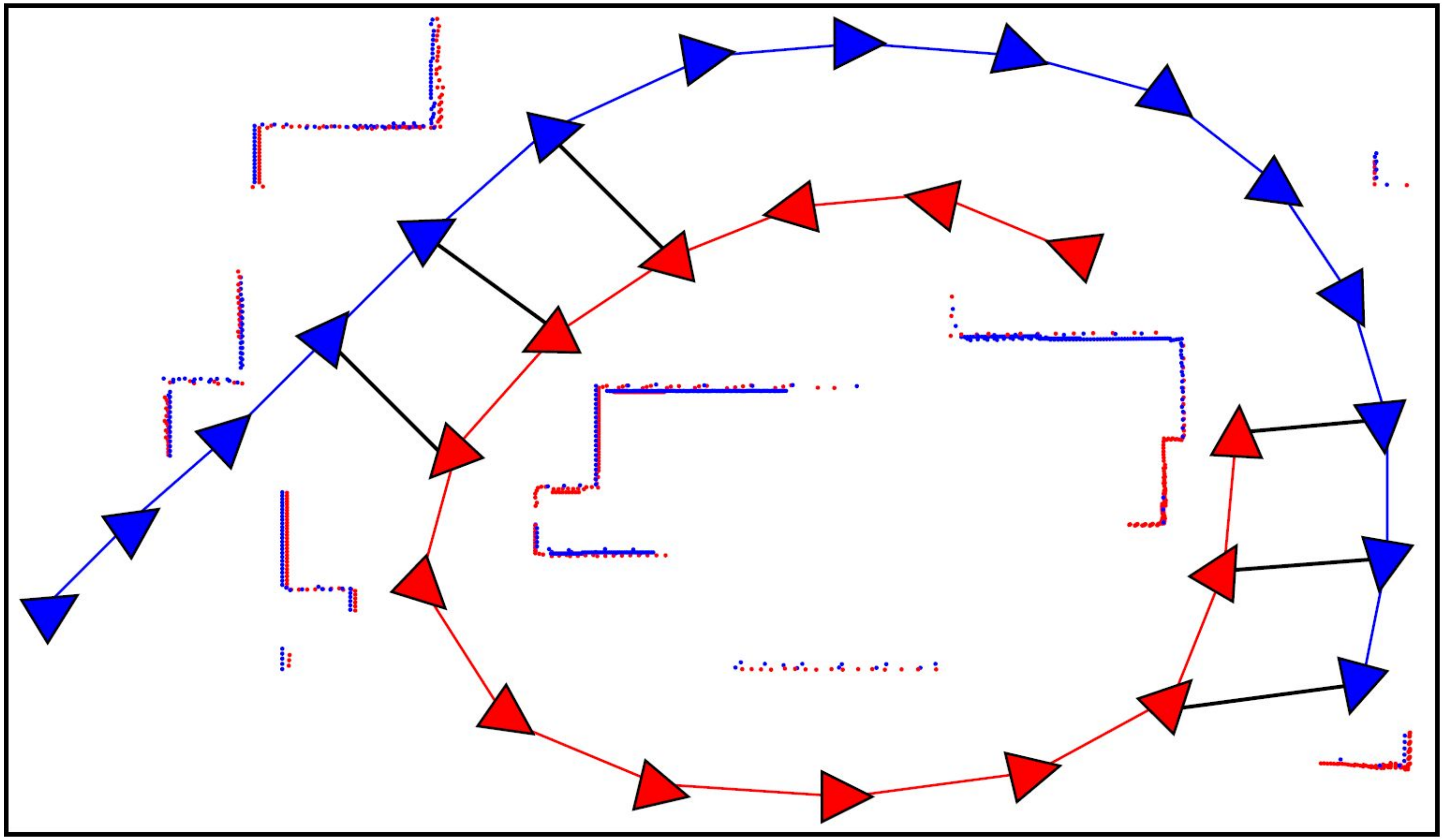
Multi-Robot SLAM using Condensed Measurements

Mayte Lázaro, Giorgio Grisetti

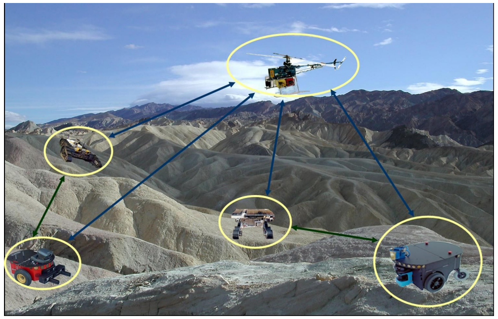
Multi-robot graph-based SLAM

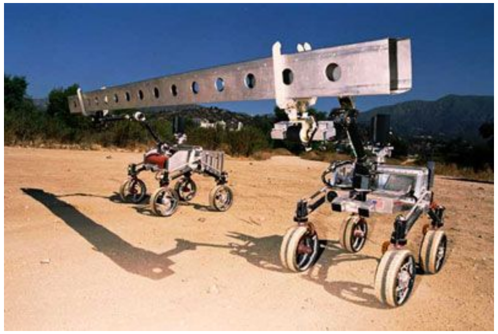
- Problem overview



Multi-robot systems

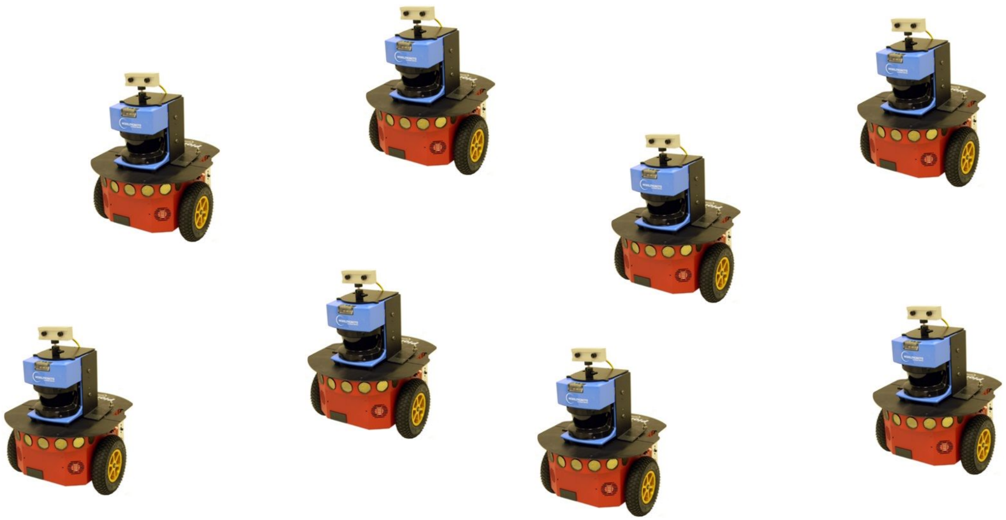
- Attractive advantages
  - Robustness
  - Accuracy
  - Scalability
  - Efficiency
  - Cooperation to perform a task
  - Cover larger environments in less time





Multi-robot systems

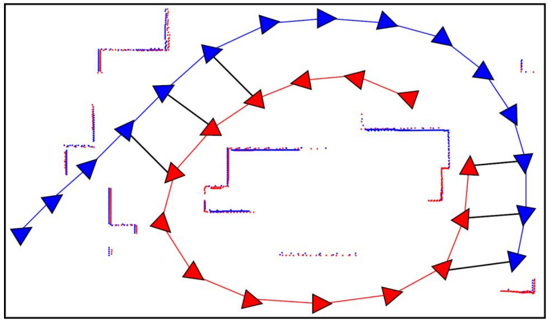
- Built on top of stable and reliable single-robot systems
- We can not “just” replicate robots



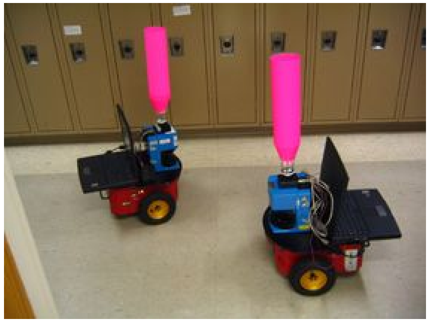
Multi-robot systems issues

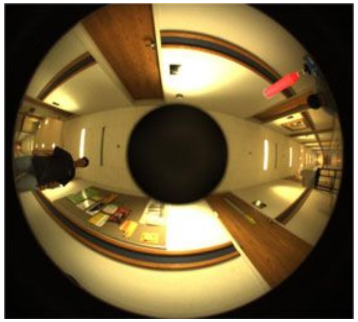
- Computational issues
  - How to manage, store and combine all the information available?
- Communication issues
  - Which kind of network?
    - Ad-hoc wireless networks, WLAN access points…
  - Which information is transmitted?
    - Bandwidth requirements
- Motion coordination
  - How the robots move to not interfere each other
- Task allocation
  - Who does what?

