A Plane-based Approach for Indoor Point Clouds Registration

Ketty FAVRE*, Muriel Pressigout, Eric Marchand, Luce Morin

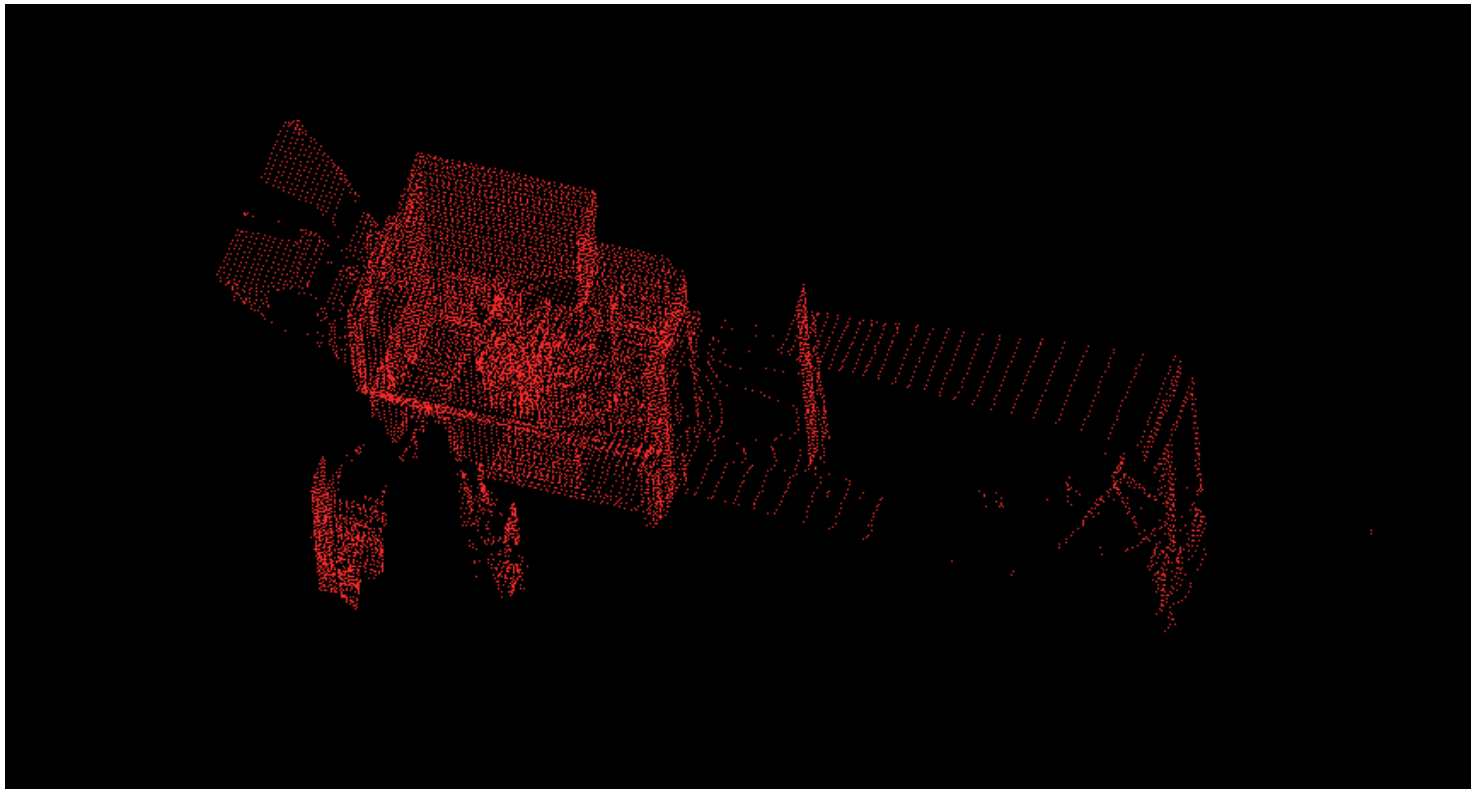
**ketty.favre@univ-rennes1.fr*

ICPR 2020

Iterative Closest Point principle

Aim: estimating the transformation ${}^{t}T_{s}$ that best registers two point clouds.

Approach: minimizing the global distance error between paired points [1].



