6DOF Point Cloud Alignment using Geometric Algebra-based Adaptive Filtering

Anas Al-Nuaimi, Wilder B. Lopes
Eckehard Steinbach, Cassio G. Lopes

Technische Universität München - Universidade de São Paulo

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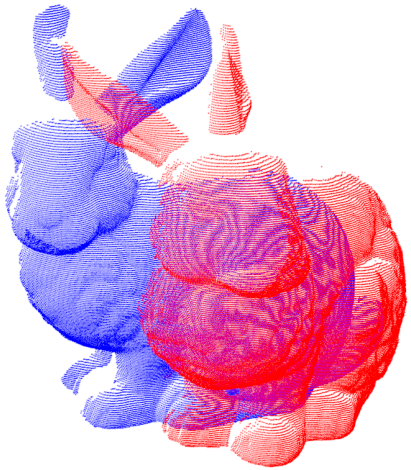
Starting with



PCDs from the Stanford Dataset

- 3D Point Clouds: Target (Red) and Source (Blue)
- No initial alignment

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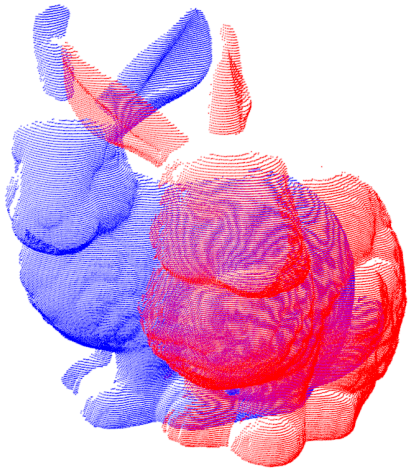

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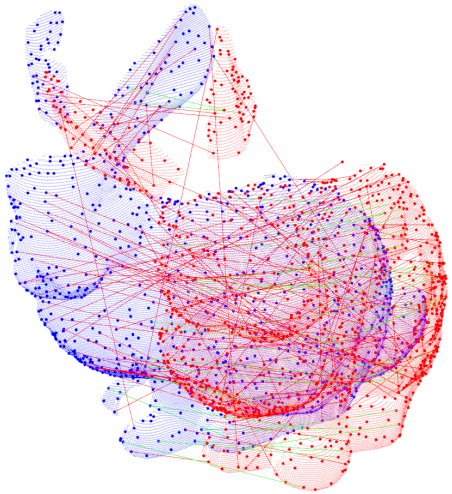

Establishing correspondences

- Keypoints extraction
- Local shape features
- We use Harris 3D with SHOT [Tombari et al.]
- True and false correspondences (1-to-1)

W. B. Lopes
wilder@usp.br

Standard Alignment Estimation

- K correspondence points
- Rigid transformation? *Least-squares problem*

W. B. Lopes
wilder@usp.br

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$$\mathcal{F}(\mathbf{R}) = \frac{1}{K}\sum_{n=1}^{K} \|y_n - \mathbf{R}x_n\|_2^2, \text{ subject to } t = \bar{y} - \mathbf{R}\bar{x}. \quad (1)$$

$\mathbf{R}$: 3×3 rotation matrix, t: 3×1 translation vector.

- Solution: SVD-based algorithms $\rightarrow$ *Outlier sensitive*

Geometric Algebra Approach

Recast the least-squares problem (1) in GA:

$$\text{Error: } e_n = y_n - \mathbf{R}x_n \Rightarrow e_n = y_n - \underbrace{\mathbf{r}x_n\widetilde{\mathbf{r}}}_{\text{Geometric Product}} . \quad (2)$$

The least-squares cost function becomes

$$\boxed{J(r) = \frac{1}{K}\sum_{n=1}^{K}|e_n|^2 = \frac{1}{K}\sum_{n=1}^{K}|y_n - rx_n\widetilde{r}|^2}, \quad (3)$$

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which is minimized by the GA Least-Mean-Squares adaptive filter (GA-LMS)

$$\boxed{r_i = r_{i-1} + \mu\Big[y_i \wedge \left(r_{i-1}x_i\widetilde{r}_{i-1}\right)\Big]r_{i-1}}. \quad (4)$$

- *"Look at" one correspondence at each iteration*
- *Enforces reduction in computational complexity*

W. B. Lopes
wilder@usp.br

Selecting the Step Size

μ is the only parameter of the GA-LMS.