Multi-robot SLAM issues

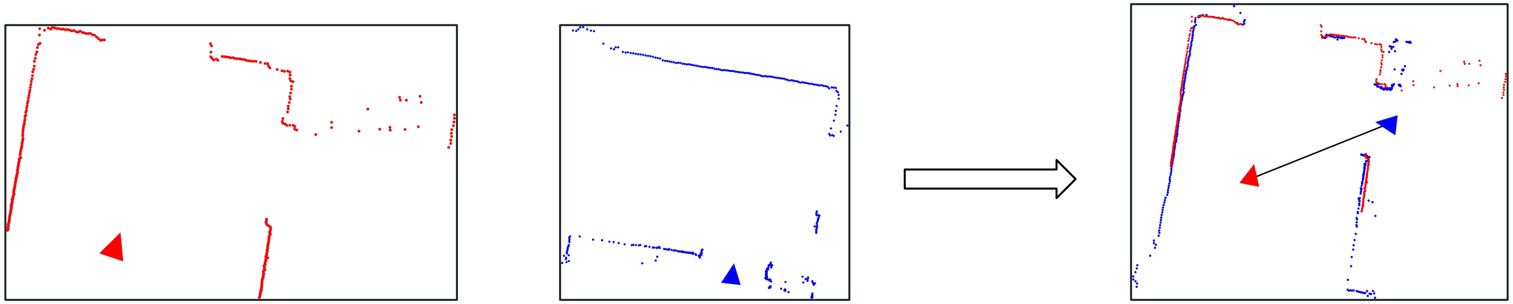


- How to obtain relative measurements between robots?
  - Robot-to-robot (inter-robot) measurements
    - Robots sense each other
    - Require robot identification system
    - Constrains robot movements



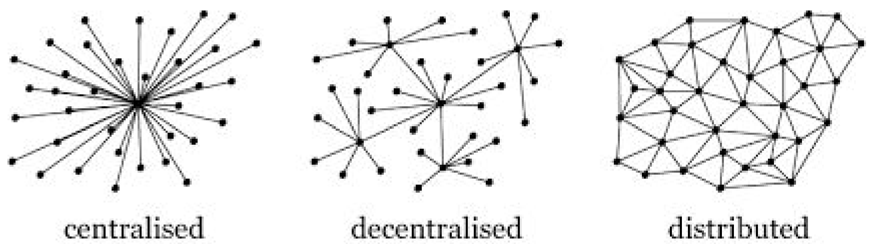


  - Common environmental (intra-robot) measurements
    - Requires to solve a data association problem



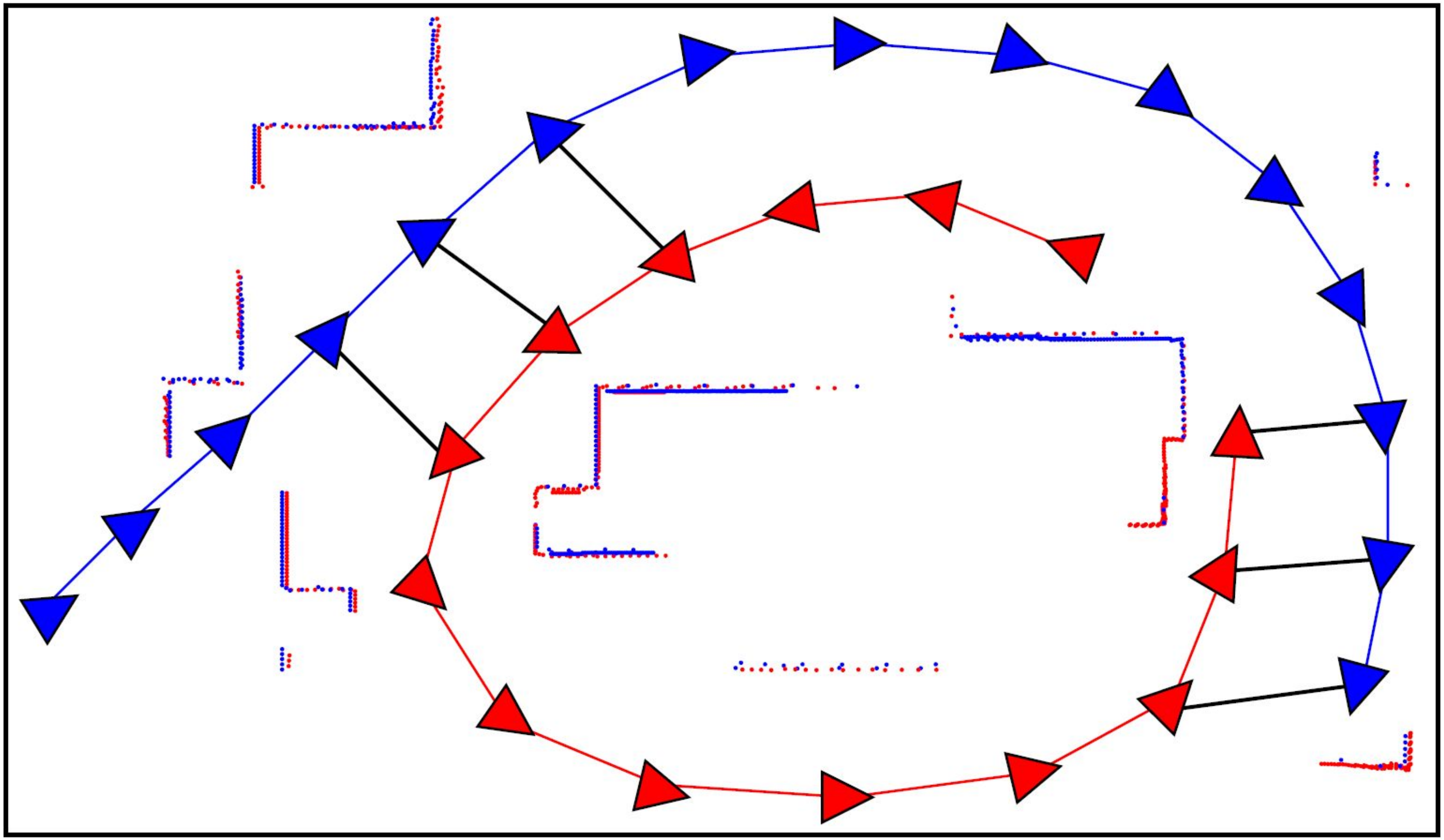
Multi-robot SLAM issues

- How to perform map estimation?
  - Centralized - single server integrates all the information
  - Decentralized - hierarchy of central servers
    - Fully - all robots estimate all
  - Distributed - robots have partial information about others



- How to transmit map information?
  - Ideally: robots share the entire graph
    - Memory ⬆⬆⬆
    - Optimization time ⬆⬆⬆
    - Bandwidth requirements ⬆⬆⬆

