Comments on :

"Fully distributed scalable smoothing and mapping with robust multi-robot data association"

Virgile Daugé*

University of Lorraine
virgile.dauge@inria.fr

July 11, 2017

Abstract

This paper's focus is on the front-end data association system. DDF-SAM algorithm provides a decentralized communication and inference scheme, but did not address the crucial issue of data association. RANSAC-based, approach for performing the between-robot data associations and initialization of relative frames of reference. They focus on the multi-robot perception problem, and present an experimentally validated end-to-end multi-robot mapping framework

I. Introduction

The inspiration for DDF-SAM [2] was decentralized data fusion (DDF). Most of the work is comming from collaborative localization communnity [3], [4].

Other approaches :

- Smoothing and mapping [5]
- relative pose graphs [6]
- particle filters [7], [8]
- manifold representaions [9]
- divide and conquer with locally optimized maps [10]

Single Robot data association has been studied extensively from Nearest Neighbor to more complex Joint Compatibility Branch and Bound [11].

The RANSAC [12] approach to data association in the presence of outliers has become a staple algorithm in computer vision for efficiently matching landmarks across frames, with variations to exploit domain structure, such as GroupSAC [13].

Recent work has addressed the decentralized resolution of inconsistencies [14], but the problem had yet to be solved sufficiently for real-time performance in robot systems

II. Problem description

We focus on the problem in which a robot r jointly estimates its trajectory X^r and a map of landmarks L both within its local sensor range, as well as landmarks observed by neighboring robots.

We consider a graph where both robot poses and landmarks are nodes and measurements are represented by edges, and wish to solve for the most probable configura- tion.

The key intuition for this approach to decentralized inference is solving the local SLAM problem on each robot and then distributing condensed versions of these local solutions to other robots, which can solve for the full neighborhood map.

*A thank you or further information

III. DDF-SAM

Composed of 3 main modules :

Local Mapping Module : optimizes for the full trajec- tory and landmark map, then compresses a local map for broadcast to neighboring robots.

Communications Module : updates a cache of con- densed maps from many robots.

Neighborhood Mapping Module : jointly estimates over landmarks in the robot's neighborhood graph and rel- ative coordinate frames to yield a neighborhood map .

IV. Multi-Robot Data asociation

the multi-robot data association module uses a triangulation-based robust estimator for matching feature maps.

i. triangle map matching

A direct application of RANSAC [12] would randomly sample (without replacement) two points from the neighborhood landmarks L and the incoming landmarks L^a as putatives, compute the corresponding transformation and verify it by counting the number of matched landmarks. Problem : there are exponentially many transformations to verify.

their approach first computes a Delaunay triangulation of the landmark positions in L and L^a , and then applies RANSAC on a set of putatives generated from the centroids of similar triangles.

They choose to use a Delaunay triangulation as a geometric feature because :

- it is unique,
- invariant to reference frame,
- and biases the set of putatives towards conservative data associations
- can be computed in $\Theta(nlogn)$

Then they matches the two sets of Triangles with RANSAC [12].

Possible enhancement : GroupSAC [13] or PROSAC [15].

V. Experiments

The graphical inference and optimization engine used is the GTSAM library, with local optimization performed with an improved version of the iSAM [16].

he neighborhood optimization approach uses batch Levenberg-Marquardt optimization.

We perform 2D triangulation with the Triangle library [17].

PB : Not directly usable in 3D.

References

[1] A. Cunningham, K. M. Wurm, W. Burgard, and F. Dellaert, "Fully distributed scalable smoothing and mapping with robust multi-robot data association", in *2012 IEEE International Conference on Robotics and Automation*, May 2012, pp. 1093–1100. DOI: 10.1109/ICRA.2012.6225356.

[2] A. Cunningham, M. Paluri, and F. Dellaert, "DDF-SAM: Fully distributed SLAM using constrained factor graphs", in *2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Oct. 2010, pp. 3025–3030. DOI: 10.1109/IROS.2010.5652875.

[3] T. Bailey, M. Bryson, H. Mu, J. Vial, L. McCalman, and H. Durrant-Whyte, "Decentralised cooperative localisation for heterogeneous teams of mobile robots", in *2011 IEEE International Conference on Robotics and Automation*, May 2011, pp. 2859–2865. DOI: 10.1109/ICRA.2011.5979850.

[4] A. Bahr, M. R. Walter, and J. J. Leonard, "Consistent cooperative localization", in *2009 IEEE International Conference on Robotics and Automation*, May 2009, pp. 3415–3422. DOI: 10.1109/ROBOT.2009.5152859.