$$\boxed{\mu(Y,X) = 15\sum_{n=1}^{K}\langle y_n x_n Q\rangle \Big/ \sum_{n=1}^{K}\langle y_n \widetilde{Q} x_n Q\rangle}, \quad Q = \sum_{n=1}^{K} y_n \wedge x_n. \tag{5}$$

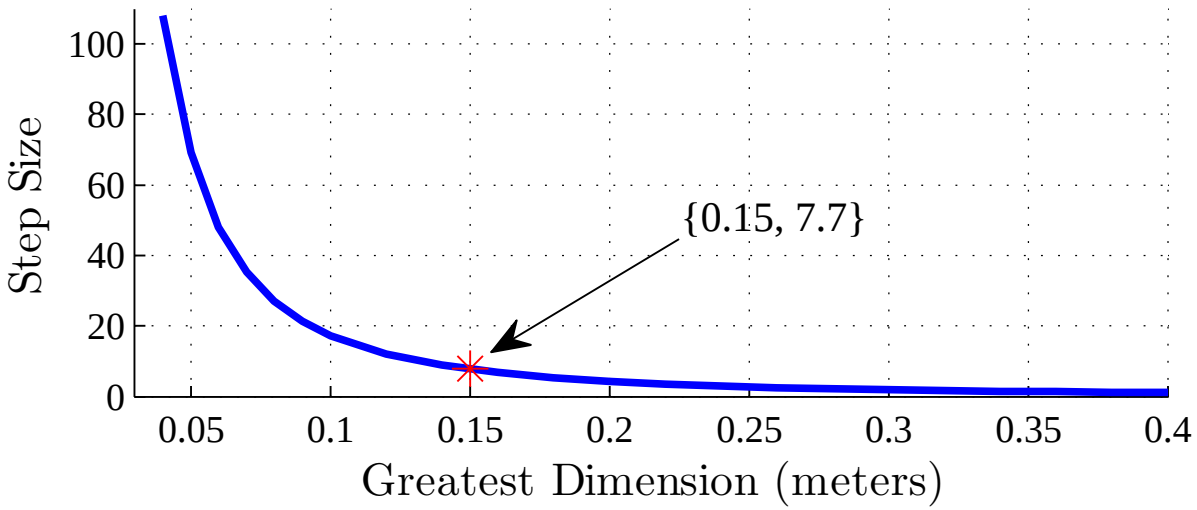
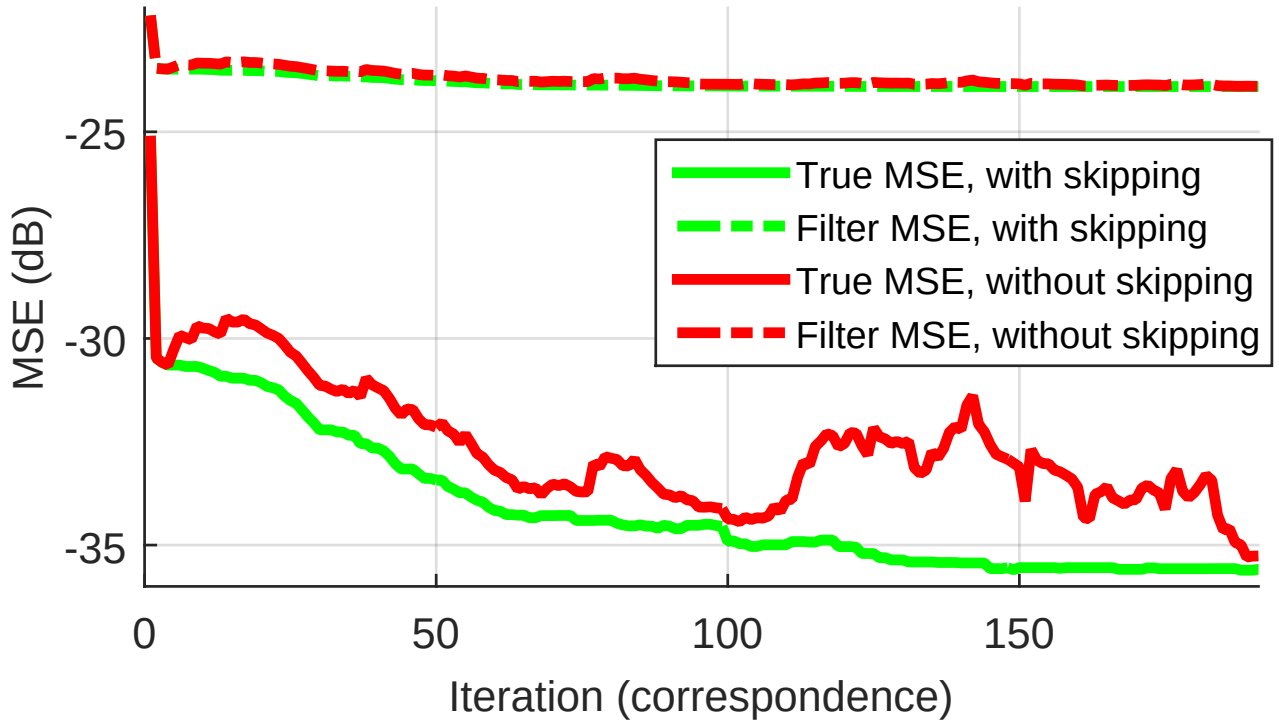