Our approach



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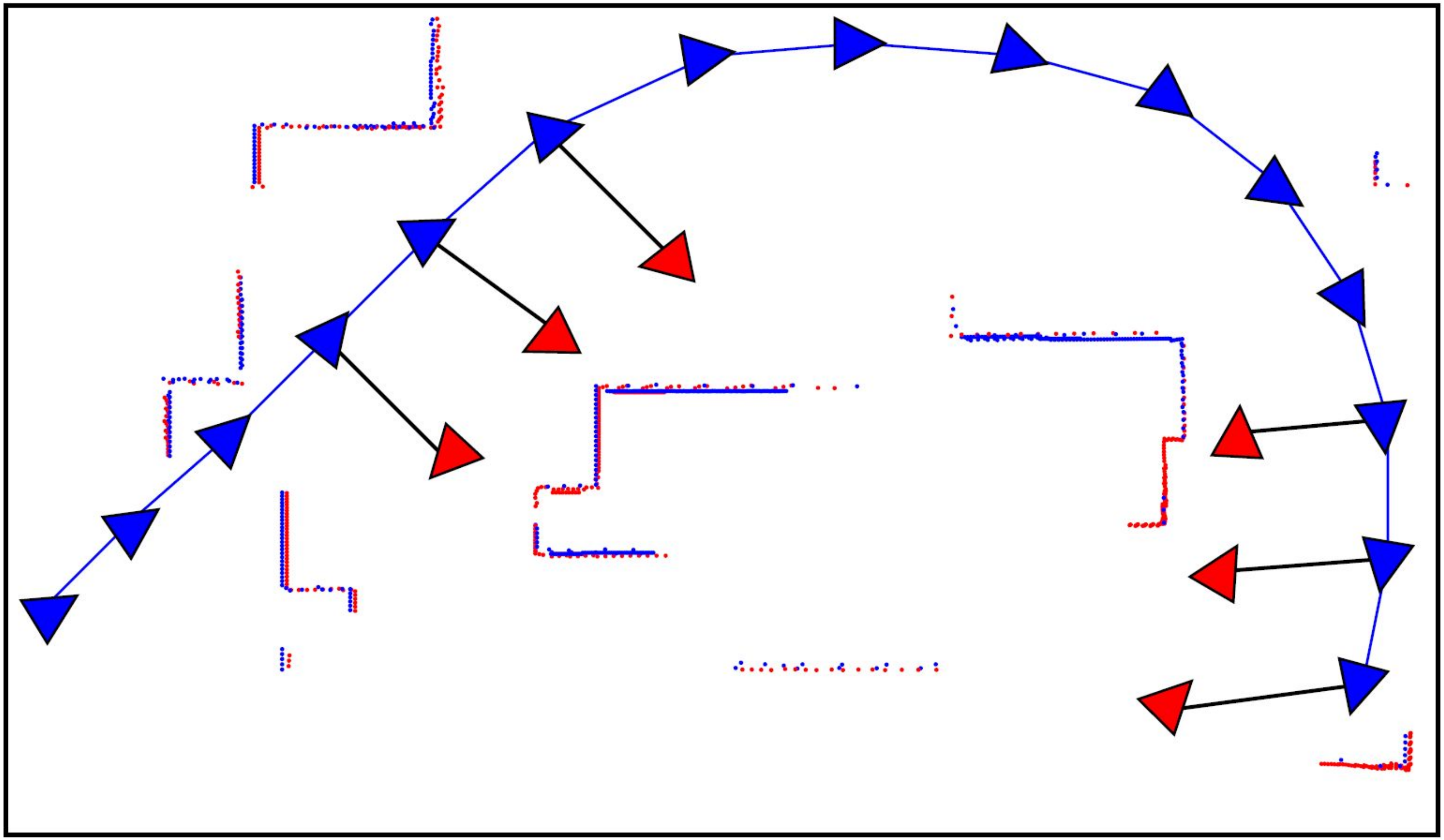

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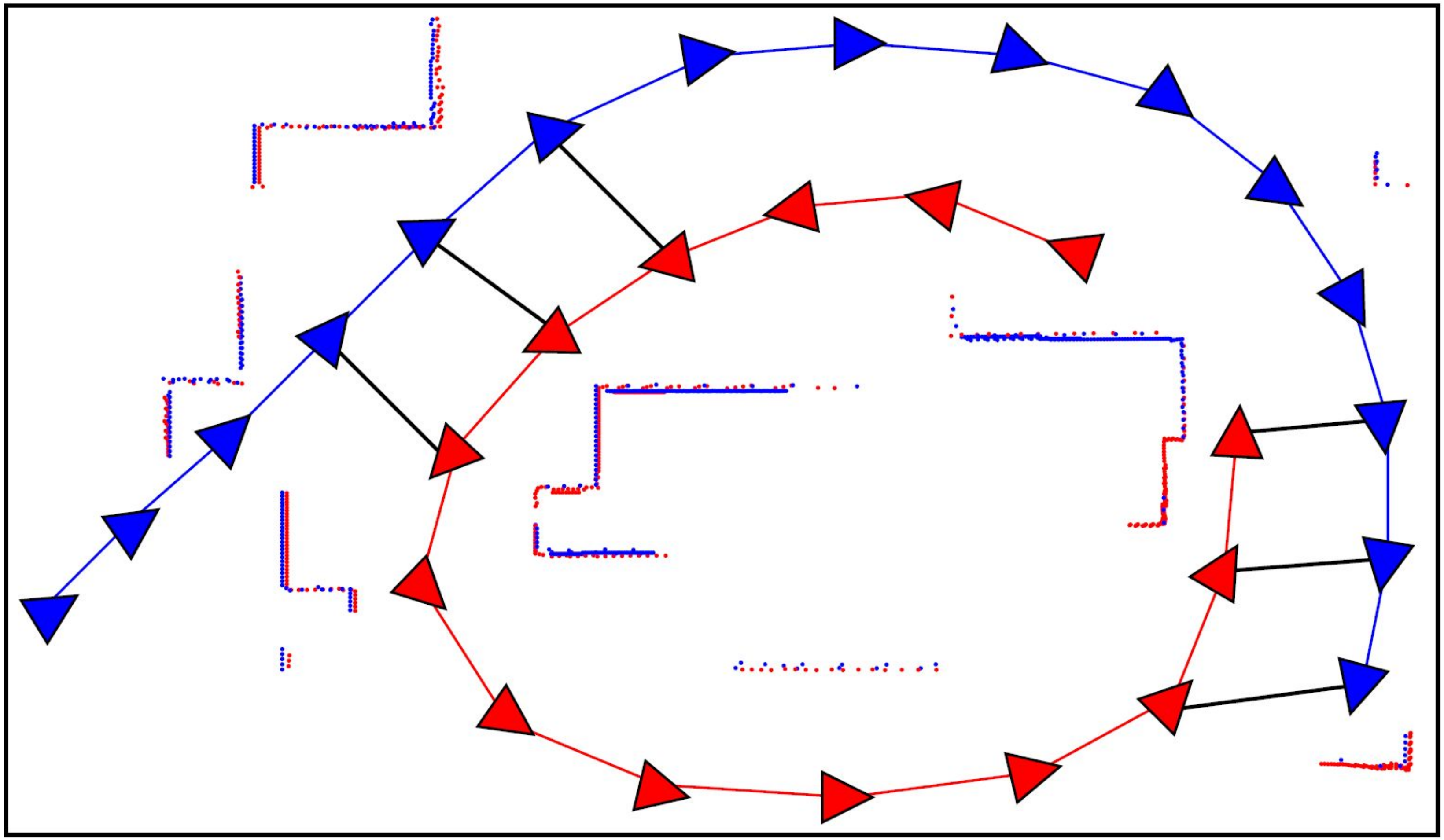

