



# Dense Accurate Urban Mapping from Spherical RGB-D Images

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October 1st, 2015

# Urban mapping from spherical stereo

Our goal: build compact maps for a posteriori localization

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# Spherical RGB-D sequence



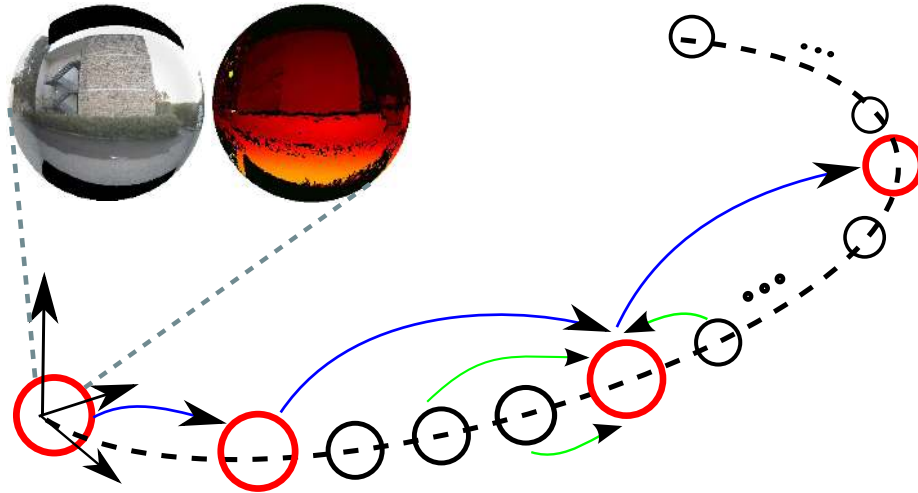


# Data acquisition

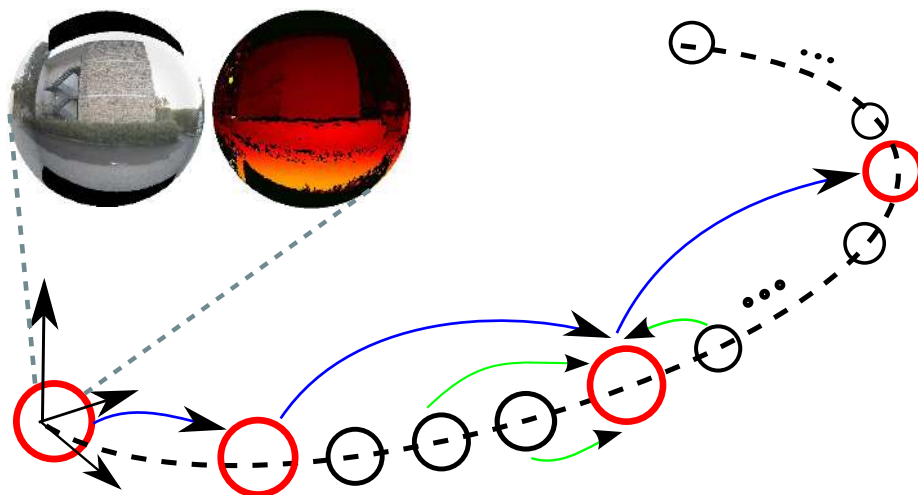


Garbejaire. Sophia-Antipolis. France

# Keyframe-based solution



# Keyframe-based solution



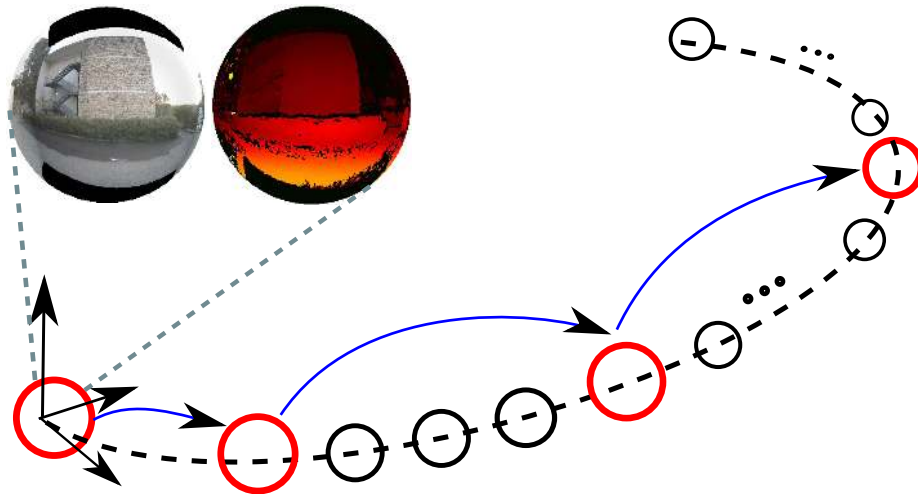
## Dense registration:

Minimize the photometric error:

$$\mathfrak{F}_S = \frac{1}{2} \sum_{\mathbf{p}^*} W^I(\mathbf{p}^*) \left\| \mathcal{I} \left( w(\mathbf{p}^*, \hat{\mathbf{T}}\mathbf{T}(\mathbf{x})) \right) - \mathcal{I}^*(\mathbf{p}^*) \right\|^2$$



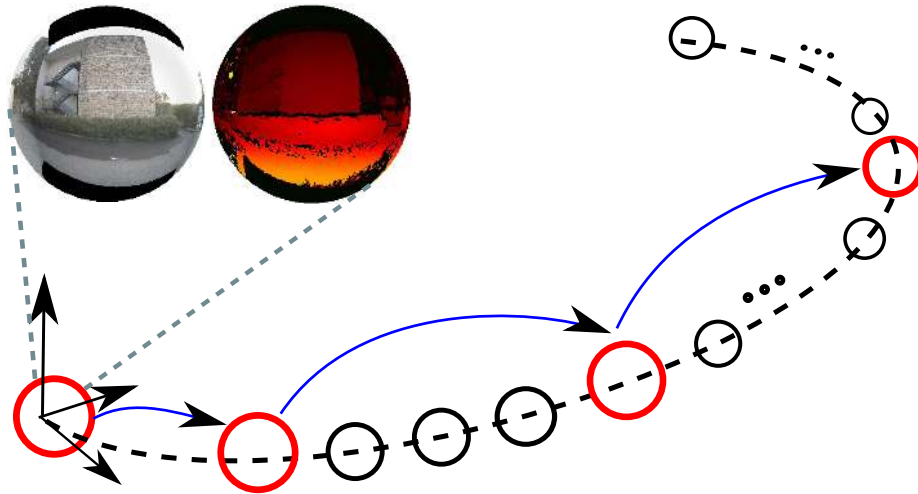
# Keyframe-based solution



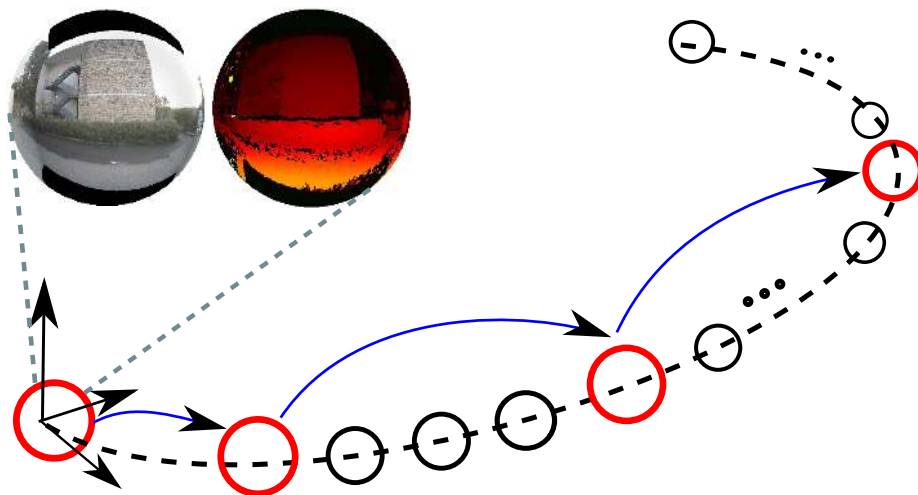
## Previous works:

- Meilland, M., Comport, A. I., Rives, P. *A spherical robot-centered representation for urban navigation*, (IROS) 2010.
- Meilland, M., Comport, A. I., Rives, P. *Dense Omnidirectional RGB-D Mapping of Large-scale Outdoor Environments for Real-time Localization and Autonomous Navigation*. Journal of Field Robotics 2015.

