

Towards a Unified Approach to Homography Estimation Using Image Features and Pixel Intensities

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1. Introduction
2. Theoretical Background
3. Proposed Method
4. Experimental Results
5. Application Examples
6. Conclusions

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Feature-Based (FB):

- Feature **extraction** and **matching**
- Large convergence basin
- Lower precision
- The information space is the feature's **coordinates**

Intensity-Based (IB):

- NO intermediate steps.
Direct estimation
- Smaller convergence basin
- Higher precision
- The information space is the pixel **intensities**

- We want the **precision** of IB methods and the **convergence** domain of FB methods
- The **Efficient Second-Order Minimization**¹ framework gives great results for IB methods, but its application to FB methods has been limited
- **Unify** minimization method, cost function, homography parametrization, Jacobians, and more

¹Selim Benhimane and Ezio Malis. “Real-time image-based tracking of planes using efficient second-order minimization”. In: *Proc. IEEE/RSJ IROS*. 2004, pp. 943–948.

Development of a vision-based estimation algorithm that:

- Accurately and robustly estimates the homography matrix between two images
- Unifies the IB and FB approaches into a single optimization procedure
- Suitable to real-time settings (>30 Hz)
- Publicly available library and ROS package

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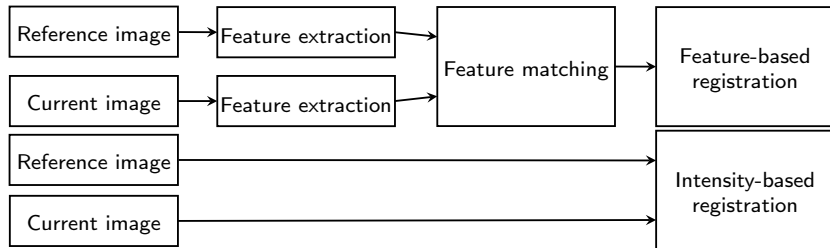
Image Registration

- The goal is to optimally align two images of the same scene
- Existing methods are a combination of these components:
 - ① information space
 - ② transformation model
 - ③ similarity measure
 - ④ search strategy



Inputs to the Image Registration

- **Feature-based:** Geometric features coordinates
- **Intensity-based:** Pixel intensity values



- **Geometric** - changes due to motion:

$$\mathbf{p} \propto \mathbf{H} \mathbf{p}^* = \mathbf{w}(\mathbf{H}, \mathbf{p}^*)$$

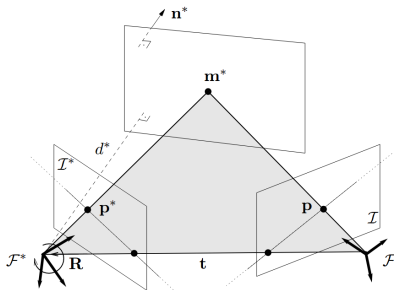
- **Photometric** - changes due to lighting:

$$\mathcal{I}'(\mathbf{p}) = \alpha \mathcal{I}(\mathbf{p}) + \beta$$

- $\text{SSD}(\mathcal{I}', \mathcal{I}^*) = \sum_i [\mathcal{I}'(\mathbf{p}_i) - \mathcal{I}^*(\mathbf{p}_i^*)]^2$
- $\text{ZNCC}(\mathcal{I}', \mathcal{I}^*) = \left\langle \frac{\mathcal{I}'_v - \bar{\mathcal{I}}'_v}{\|\mathcal{I}'_v - \bar{\mathcal{I}}'_v\|}, \frac{\mathcal{I}^*_v - \bar{\mathcal{I}}^*_v}{\|\mathcal{I}^*_v - \bar{\mathcal{I}}^*_v\|} \right\rangle$

Plane-induced Homography

The homography relates coordinates of the same scene point in two separate views of a planar object



$$p \propto H p^*$$

- **ESM:**

- The ESM increment is defined as:

$$\tilde{\mathbf{x}}_n = -2(\mathbf{J}(\hat{\mathbf{x}}_n) + \mathbf{J}(\mathbf{x}^*))^+ \mathbf{f}(\hat{\mathbf{x}}_n),$$

where $\mathbf{J}(\mathbf{x})$ is the Jacobian of function $\mathbf{f}$

- Note that ESM only requires calculating the first-order derivatives
- **Multiresolution Pyramid:**
 - Increase in the computational efficiency
 - Avoidance of spurious local minima
 - Larger domain of convergence