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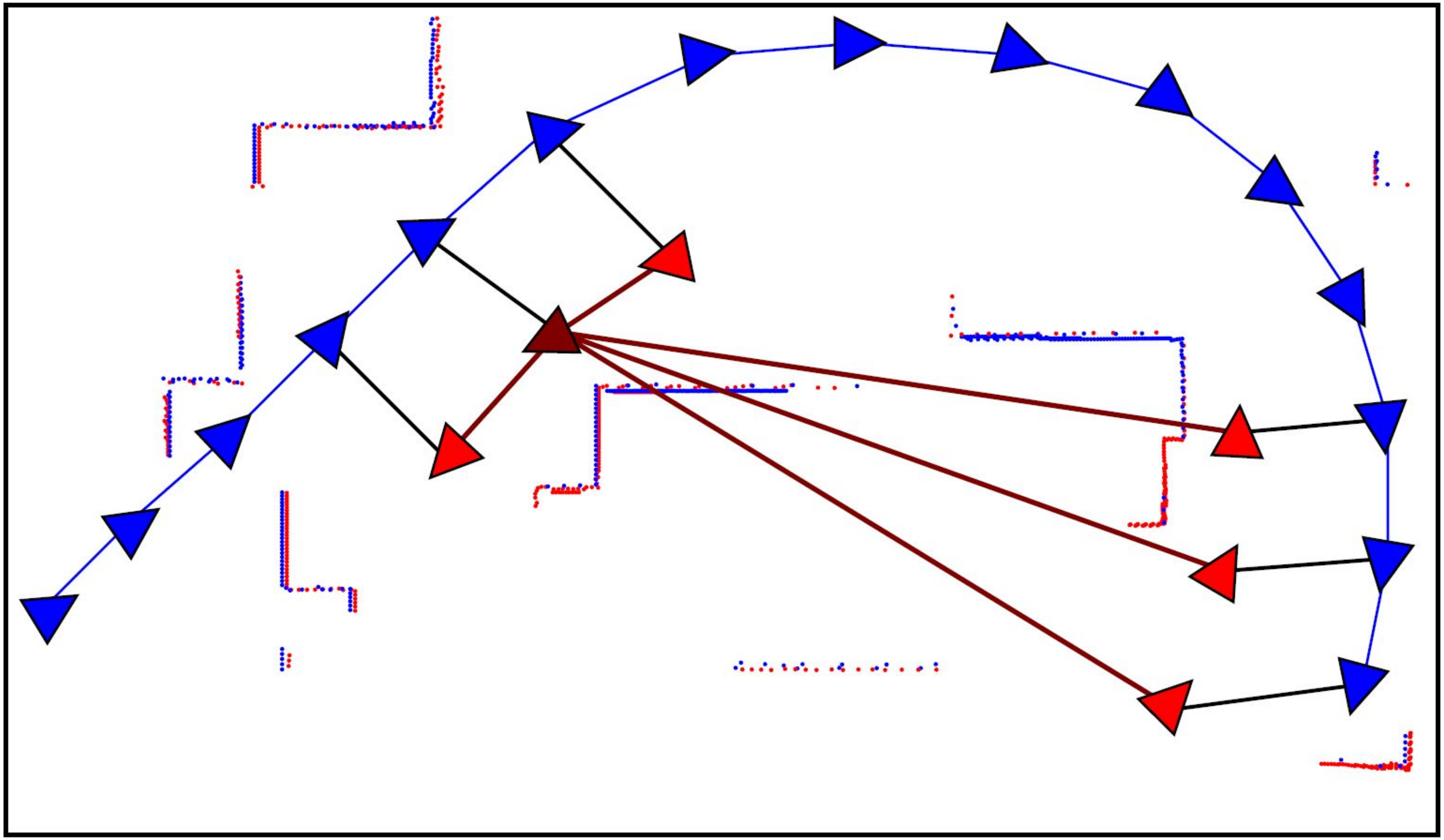


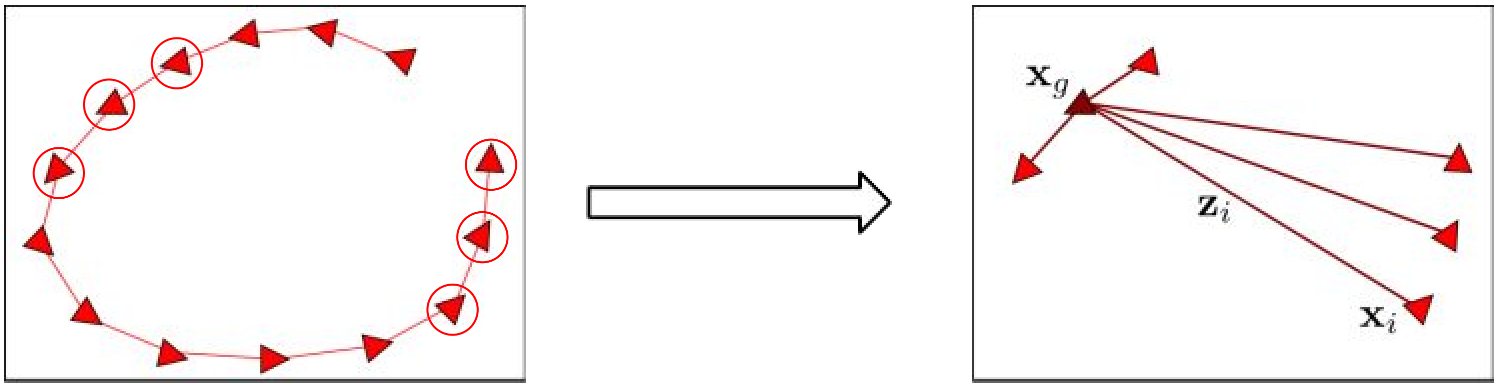
Our approach

- General MR-SLAM system working in unknown environment
- Robots work on their own reference frame
- Limited communications
  - Wireless in ad-hoc mode: robots communicate when close
- Works on raw data (no feature extraction)
- Condensed graphs
  - Easily managed by the optimization back-end
  - Graphs are minimally augmented
  - Reduce the amount of data to be transmitted
- No assumption about their relative positions
  - Robust map alignment procedure to obtain intra-robot measurements

M. T. Lázaro, L. M. Paz, P. Piniés, J. A. Castellanos and G. Grisetti, “Multi-Robot SLAM using Condensed Measurements.” *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).* Tokyo Big Sight, Japan, Nov 3-8, 2013.

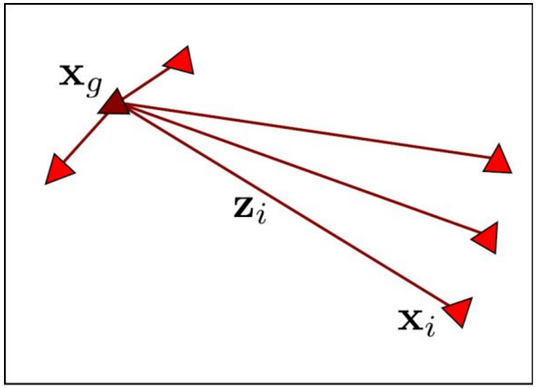
Condensed graphs

- Summarized representation of the graph



- A condensed graph contains
  - The nodes $\mathbf{x}_\mathbf{i}$ of interest for the other robot
  - A central node (gauge, $\mathbf{x}_\mathbf{g}$)
  - A set of “virtual” measurements $\mathbf{z}_\mathbf{i}$ connecting $\mathbf{x}_\mathbf{g}$ with each $\mathbf{x}_\mathbf{i}$
    - Contain the knowledge that $\mathbf{x}_\mathbf{g}$ has about $\mathbf{x}_\mathbf{i}$ in the global graph

Condensed measurements



- For each measurement $\mathbf{z}_i$ we need to compute:
  - Its mean $\hat{\mathbf{z}}_i$
  - Its information matrix Ω_i
- The error function relates the measurement and the current configuration of nodes

$\mathrm{t2v}((\mathbf{X}_g)^{-1}\mathbf{X}_i)$

$$\mathbf{e}_i(\mathbf{x}_g, \mathbf{x}_i) = \boxed{\mathbf{h}(\mathbf{x}_g, \mathbf{x}_i)} \boxminus \mathbf{z}_i$$