# This paper



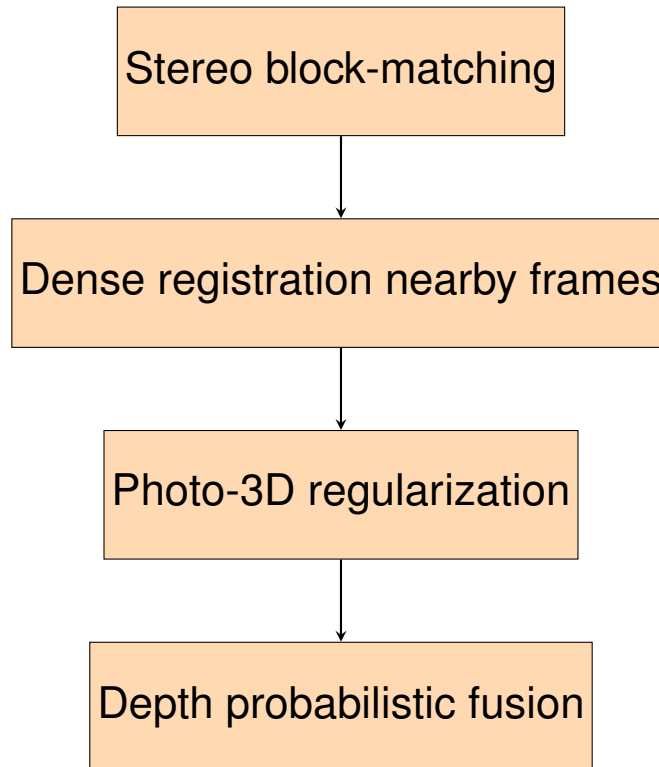
# This paper



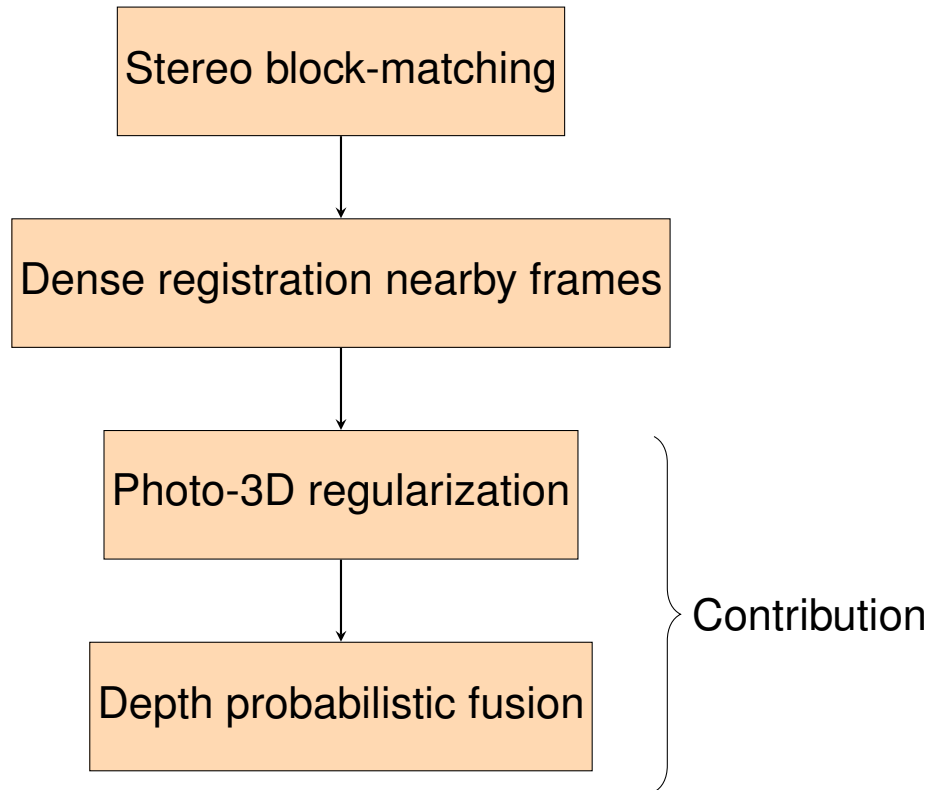
## Improve keyframes by merging information of nearby frames

- More accurate depth images
- Reduce uncertainty
- Keyframe completeness (gap filling)