Point cloud registration by ICP

Iterative Closest Point principle

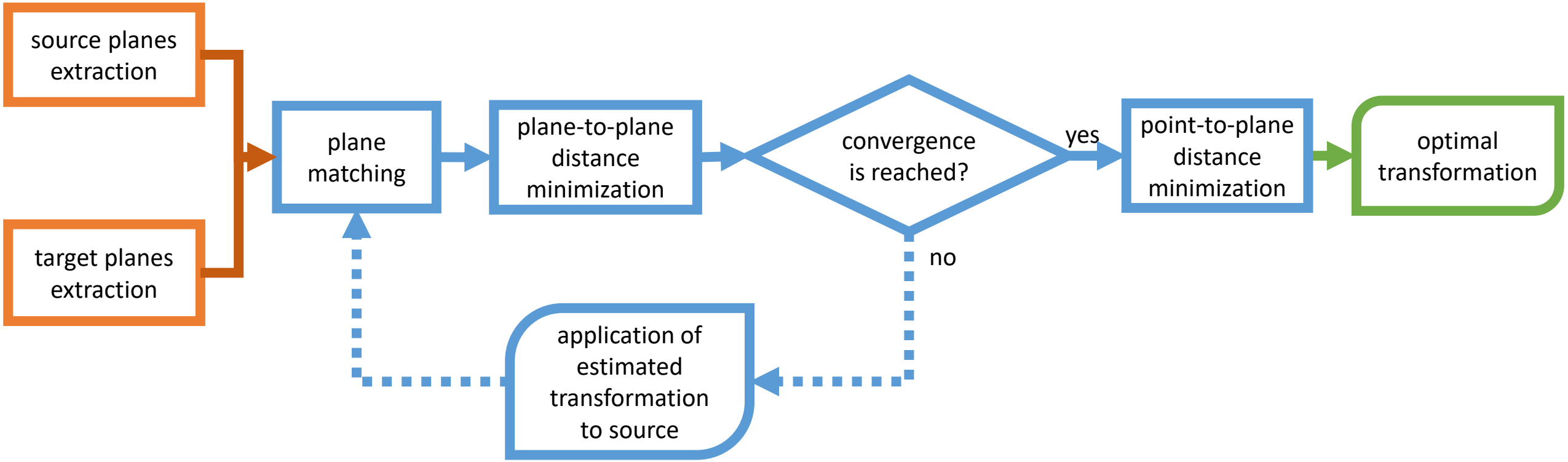
Main drawbacks of ICP algorithm:

- sensitive to initialization;
- matching step can be time consuming (due to number of input points).

Contributions

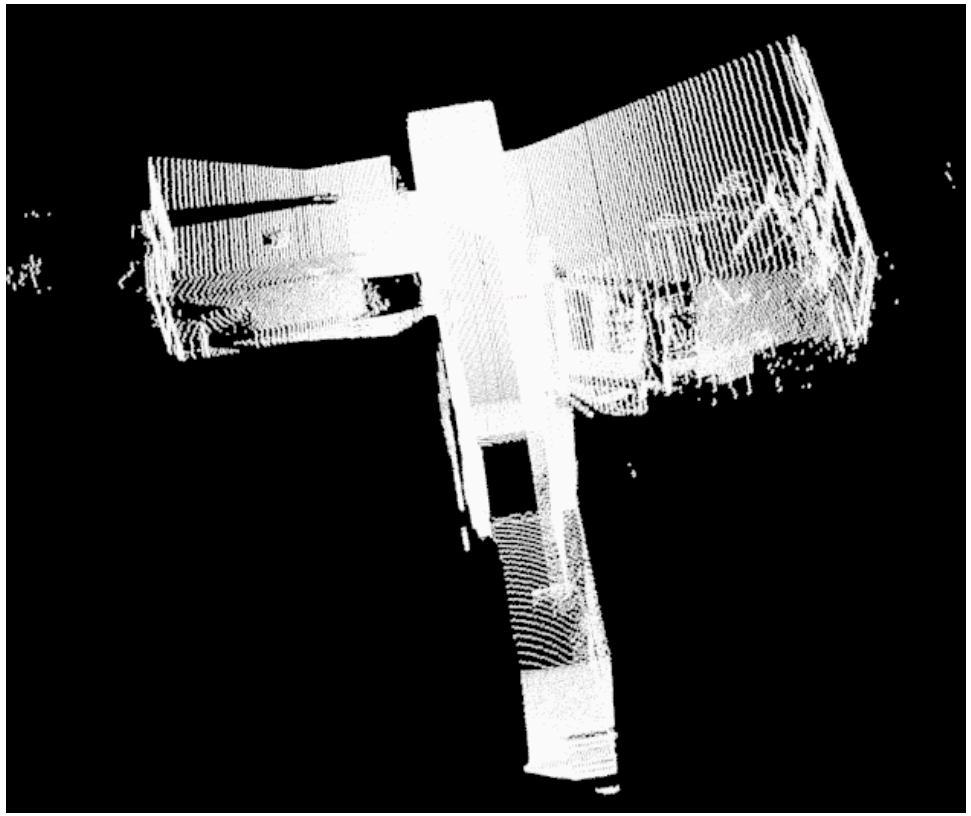
- An algorithm performing fast and accurate registration in challenging datasets;
- a two-step minimization method performing successively plane-to-plane and point-to-plane distance minimization;
- a method robust to large motion or inaccurate initialization;
- an efficient score metric for finding best planes correspondences.