- To compute $\mathbf{z}_i$
  - Select a gauge $\mathbf{x}_g$ from the vertices of interest and “fix” it
  - Solve the graph
  - At this point the measurement satisfies $\mathbf{e}_i(\mathbf{x}_g, \mathbf{x}_i) = 0$
  - The mean is the one that fully satisfies $\mathbf{z}_i = \mathbf{h}(\mathbf{x}^*_g, \mathbf{x}^*_i)$
  - The information matrix can be computed from the marginal covariances of the increments:

$$\mathbf{e}_i(\mathbf{x}_g, \mathbf{x}_i \boxplus \Delta\mathbf{x}_i) = \mathbf{h}(\mathbf{x}_g, \mathbf{x}_i \boxplus \Delta\mathbf{x}_i) \boxminus \mathbf{z}_i$$

fixed

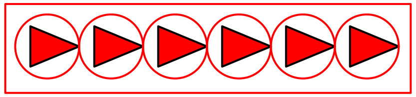
known from solution

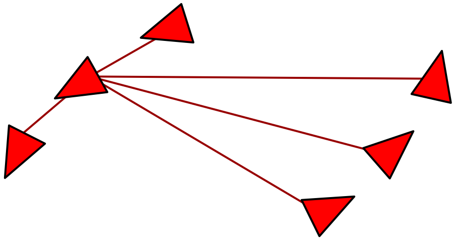
where can we get its covariance?

Condensed measurements

- In our implementation, we use the unscented transform to estimate the information matrices of the measurements.
  - The ith block of $\mathbf{H}^{-1}$ corresponds to the covariance of $\mathbf{\Delta x}_i$
  - We extract a set of sigma points $\sigma^k_{\mathbf{\Delta x i}}$ from this block
  - We project each sigma point through the error function as

$$\sigma^k = \mathbf{e}_i(\mathbf{x}^*_g, \mathbf{x}^*_i \boxplus \sigma^k_{\mathbf{\Delta x i}})$$

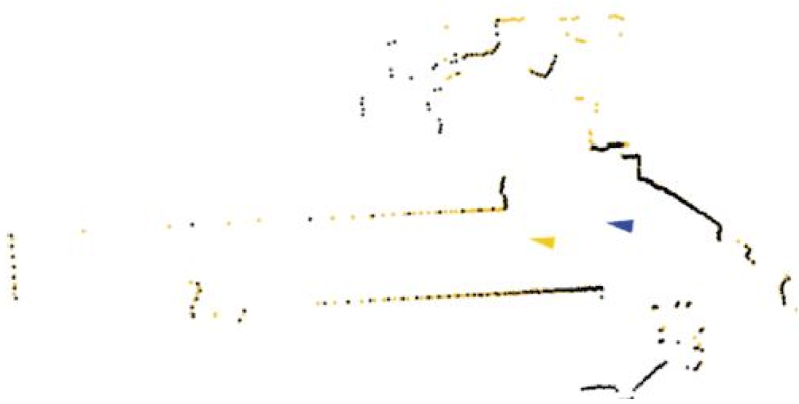
  - We recover the covariance of the measurement from the sigma points and we invert it to determine Ω_i
- In summary:
  - Given a list of nodes: 
  - Obtain a condensed graph relating these nodes:



Grisetti, Giorgio, Rainer Kümmerle, and Kai Ni. "Robust optimization of factor graphs by using condensed measurements." *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. Vilamoura, Portugal. Oct. 7-12, 2012, p. 581-588.

Scan Matching

- Given two scans $\mathbf{s}_1$ and $\mathbf{s}_2$, compute a transformation $\mathbf{T}$ that aligns the scans
- Based on correlative scan matching (Olson, ICRA 2009)
  - Search the solution over the space of possible transformations that minimizes the error
  - The region search is derived from a prior

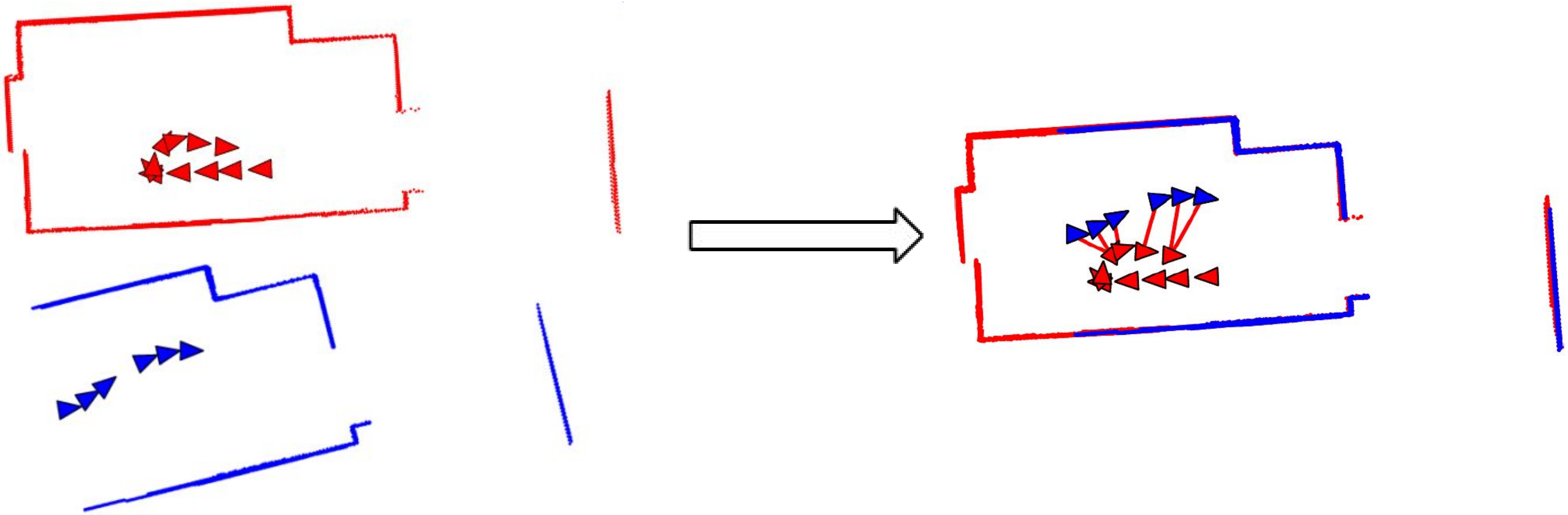


Scan Matching

- Consecutive scans
  - Initial guess: odometry (x, y, θ)
  - Search region: e.g., ($x \pm 0.3$m, $y \pm 0.3$m, $\theta \pm 0.2$rad)
  - High resolution search: e.g., (0.025m, 0.00625rad)
  - ~9-15 ms
- Can also be applied to match local maps from different robots
  - Problem: Don’t have initial guess
    - We know they are rather close ($x,y \pm 10$m, $\theta \pm \pi$ rad)
  - Huge increase of the computation
    - Reduced with hierarchical search (4 levels, from 0.8m, 0.1rad to 0.1m 0.025rad)
    - Up to 200 ms