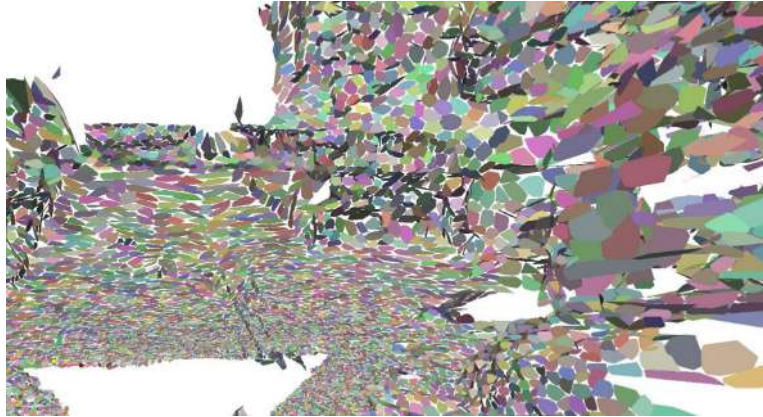
# Our approach



# Our approach



# Regularization



## "Superpatches" for photo-geometric regularization

- Region growing enforcing isotropic 3D planar patches (same area)
- Superpixel colour segmentation: are combined in  $\mathcal{P}_f(d_f, \mathbf{n}_f)$ .

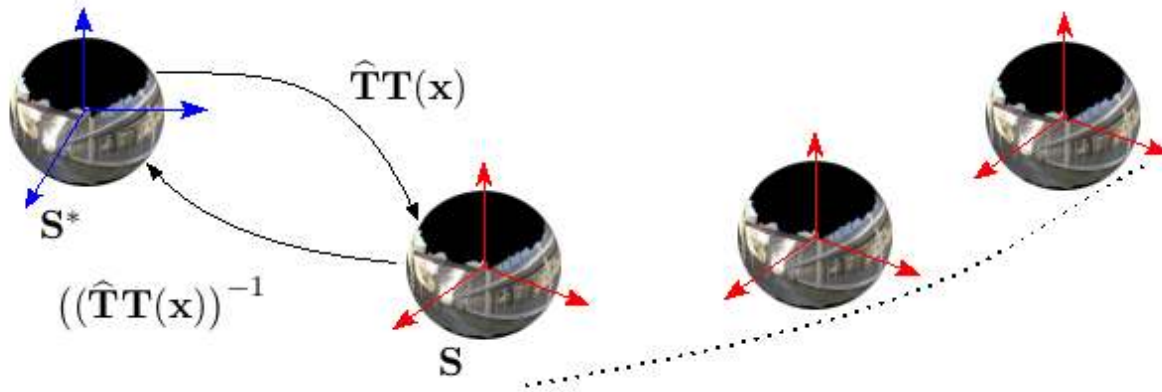
Patches geometrically and photometrically consistent are merged:

$$\|d_i \mathbf{n}_i - d_s \mathbf{n}_s\|_2 < \epsilon_1$$

$$\|\mathbf{n}_i^T \mathbf{n}_s\|_1 - 1 < \epsilon_2$$



# Fusion



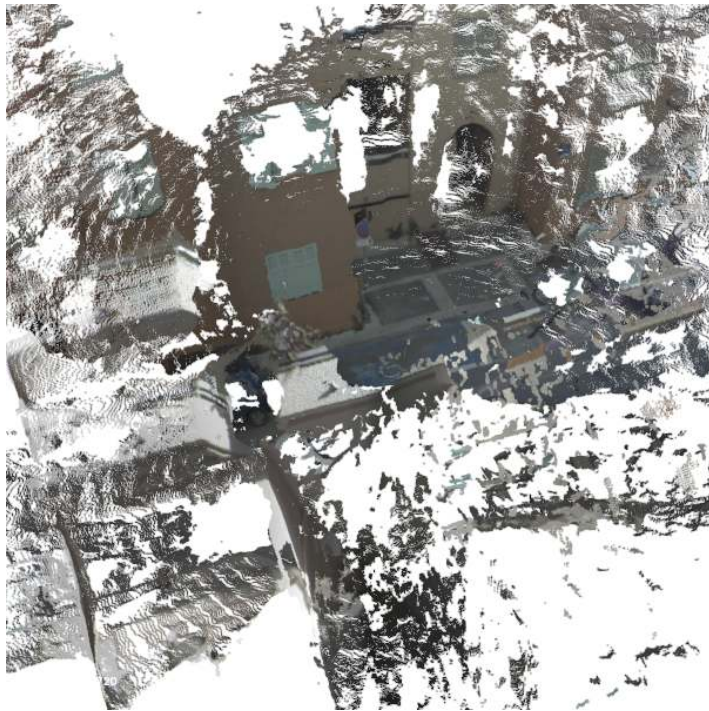
## Probabilistic depth averaging

- Sliding window:

$$\begin{cases} \mathcal{D}_F^*(\mathbf{p}) = \frac{W^*(\mathbf{p})\mathcal{D}^*(\mathbf{p}) + W_w(\mathbf{p})\mathcal{D}_w(\mathbf{p})}{W^*(\mathbf{p}) + W_w(\mathbf{p})} \\ W_F^*(\mathbf{p}) = W^*(\mathbf{p}) + W_w(\mathbf{p}) \end{cases}$$

# Results

- Improved consistency



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We obtain a full sequence with improved depth images

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## Localization methods

- Photo-consistency

$$\tilde{\mathfrak{I}}_S = \frac{1}{2} \sum_{\mathbf{p}^*} W^I(\mathbf{p}^*) \left\| \mathcal{I} \left( w(\mathbf{p}^*, \hat{\mathbf{T}}\mathbf{T}(\mathbf{x})) \right) - \mathcal{I}^*(\mathbf{p}^*) \right\|^2$$

- Dense RGB-D

$$\begin{aligned} \tilde{\mathfrak{I}}_S = & \frac{1}{2} \sum_{\mathbf{p}^*} W^I(\mathbf{p}^*) \left\| \mathcal{I} \left( w(\mathbf{p}^*, \hat{\mathbf{T}}\mathbf{T}(\mathbf{x})) \right) - \mathcal{I}^*(\mathbf{p}^*) \right\|^2 + \\ & \frac{\lambda^2}{2} \sum_{\mathbf{p}^*} W^D(\mathbf{p}^*) \left\| \mathbf{n}^T \left( g(w(\mathbf{p}^*, \hat{\mathbf{T}}\mathbf{T}(\mathbf{x}))) - \hat{\mathbf{T}}\mathbf{T}(\mathbf{x})g^*(\mathbf{p}^*) \right) \right\|^2 \end{aligned}$$

# Results

We obtain a full sequence with improved depth images

## Localization methods

- Photo-consistency

$$\tilde{\mathfrak{I}}_S = \frac{1}{2} \sum_{\mathbf{p}^*} W^I(\mathbf{p}^*) \left\| \mathcal{I} \left( w(\mathbf{p}^*, \hat{\mathbf{T}}\mathbf{T}(\mathbf{x})) \right) - \mathcal{I}^*(\mathbf{p}^*) \right\|^2$$

- Dense RGB-D

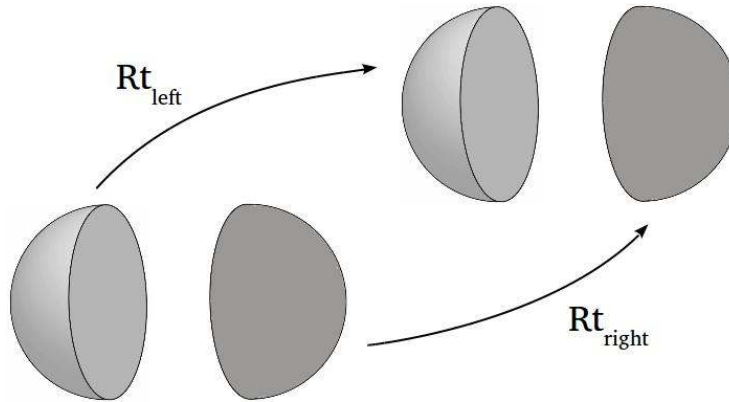
$$\begin{aligned} \tilde{\mathfrak{I}}_S = & \frac{1}{2} \sum_{\mathbf{p}^*} W^I(\mathbf{p}^*) \left\| \mathcal{I} \left( w(\mathbf{p}^*, \hat{\mathbf{T}}\mathbf{T}(\mathbf{x})) \right) - \mathcal{I}^*(\mathbf{p}^*) \right\|^2 + \\ & \frac{\lambda^2}{2} \sum_{\mathbf{p}^*} W^D(\mathbf{p}^*) \left\| \mathbf{n}^T \left( g(w(\mathbf{p}^*, \hat{\mathbf{T}}\mathbf{T}(\mathbf{x}))) - \hat{\mathbf{T}}\mathbf{T}(\mathbf{x})g^*(\mathbf{p}^*) \right) \right\|^2 \end{aligned}$$