Proposed method framework

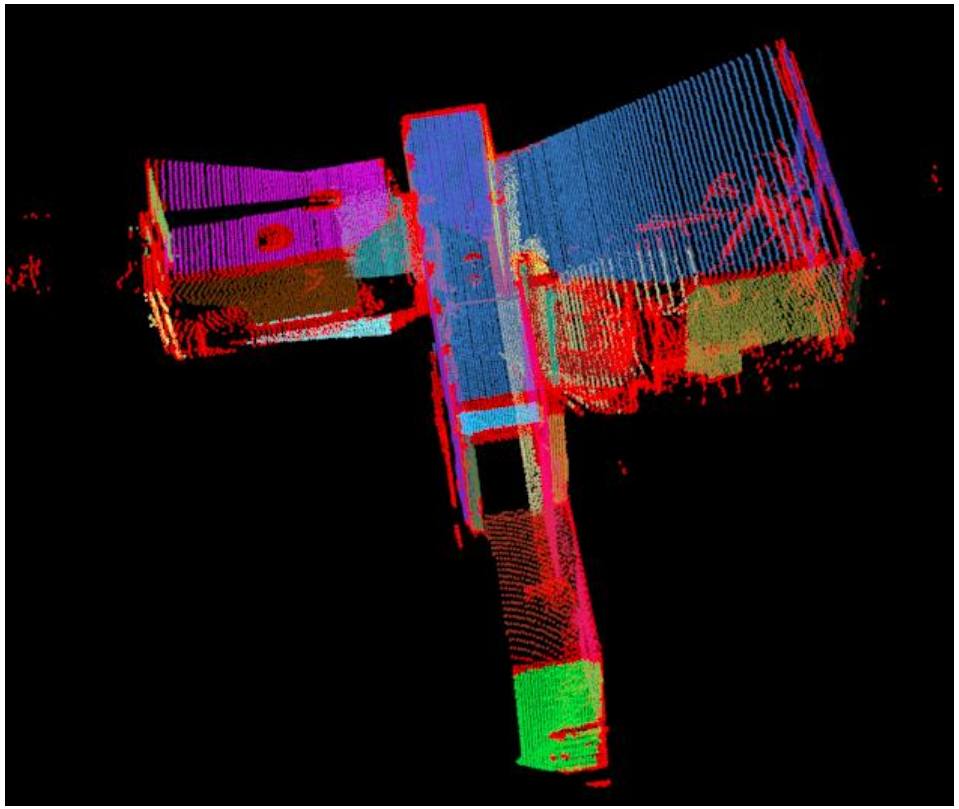


Plane Extraction

Based on region growing segmentation [2].



Input point cloud.



Plane extraction result. Each extracted plane is in a different color. Red points are outliers.