Figure : Step-size recommendation for the Stanford Bunny set.

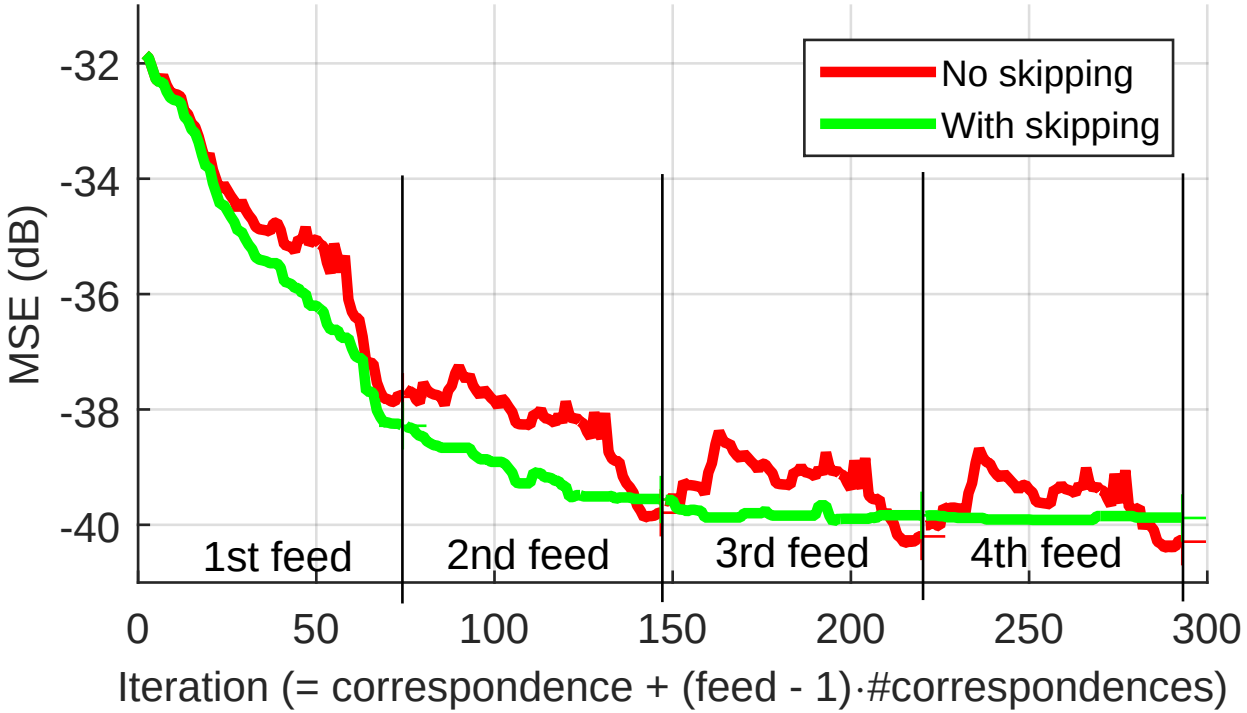
Iteration Skipping



- Skip current MSE iteration if higher than previous one
- Reduces contributions from outliers

W. B. Lopes
wilder@usp.br

Sample Refeeding



- We extract further information from already processed samples;
- Useful when the number of correspondences is small and/or step size is not large enough;

