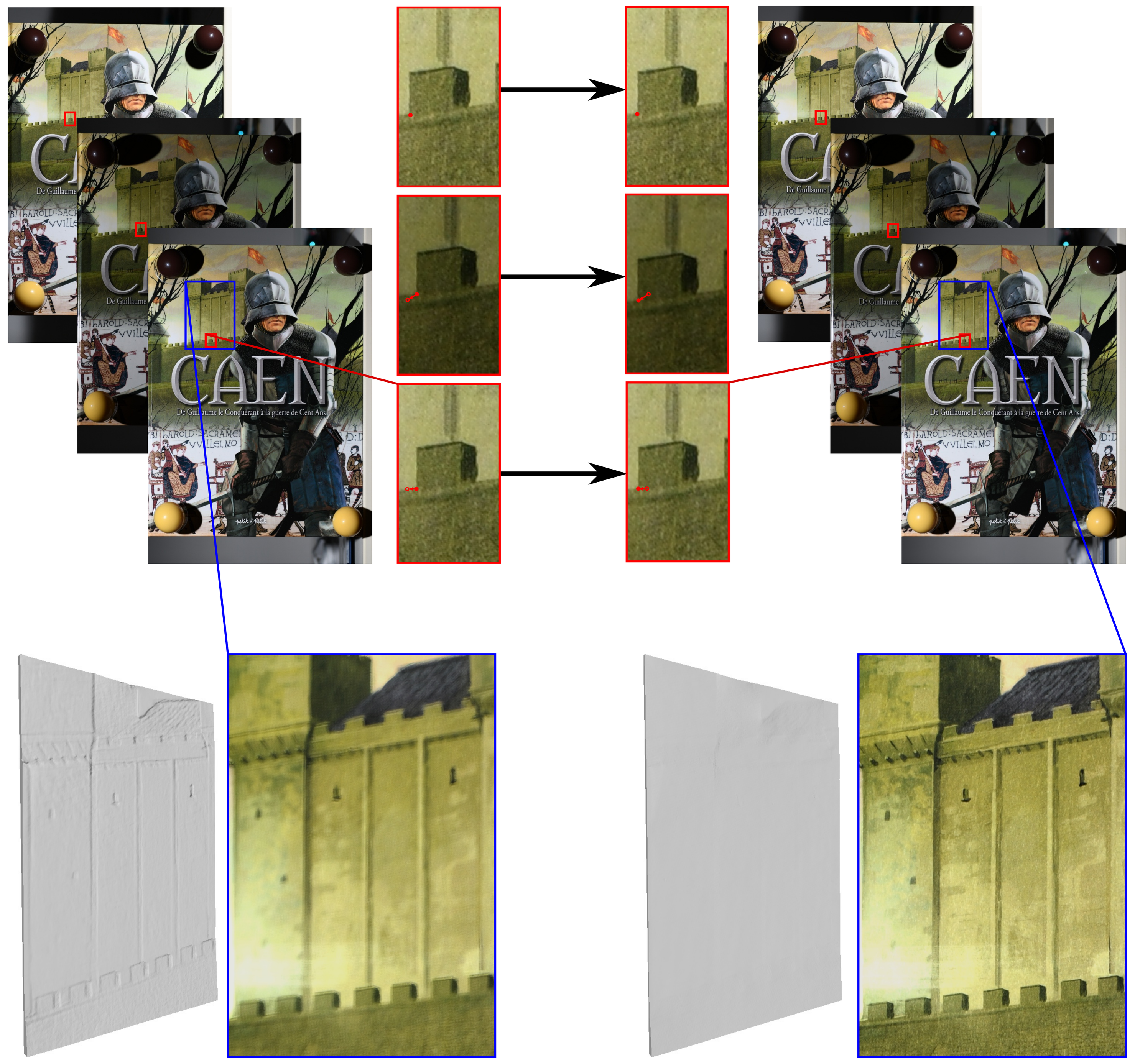


Fig 2. Hallucinated geometry (bottom left) due to slightly misaligned images. Registration enables the correct 3D reconstruction of the flat book cover (bottom right).