Plane matching

Correspondences characteristics:

- the distance between the projections of the origin on source and target plane:

$$d_o = \| {}^s\rho^s\mathbf{n} - {}^t\rho^t\mathbf{n} \|$$

- the distance between the centroids of source and target plane:

$$d_c = \| \bar{\mathbf{p}}_s - \bar{\mathbf{p}}_t \|$$

- the area ratio between planes:

$$S_r = \frac{min({}^sS, {}^tS)}{max({}^sS, {}^tS)}$$

- the dot product of the normals of the planes:

$$\phi_n = {}^s\mathbf{n} \cdot {}^t\mathbf{n}$$

$$\boxed{score = \alpha \cdot \hat{d}_o + \beta \cdot \hat{d}_c + \gamma \cdot (1 - \hat{S}_r) + \delta \cdot (1 - \hat{\phi}_n)}$$

with $\alpha + \beta + \gamma + \delta = 1$

Correspondences choice:

- All correspondences with a score smaller than a threshold are kept.

Distances minimization

Plane-to-plane distance definition:

$$\mathbf{d}_i^{\Pi} = \begin{pmatrix} {}^t\mathbf{R}_s\,{}^s\mathbf{n}_i - {}^t\mathbf{n}_i \\ \left[{}^t\mathbf{R}_s\,{}^s\mathbf{n}_i\right]^\top {}^t\mathbf{t}_s + {}^s\rho_i - {}^t\rho_i \end{pmatrix}$$

- initialized with a closed-form method using a RANSAC to find inliers;
- solved using a Gauss-Newton approach.

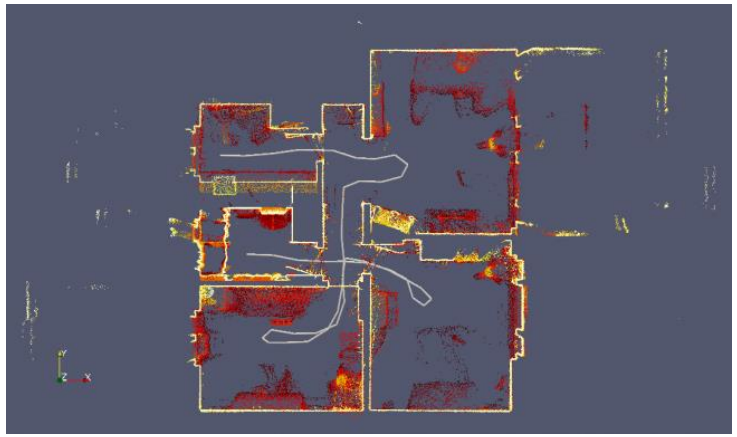
Point-to-plane distance definition:

$$d_i^{\perp} = \left\| {}^t\mathbf{n}_i^\top \cdot \left({}^t\mathbf{T}_s\,{}^s\mathbf{p}_i - {}^t\mathbf{p}_i\right) \right\|^2$$

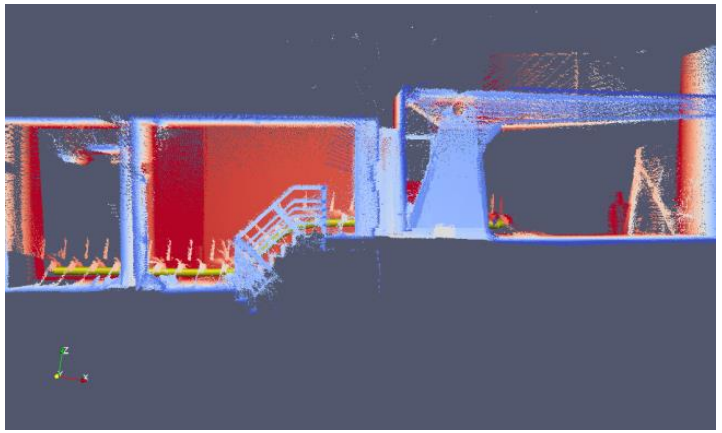
- solved using a Gauss-Newton approach using M-estimators.

Experiments

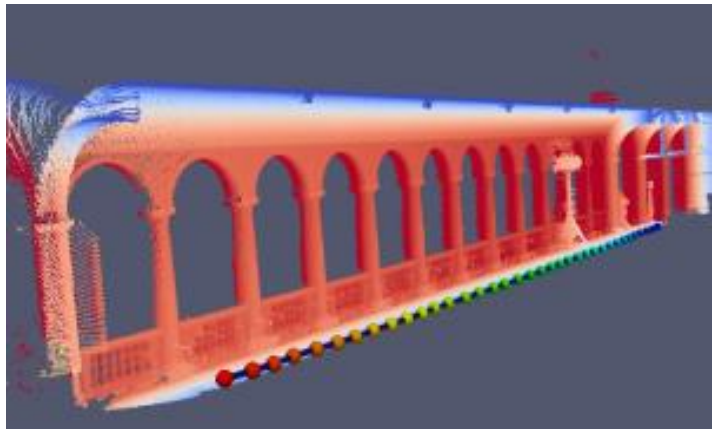
- The Autonomous Labs Systems dataset [3], including ground truth, is used to evaluate the accuracy of the method.
- Only the indoor environments are evaluated.