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We want to find a vector $\mathbf{x}^* \in \mathbb{SL}(3) \times \mathbb{R}^2 = \{\mathbf{H}^*, \alpha^*, \beta^*\}$ such that:

$$\alpha^* \mathcal{I}(\mathbf{w}(\mathbf{H}^*, \mathbf{p}_i^*)) + \beta^* = \mathcal{I}^*(\mathbf{p}_i^*), \quad \forall i = 1, \dots, m \quad (1)$$

$$\mathbf{w}(\mathbf{H}^*, \mathbf{q}_j^*) = \mathbf{q}_j, \quad \forall j = 1, \dots, n \quad (2)$$

- 2 different information types: Coordinates AND Intensities
- Proposed cost function:

$$\min_{\mathbf{x}=\{\mathbf{H}, \alpha, \beta\}} \quad \frac{1}{2} \left(w_{IB} \|\mathbf{y}_{IB}(\mathbf{x})\|^2 + w_{FB} \|\mathbf{y}_{FB}(\mathbf{x})\|^2 \right)$$

with $w_{IB} + w_{FB} = 1$

The Jacobian derivation is simply the stacking of the IB and FB Jacobians

$$\mathbf{J}_{UN} = \begin{bmatrix} \frac{w_{IB}}{m} \mathbf{J}_{IB} \\ \frac{w_{FB}}{2n} \mathbf{J}_{FB} \end{bmatrix}$$

The choice of weights depends on the distance of feature correspondences

$$RMSD(\mathbf{y}_{FB}) = \sqrt{\frac{\sum_{j=1}^n d_j^2}{n}} = d_{FB}$$

$$w_{FB} = 1 - e^{-d_{FB}}$$

Local vs Global Feature Search



Local Search

Features in current *template*



Global Search

Features in current *image*



Sliding Window Predictor

Idea: Generate multiple candidates solutions, evaluating them according to ZNCC metric, and choose the best one.

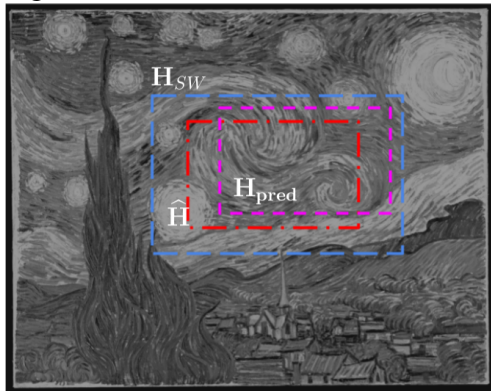


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Benchmark Tests Procedure

Randomly generate test homographies and evaluates if the estimation correctly recovers it