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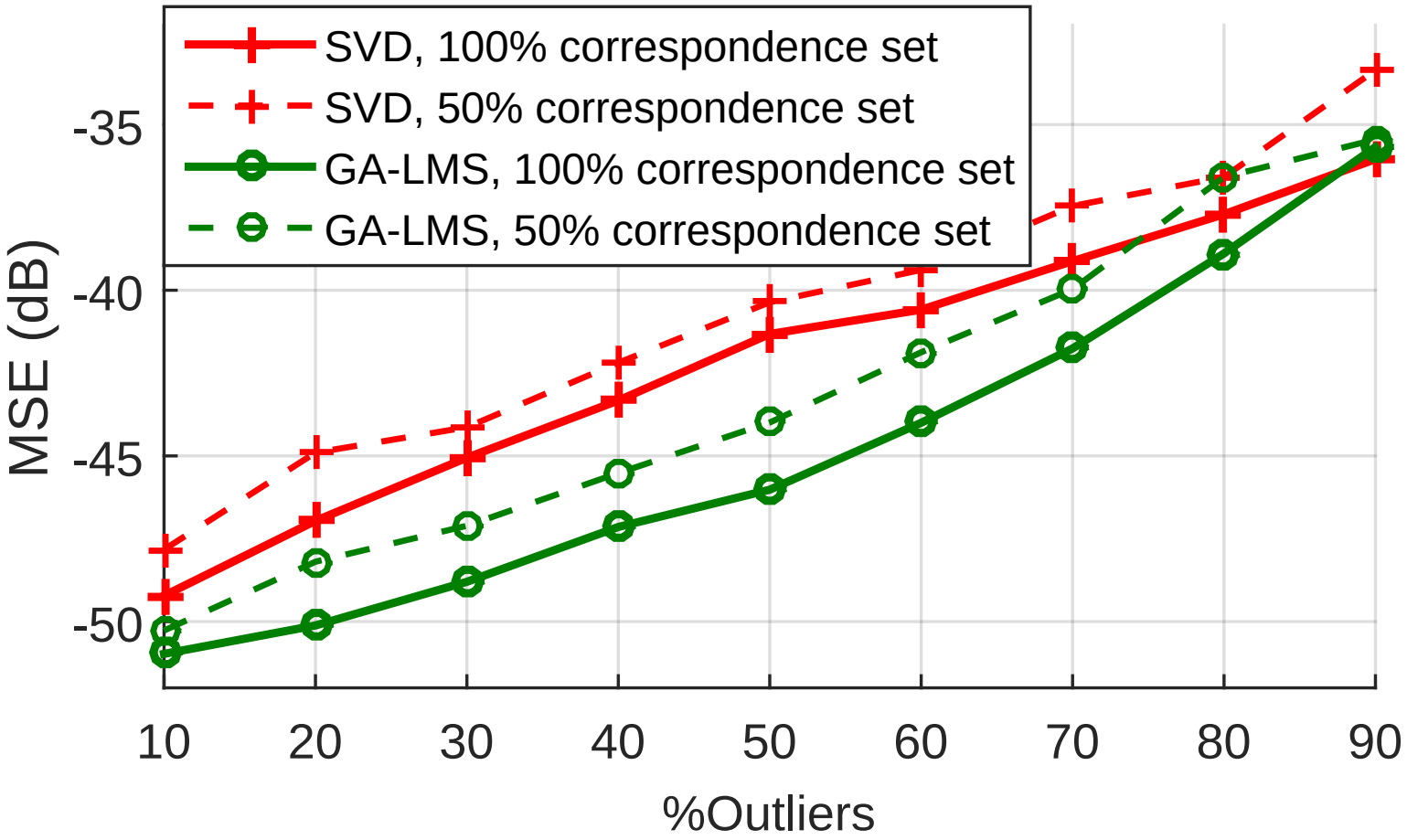
wilder@usp.br

Evaluation and Comparison



W. B. Lopes
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Contributions of this work

1. A rule to set the GA-LMS step size as a function of the PCD dimensions and the correspondences is provided
2. The adaptive nature of the GA-LMS is exploited to make it more outlier-resilient than standard SVD-based least-squares estimator
3. The robustified GA-LMS is shown to be successful as the minimizer of a 6DOF alignment algorithm

W. B. Lopes
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See you in the poster session!

W. B. Lopes
wilder@usp.br