Apartment sequence



Stairs sequence



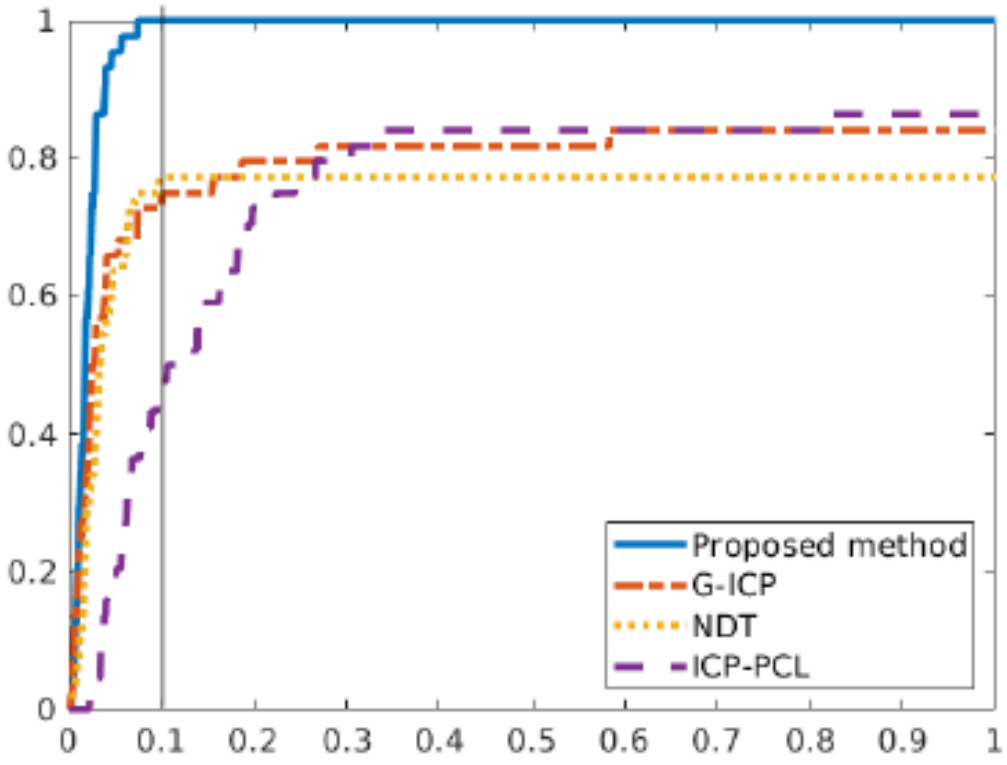
ETH sequence

Experiments: Comparison with state of the art algorithms

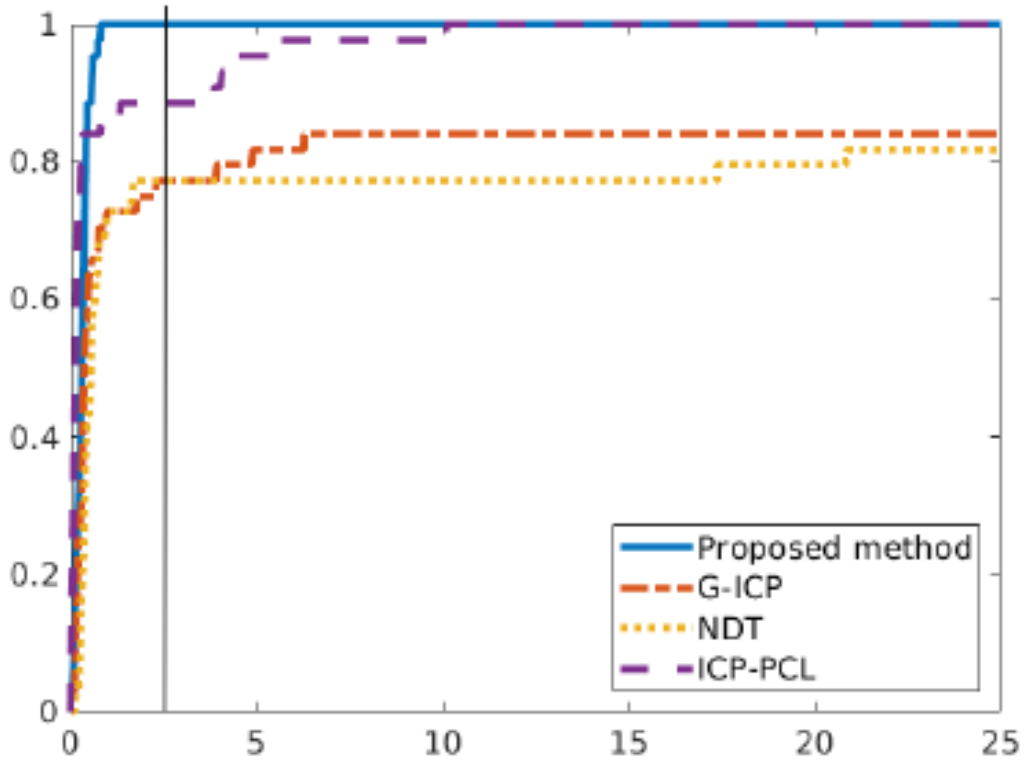
Successful registration [4]:

- translation error smaller than **10cm;**
- rotation error smaller than **2.5°.**

$$\Delta_t = \|{}^t\hat{\mathbf{t}}_s - {}^t\mathbf{t}_s^*\| \qquad \Delta_r = arccos\left(\frac{trace({}^t\mathbf{R}_s^{*-1}{}^t\hat{\mathbf{R}}_s) - 1}{2}\right)$$



Cumulative probabilities of translation error



Cumulative probabilities of rotation error

Experiments: Comparison with state of the art algorithms

Successful registration [4]:

- translation error smaller than **10cm;**
- rotation error smaller than **2.5°.**

$$\Delta_t = \|{}^t\hat{\mathbf{t}}_s - {}^t\mathbf{t}_s^*\| \qquad \Delta_r = arccos\left(\frac{trace({}^t\mathbf{R}_s^{*-1}\,{}^t\hat{\mathbf{R}}_s) - 1}{2}\right)$$

Percentage of successful registration (translation and rotation combined) for the evaluated algorithms on each considered sequence [3].

Sequence	Proposed method	G-ICP[5]	NDT[4]	ICP-PCL
Apartment	**100**	75	77	43
ETH	**100**	**100**	**100**	**100**
Stairs	**100**	97	97	90

Experiments: Comparison with state of the art algorithms