[5] L. A. A. Andersson and J. Nygards, "C-SAM: Multi-robot SLAM using square root information smoothing", in *2008 IEEE International Conference on Robotics and Automation*, May 2008, pp. 2798–2805. DOI: 10.1109/ROBOT.2008.4543634.

[6] B. Kim, M. Kaess, L. Fletcher, J. Leonard, A. Bachrach, N. Roy, and S. Teller, "Multiple relative pose graphs for robust cooperative mapping", in *2010 IEEE International Conference on Robotics and Automation*, May 2010, pp. 3185–3192. DOI: 10.1109/ROBOT.2010.5509154.

[7] A. Howard, "Multi-robot simultaneous localization and mapping using particle filters", *The International Journal of Robotics Research*, vol. 25, no. 12, pp. 1243–1256, Dec. 2006, ISSN: 0278-3649, 1741-3176. DOI: 10.1177/0278364906072250. [Online]. Available: http://journals.sagepub.com/doi/10.1177/0278364906072250 (visited on 07/11/2017).

[8] L. Carlone, M. K. Ng, J. Du, B. Bona, and M. Indri, "Rao-blackwellized particle filters multi robot SLAM with unknown initial correspondences and limited communication", in *2010 IEEE International Conference on Robotics and Automation*, May 2010, pp. 243–249. DOI: 10.1109/ROBOT.2010.5509307.

[9] A. Howard, G. S. Sukhatme, and M. J. Mataric, "Multirobot simultaneous localization and mapping using manifold representations", *Proceedings of the IEEE*, vol. 94, no. 7, pp. 1360–1369, Jul. 2006, ISSN: 0018-9219. DOI: 10.1109/JPROC.2006.876922.

[10] K. Ni and F. Dellaert, "Multi-level submap based SLAM using nested dissection", in *2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Oct. 2010, pp. 2558–2565. DOI: 10.1109/IROS.2010.5650197.

[11] J. Neira and J. D. Tardos, "Data association in stochastic mapping using the joint compatibility test", *IEEE Transactions on Robotics and Automation*, vol. 17, no. 6, pp. 890–897, Dec. 2001, ISSN: 1042-296X. DOI: 10.1109/70.976019.

[12] M. A. Fischler and R. C. Bolles, "Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography", *Communications of the ACM*, vol. 24, no. 6, pp. 381–395, 1981. [Online]. Available: http://dl.acm.org/citation.cfm?id=358692 (visited on 07/11/2017).

[13] K. Ni, H. Jin, and F. Dellaert, "Groupsac: Efficient consensus in the presence of groupings", in *2009 IEEE 12th International Conference on Computer Vision*, Sep. 2009, pp. 2193–2200. DOI: 10.1109/ICCV.2009.5459241.

[14] R. Aragues, E. Montijano, and C. Sagues, "Consistent data association in multi-robot systems with limited communications", in *Robotics: Science and Systems*, 2011, pp. 97–104. [Online]. Available: https://books.google.com/books?hl=en&lr=&id=q9TxCwAAQBAJ&oi=fnd&pg=PA97&dq=%22failures.+Information+is+exchanged+exclusively%22+%22and+visual+methods+for+feature-based+maps+%5B12%5D,+%5B17%5D.%22+%22estimates+of+a+common+element.+It+is+of+high%22+%22simultaneously.+The+Combined+Constraint%22+&ots=75k7Gmt9_8&sig=3NJp7_DxIdvtKRO-3uQoVH15_E4 (visited on 07/11/2017).

[15] O. Chum and J. Matas, "Matching with PROSAC - progressive sample consensus", in *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, vol. 1, Jun. 2005, 220–226 vol. 1. DOI: 10.1109/CVPR.2005.221.

[16] M. Kaess, A. Ranganathan, and F. Dellaert, "Isam: Incremental smoothing and mapping", *IEEE Transactions on Robotics*, vol. 24, no. 6, pp. 1365–1378, Dec. 2008, ISSN: 1552-3098. DOI: `10.1109/TRO.2008.2006706`.

[17] J. R. Shewchuk, "Triangle: Engineering a 2d quality mesh generator and delaunay triangulator", in *Applied computational geometry towards geometric engineering*, Springer, 1996, pp. 203–222. [Online]. Available: `https://link.springer.com/chapter/10.1007/BFb0014497` (visited on 07/11/2017).