Robust map alignment

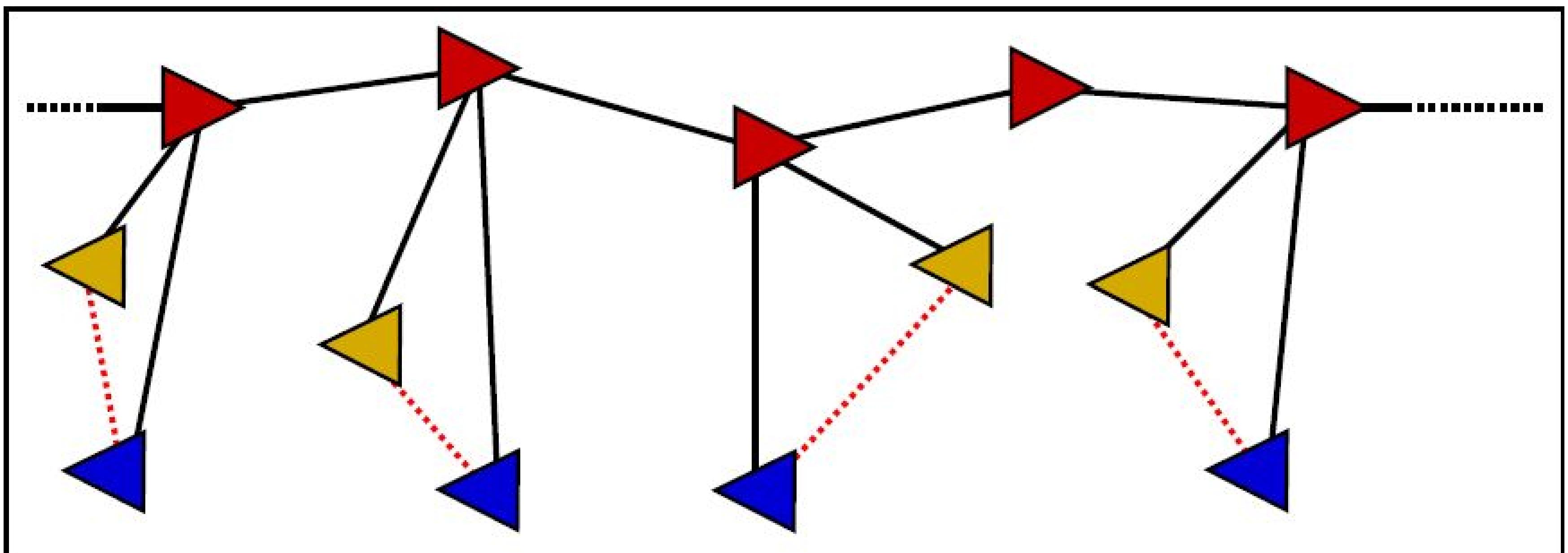
- Goal: find a set of consistent edges that align two local maps



- Works in the *front-end*
  - Local maps from the same robot ➜ Loop closures
  - Local maps from different robots ➜ Intra-robot constraints

Robust map alignment

- Voting scheme
    - For each candidate edge
        - Compute the transformation that makes the **chi2** error of the edge = 0
        - Apply this transformation to the rest of nodes and see how well they fit
        - Count number of inliers based on a threshold



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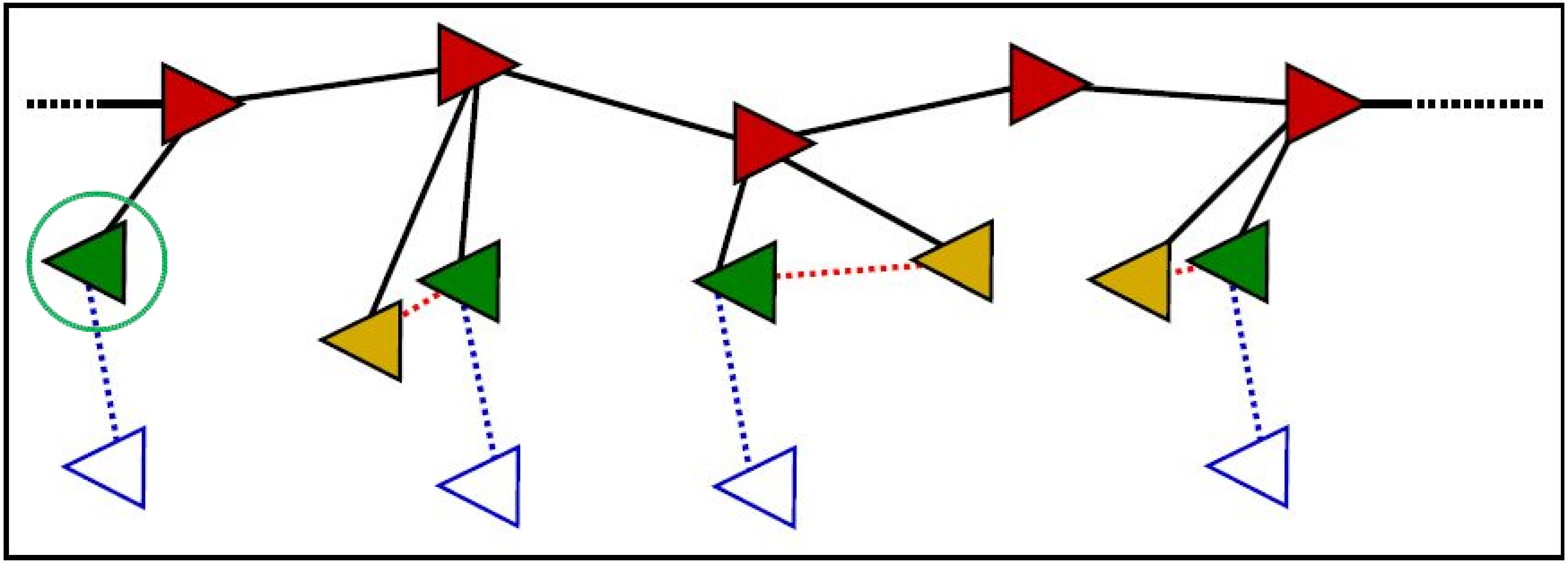

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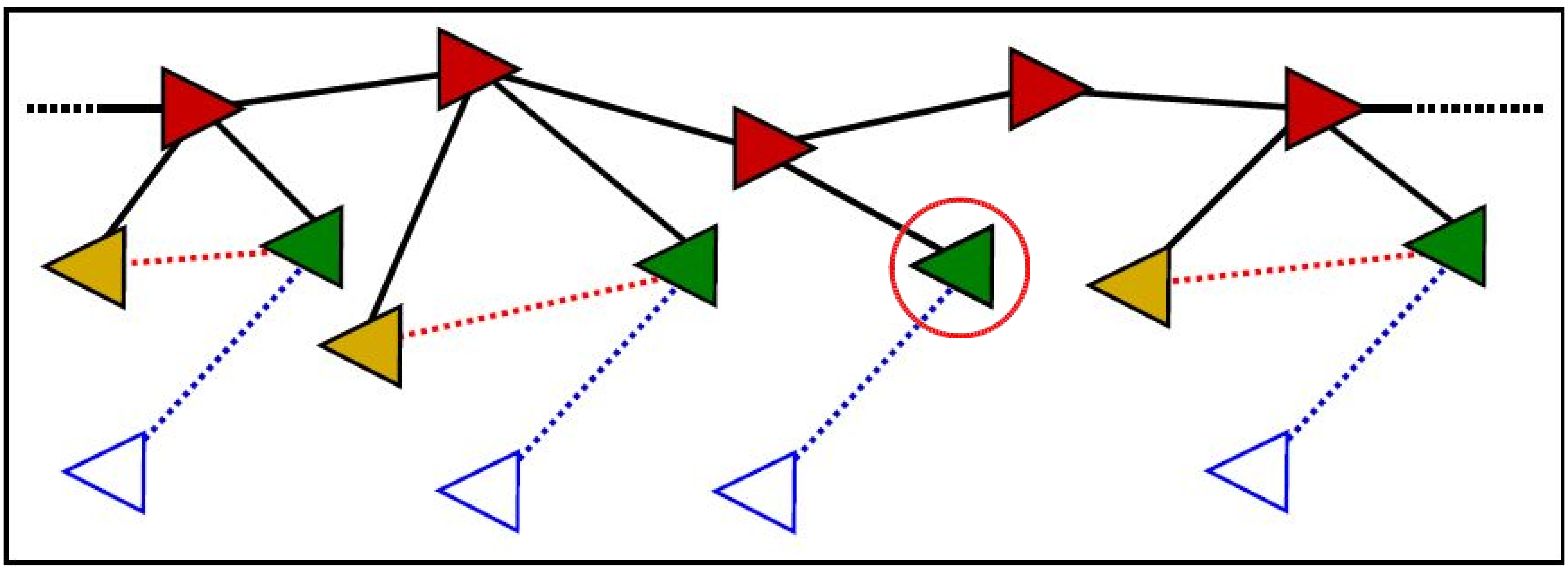
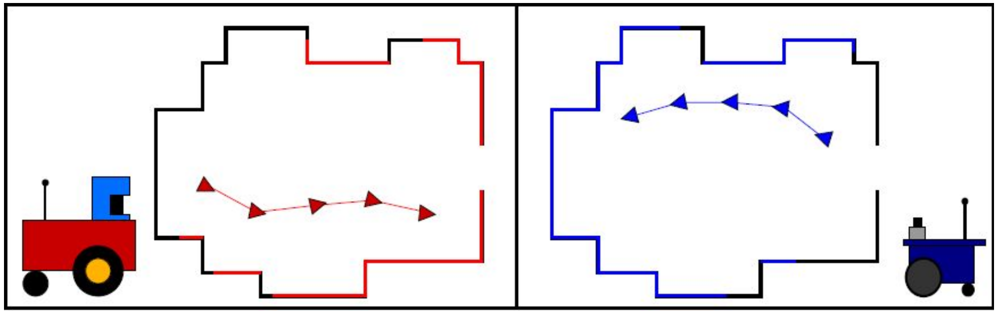
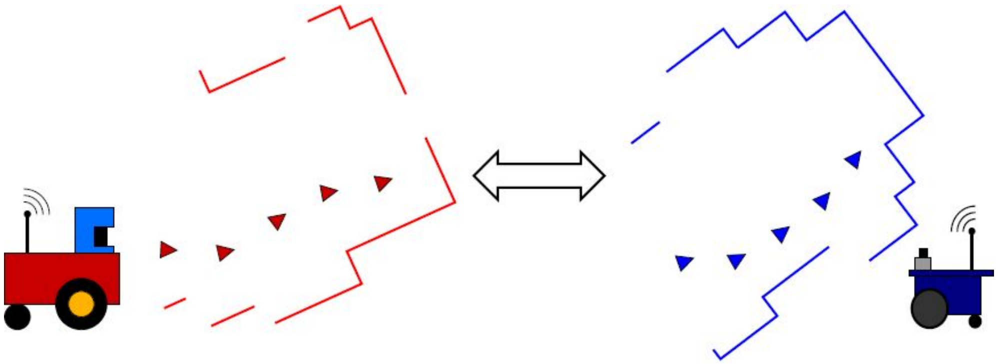


