Pose Fusion with Chain Pose Graphs for Automated Driving

HMW-Alexander

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Contents

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1 Basic Information

1.1 Authors

- **Christian Merfels** is with Volkswagen Group Research, Wolfsburg, and Institute of Geodesy and Geoinformation, University of Bonn, Germany.
- **Cyrill Stachniss** is with Institute of Geodesy and Geoinformation, University of Bonn, Germany.

1.2 Conference

2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)

1.3 Abstract

- Combining multiple localization systems in a **plug and play manner**.
- Formulate this approach as a **sliding window pose graph**.
- The pose fusion approach scales from a filtering-based to a batch solution by increasing the size of the sliding window.
- The experiment runs at 20Hz on both simulated and real data.

1.4 Keywords

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2 Introduction

2.1 Problem & Solution

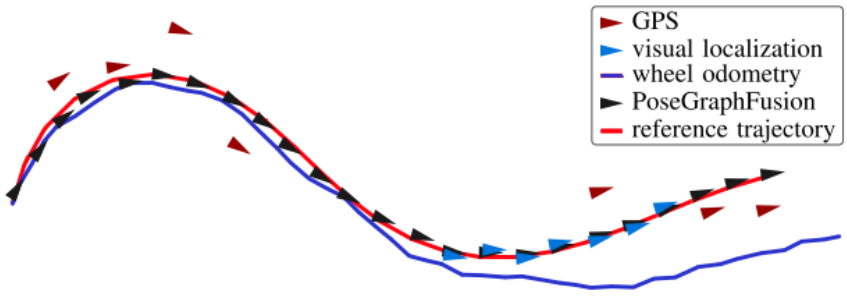
Individual localization system is not enough, and the combination of orthogonal localization systems is more powerful.

2.2 Objective

This paper provides an approach to multi-sensor data fusion decouples the localization from the fusion task, which eneables the ability to incorporate third-party localization modules for which source code is unavailable.

2.3 Formulation

A coarse localization (red triangles), a precise but only temporary available localization (blue triangles), and odometry as dead reckoning trajectory (blue) are used to estimate the true trajectory (red) of a vehicle. The estimated poses are shown as black triangles: the goal is to approximate the unknown red line as closely as possible with the black triangles.



2.4 Contributions

- efficient sensor fusion of generic odometry and global pose inputs ⇒ an intuitive architecture for pose estimation and timing issues.
- graph construction algorithm ⇒ a sparse block-tridiagonal structure of the system matrix ⇒ fast solution

3 Related Work

3.1 Multi-sensor data fusion for navigation systems

- **filtering-based approaches**: Kalman filter and its variants
  - feature: rely at a very early stage on the Markov assumption and marginalize all older information
  - problem: prematurely incorporating the linearization error.
- **sliding window smoothing algorithms**: compute the maximum likelihood (ML) estimate by nonlinear least squares optimization to a Bayesian network, Markov random field (MRF), or factor graph.
  - feature: consider all past measurements up to the current one; and also consider future measurements for offline batch optimization.
  - solution: online batch optimization becomes feasible through the usage of incremental smoothing techniques, such as iSAM2[1], that recalculate only the part of the graph that is affected by new measurements.
  - Some implementations keep the size of the graph bounded by simply discarding older nodes and edges, thus potentially obtaining overconfident estimates.

3.2 Methodical origin

- Sibley et al.[2], who are the first to introduce the concept of a slibing window filter in the context of robotics.
- Differences:
  - apply this to the use case of pose fusion
  - special design for a faster way of solving the nonlinear least squares equations, performing marginalization, and estimating the uncertainty of the output.
  - provide a way of semantically reasoning about the prior information arising from marginalization by deriving a prior node.

4 Pose Graph Fusion

4.1 Nonlinear least squares problem

This paper exploits the state-of-the-art graph optimization framework g2o[3].

The key idea is that given the state vector $x = (x_1^T, ..., x_m^T)^T$ and a set of measurements, where z_{ij} is the mean and Ω_{ij} is the information matrix of a single measurement relating x_i to x_j, least squares estimation seeks the state

$$x^* = \arg\min_x \sum_{i,j} e_{ij}^T \Omega_{ij} e_{ij} \quad (1)$$

[1] M. Kaess, H. Johannsson, R. Roberts, V. Ila, J. Leonard, and F. Del- laert, iSAM2: Incremental Smoothing and Mapping using the Bayes tree, Int. Journal of Robotics Research, pp. 216235, 2012.