Augmented Lagrangian framework

Equation (1) is transformed into (2) to take sparse outliers into account.

$$\min_{\substack{A \in \mathbb{R}^{n \times m} \\ \theta \in \mathbb{R}^{mp}}} \quad \operatorname{rank}(A) + \lambda \left\| \operatorname{vec}(A) - W(u;\theta) \right\|_0 \qquad (2)$$

Then the rank of A is relaxed to the nuclear norm (sum of singular values) and the zero-norm is relaxed to the one-norm (sum of absolute values) in equation (3). When W is the identity, it is the low-rank image correction technique advocated in [2].

$$\min_{\substack{A \in \mathbb{R}^{n \times m} \\ \theta \in \mathbb{R}^{mp}}} \quad \|A\|_\star + \lambda \left\| \operatorname{vec}(A) - W(u;\theta) \right\|_1 \qquad (3)$$

We rewrite (3) into the equivalent constrained problem (4).

$$\begin{aligned} \min_{\substack{A \in \mathbb{R}^{n \times m} \\ e \in \mathbb{R}^{mn} \\ \theta \in \mathbb{R}^{mp}}} \quad & \|A\|_\star + \lambda \|e\|_1 , \qquad (4) \\ \text{s.t.} \quad & \operatorname{vec}(A) = W(u;\theta) + e . \end{aligned}$$

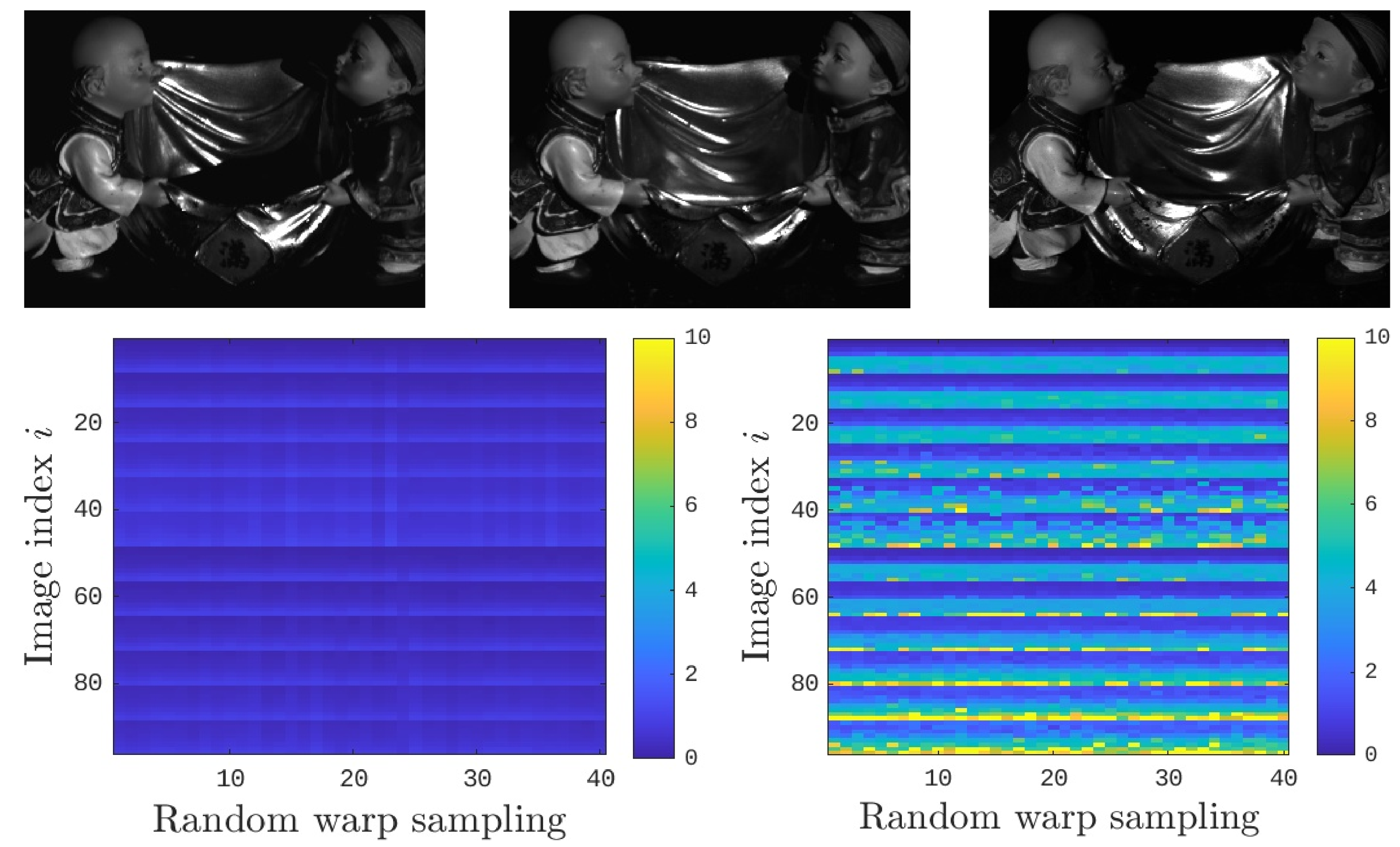
And we consider the augmented Lagrangian associated with this constrained optimization problem.