- Accuracy: average trajectory error (with/without motion model)

	Av. Rot. Error (deg)			Av. Trans. Error (mm)		
	<i>Raw</i>	<i>RF</i>	<b>Improv.</b>	<i>Raw</i>	<i>RF</i>	<b>Improv.</b>
Dense RGB-D	0.51	0.12	<b>86 %</b>	3.4	1.1	<b>67 %</b>
Photo-consistency	0.47	0.12	<b>74 %</b>	2.9	1.3	<b>55 %</b>

# Results

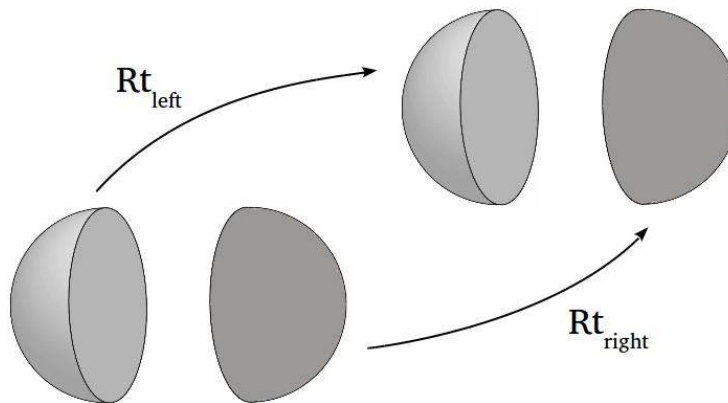
- Accuracy: average deviations of half-sphere registration





# Results

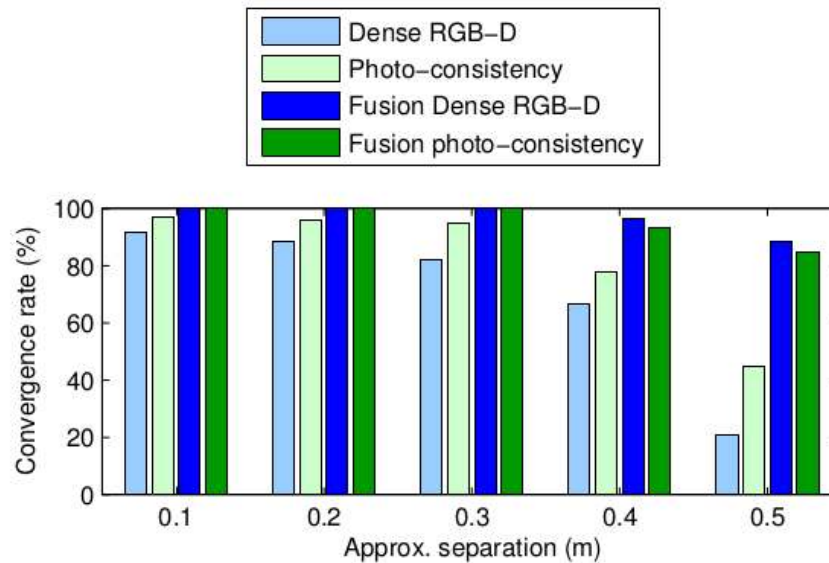
- Accuracy: average deviations of half-sphere registration



	Av. Rot. Deviation (deg)			Av. Trans. Deviation (mm)		
	<i>Raw</i>	<i>RF</i>	<b>Improv.</b>	<i>Raw</i>	<i>RF</i>	<b>Improv.</b>
Dense RGB-D	0.87	0.16	<b>80 %</b>	2.3	0.89	<b>61 %</b>
Photo-consistency	0.55	0.18	<b>67 %</b>	1.8	0.88	<b>51 %</b>

# Results

- Dense registration convergence



# Summary

Exploit the information of the sequence to improve depth images

## Conclusions

- More robust and accurate a posteriori localization
- Applicable to any kind of Depth or RGB-D sequence (eg. 3D-LIDAR, ToF, Kinect, etc.)
- More consistent and compact maps (~20% less keyframes)



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