Multi-robot SLAM pipeline

- Each robot runs a single-robot SLAM and builds its own graph

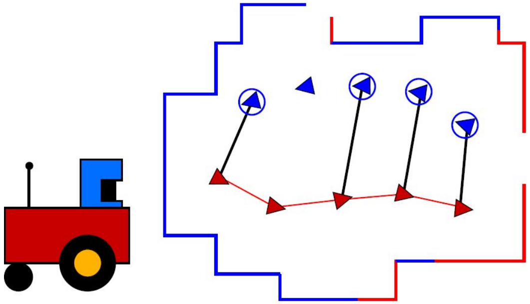


- When they are in communication range
  - Local map message:
    - Last raw measurement (laser scan) of the current node
    - Updated estimates of the last N nodes

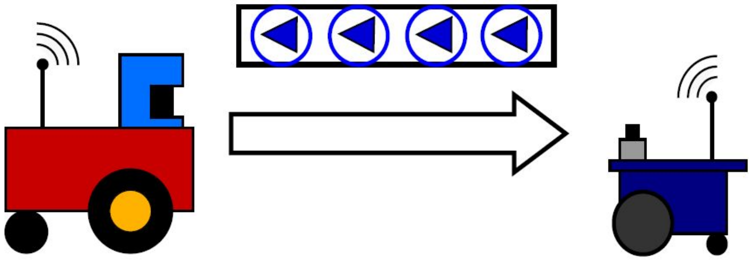


Multi-robot SLAM pipeline

- Each robot executes scan matching to align the local maps
- Using the robust map alignment validation it obtains a set of consistent edges connecting both maps

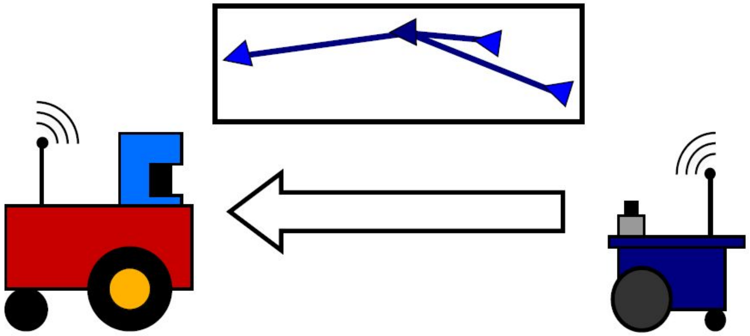


- Condensed graph message:
  - List of nodes of the other robot's local map it has matched
  - The condensed graph containing the edges the other robot has matched

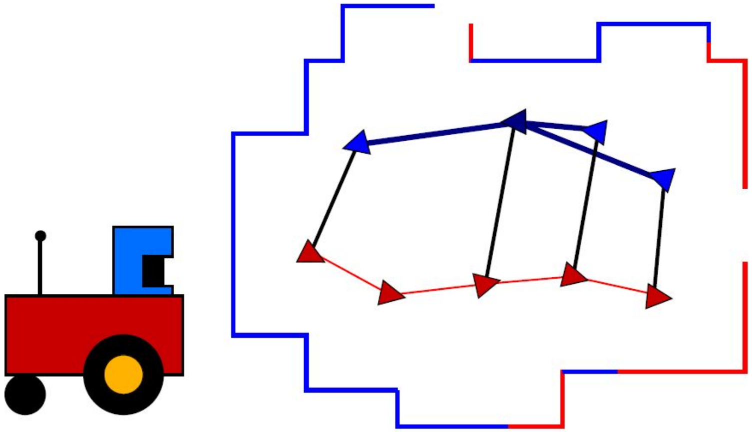


Multi-robot SLAM pipeline

- The other robot computes the condensed graph from its own map containing the nodes matched by the other robot