$$\mathcal{L}^\sharp_\rho(A, e, \theta, y) := \|A\|_\star + \lambda \|e\|_1 + \langle y | W(u;\theta) + e - \operatorname{vec}(A) \rangle + \frac{\rho}{2} \left\| W(u;\theta) + e - \operatorname{vec}(A) \right\|^2 \qquad (5)$$

Finally, we solve (4) by alternating minimizations of (5) with regard to the primal variables A, e and θ, and a dual ascent step over the dual variable y (ADMM [3]).

$$\begin{aligned} A^{(k+1)} &= \operatorname*{argmin}_A \ \mathcal{L}^\sharp_\rho(A, e^{(k)}, \theta^{(k)}, y^{(k)}), \\ e^{(k+1)} &= \operatorname*{argmin}_e \ \mathcal{L}^\sharp_\rho(A^{(k+1)}, e, \theta^{(k)}, y^{(k)}), \\ \theta^{(k+1)} &= \operatorname*{argmin}_\theta \ \mathcal{L}^\sharp_\rho(A^{(k+1)}, e^{(k+1)}, \theta, y^{(k)}), \\ y^{(k+1)} &= y^{(k)} + \rho \left(W(u;\theta^{(k+1)}) + e^{(k+1)} - \operatorname{vec}(A^{(k+1)}) \right), \end{aligned}$$

Empirical evaluation



(a) Harvest, lowrr

(b) Harvest, imregtform

Fig 4. Mean displacement error, in pixels, of every warp estimation for our approach (lowrr) and the imregtform Matlab's algorithm, on the "Harvest" sequence of the DiLiGenT dataset [4].

References

[1] Woodham, R.J.: Photometric method for determining surface orientation from multiple images. Opt. Eng. 19(1), 134–144 (1980).

[2] Wu, L., Ganesh, A., Shi, B., Matsushita, Y., Wang, Y., Ma, Y.: Robust photometric stereo via low-rank matrix completion and recovery. In: ACCV. pp. 703–717 (2010)

[3] Boyd, S., Parikh, N., Chu, E., Peleato, B., Eckstein, J.: Distributed optimization and statistical learning via the alternating direction method of multipliers. Founds. and Trends in Mach. Learn. 3, 1–122 (2010)

[4] Shi, B., Mo, Z., Wu, Z., Duan, D., Yeung, S., Tan, P.: A benchmark dataset and evaluation for non-Lambertian and uncalibrated photometric stereo. PAMI 41(2), 271–284 (2019)

[5] Open source implementation of lowrr: https://github.com/mpizenberg/lowrr

[6] Web demo of the code: https://lowrr.pizenberg.fr

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