Reference Image



Reference Template



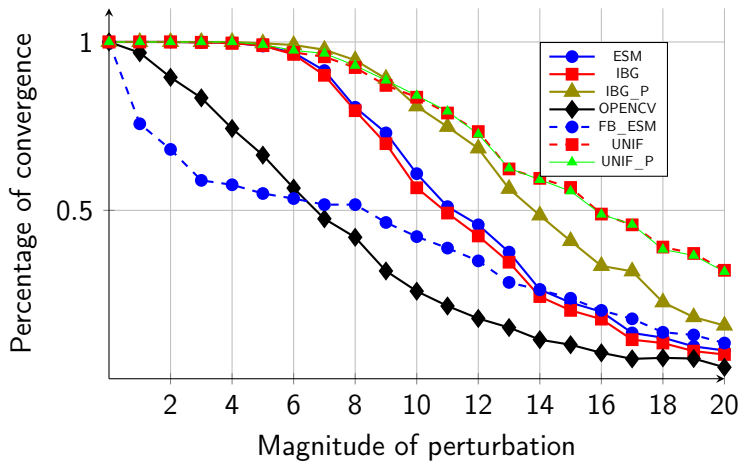
Transformed with $\sigma = 5$



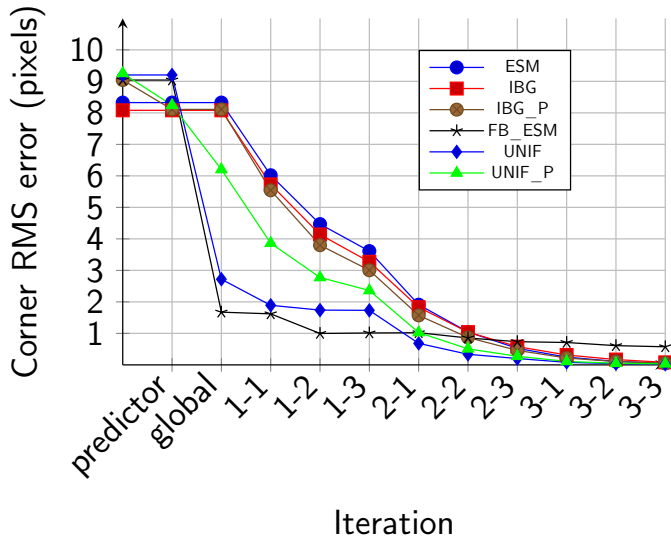
Transformed with $\sigma = 10$

Convergence criteria: RMS of corner point error < 1 pixels

Percentage of Convergence



Rate of Convergence ($\sigma = 10$)



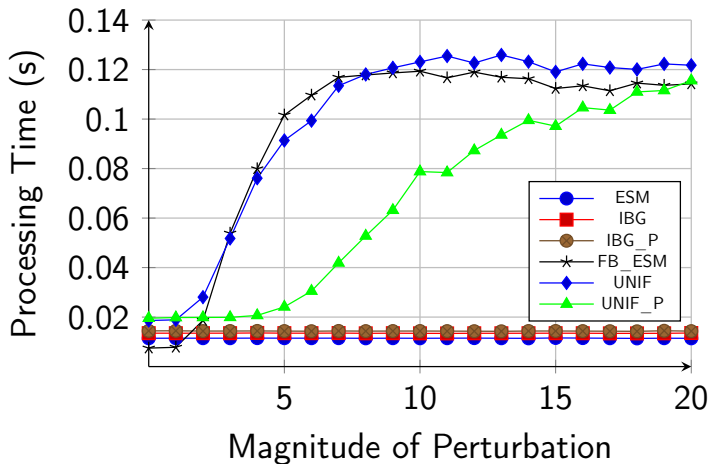
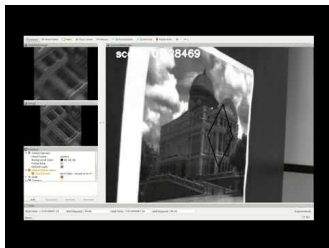


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The proposed algorithm is available as a ready to use C++ library and as a ROS package, with its technical report² at:

https://github.com/visiotec/vtec_ros



²Lucas Nogueira, Ely de Paiva, and Geraldo Silveira. *VTEC robust intensity-based homography optimization software*. Tech. rep. CTI-VTEC-TR-01-19. Brazil: CTI, 2019.

Unified Visual Tracking

Using the proposed unified method, we built a visual tracker. An important improvement is the implicit ability to reinitialize itself.

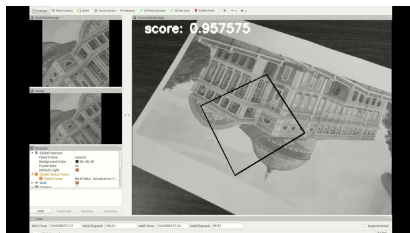


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Conclusions And Future Work

- The unified method has the convergence of FB and the precision of IB methods
- Further tests can be conducted in the FB component: other feature detectors; choice of weights; outlier rejection
- Application to homography-based visual servoing
- Different camera sensor types: omnidirectional, color images
- Extension to nonplanar surfaces

Thank you!