Processing time in milliseconds for each tested algorithm for all sequences.

Sequence	Proposed method	G-ICP[5]	NDT[4]	ICP-PCL
Apartment	500	1790	**233**	339
ETH	1000	1800	**484**	808
Stairs	360	1300	**211**	375

Conclusion

A plane-based registration algorithm:

- accurate in challenging datasets;
- robust to large motion between scans;
- fast to compute registration.

References

[1] P.J. Besl and N. D. McKay, “A method for registration of 3-D shapes” IEEE PAMI 1992, vol. 14, pp. 239–256.

[2] T. Rabbani, F. A. van den Heuvel, and G. Vosselman, “Segmentation of point clouds using smoothness constraints,” in ISPRS 2006 : Proceedings of the ISPRS commission Vsymposium Vol. 35, part 6 : image engineering and vision metrology, Dresden, Germany 25-27 September 2006, pp. 248–253, 2006.

[3] F. Pomerleau, M. Liu, F. Colas, R. Siegwart, “Challenging data sets for point cloud registration algorithms” The International Journal of Robotics Research, vol.31, pp.1705-1711, Dec. 2012.

[4] Martin Magnusson et al. Beyond points: Evaluating recent 3D scan-matching algorithms. In 2015 IEEE ICRA, pages 3631–3637, May 2015.

[5] Segal et al. : Generalized-ICP. In 2009 Robotics : Science and Systems.

Thank you for your attention

contact : *ketty.favre@univ-rennes1.fr*