[2] G. Sibley, L. Matthies, and G. Sukhatme, SlidingWindow Filter with Application to Planetary Landing, Journal of Field Robotics, vol. 27, no. 5, pp. 587608, 2010

[3] R. K ummerle, G. Grisetti, H. Strasdat, K. Konolige, and W. Burgard, g2o: A General Framework for Graph Optimization, in Proc. IEEE Int. Conf. Robotics and Automation (ICRA), 2011, pp. 36073613.

that best explains all measurements given the $\updownarrow_2$ norm. The vector error function $e_{ij} = e(x_i, x_j, z_{ij})$ measures how well the constraint from the measurement z_{ij} is satisfied. Solving (1) requires iteratively solving a linear system with the system matrix H and the right-hand side vector b such that

$$H = \sum_{i,j} J_{ij}(x)^T \Omega_{ij} J_{ij}(x)$$

$$b^T = \sum_{i,j} e_{ij}^T \Omega_{ij} J_{ij}(x)$$

where $J_{ij}(x)$ refers to the Jacobian of the error function computed in state x.

4.2 Sliding window chain pose graph fusion

4.2.1 About the online state estimation system

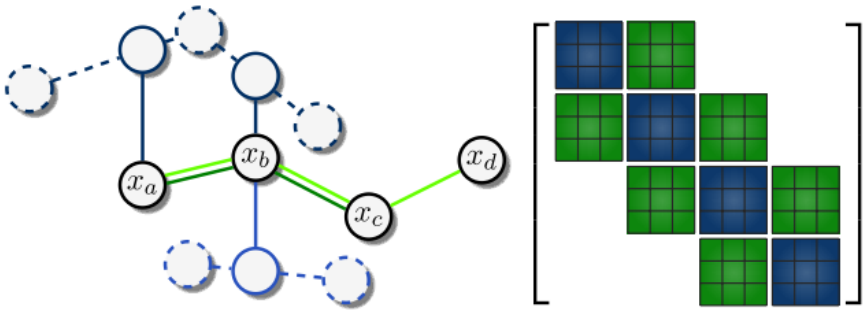
- general nonlinear least squares estimation taks into account all available information within the full pose graph
- to keep the problem computationally tractable, it is necessary to limit the considered information.
- this approach achieves this by marginalizing out prior state state variables and the state vector x in a sliding window pose graph is reduced to the M most recent states $x = (x_{t-M+1}^T, ..., x_t^T)^T$.

4.2.2 About the graph structure

- global pose source: measure poses within a global coordinate system, e.g. Universal Transverse Mercator (UTM) coordinate
- local pose source: measure spatial transformations relative to the previous pose, e.g. odometry
- hidden nodes (from MRFs): state variables
- observed nodes (from MRFs): global pose constraints, connected to hidden nodes to constrain them in the global coordinate frame.
- edge between hidden nodes: local pose constraints.
- The resulting form or the graph is called **chain pose graph**.

4.2.3 About the algorithm working frequency

- Related graph-based approaches.
  - generate a hidden node (state variables) every time a measurement arrives
  - or tie their generation to a specific pose source
- This approach constructs a hidden node every time stamp.
  - it queries all global pose sources for measurements and interpolate one observed node per source at the timestamp of the hidden node if measurements are available.
  - it queries each local pose source to interpolate the edges between all two successive hidden nodes.
  - enforce a certain matrix structure for H, to include all measurement sources in a generic way independetly of their specific output frequencies, and to a priori relate the number of state variables to the length of the interval of the sliding window.



(a) A chain pose graph.

(b) Corresponding block-tridiagonal structure of the system matrix.

Fig. 3. A chain pose graph and the corresponding structure of the system matrix. The black circles are hidden nodes, the dashed blue circles are global pose measurements from two different sources, the non-dashed blue circles are observed nodes, and the green edges are odometry constraints. Note how the raw global pose measurements are interpolated (dashed blue lines) at the same timestamps as the hidden nodes to obtain the observed nodes.

4.2.4 About the system matrix