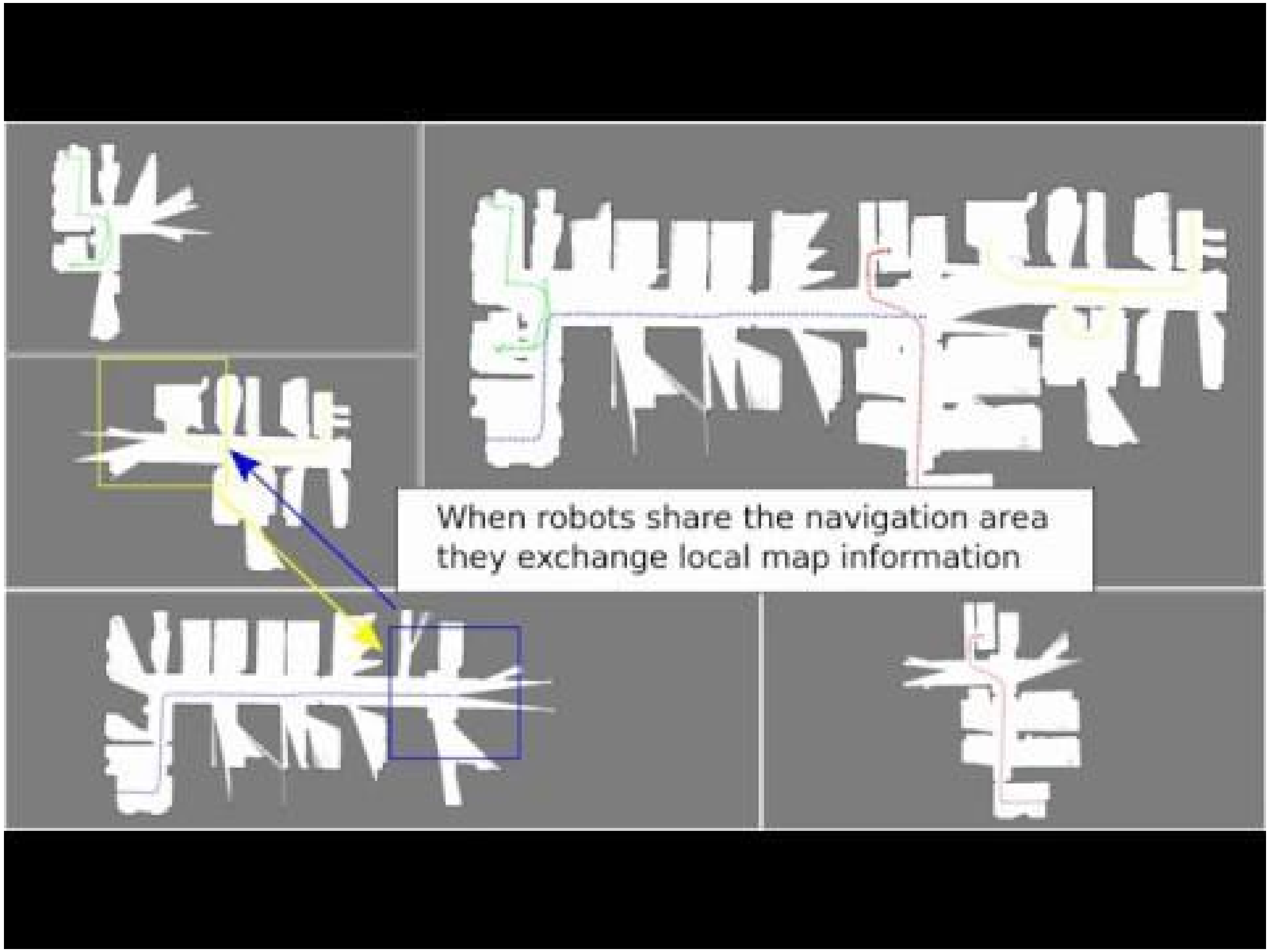


- Finally, the robot adds the condensed measurements to its own graph



Multi-robot SLAM pipeline

- Video



Results

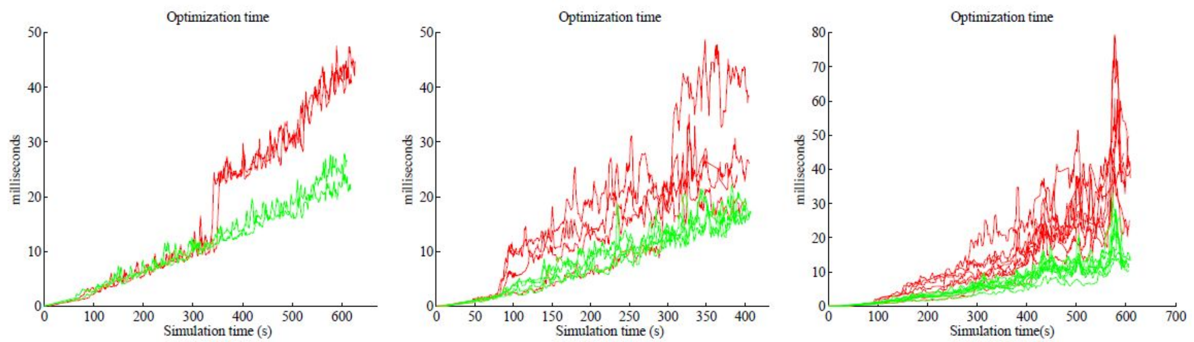
- Implemented in C++ as a ROS package
  - https://github.com/mtlazaro/cg_mrslam
- **g²o** framework for graph optimization
- Simulation with 2, 4, 8 robots

	Accuracy	
	Condensed Graphs	Ideal
2 robots	1.404	1.442
4 robots	1.572	1.548
8 robots	1.884	1.899

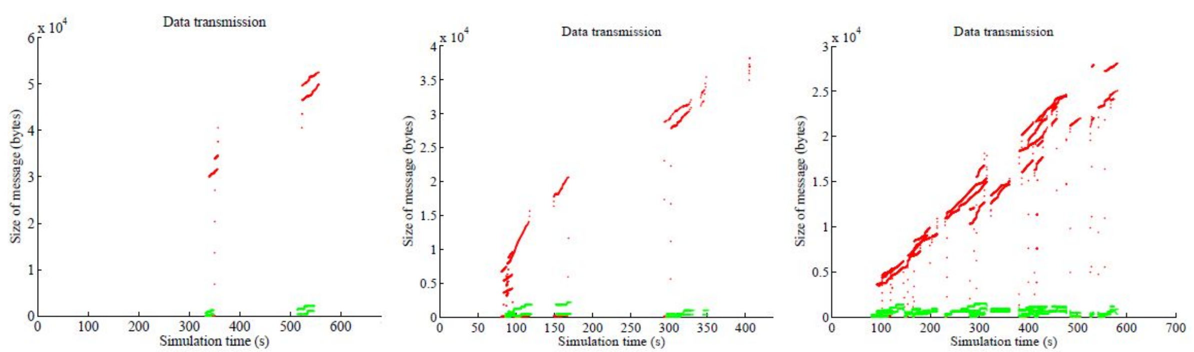
Results

- Optimization times and bytes transmitted through the network

Full-graph vs condensed-graph



(a) Times 2 robots (b) Times 4 robots (c) Times 8 robots

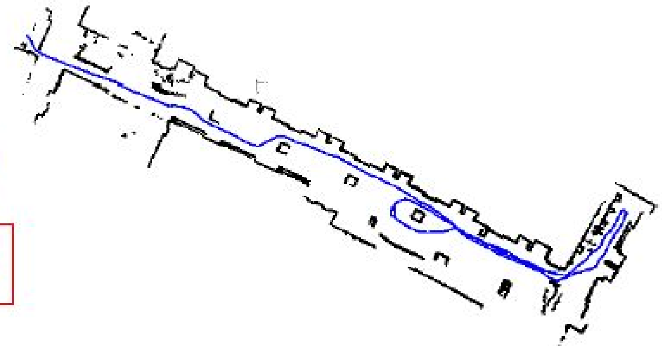


(d) Bytes 2 robots (e) Bytes 4 robots (f) Bytes 8 robots

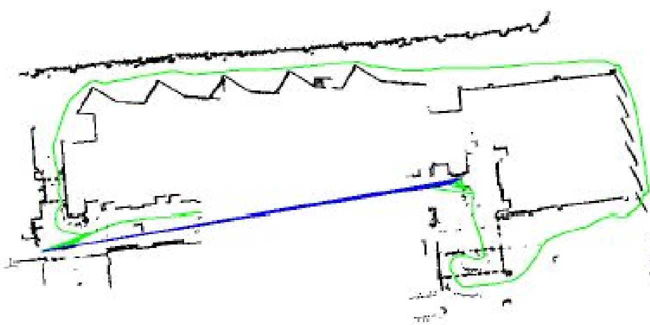
Results

- Real world experiments

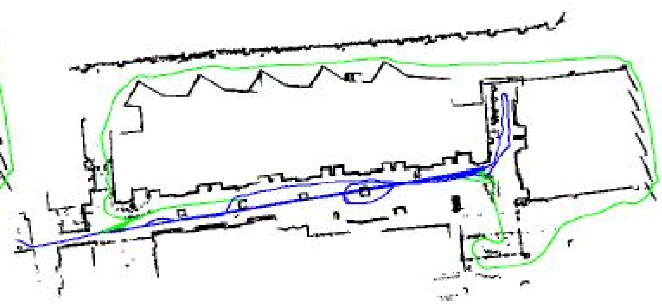
(a) Map robot 1



(b) Map robot 2



(c) Map robot 1 + condensed graph from robot 2

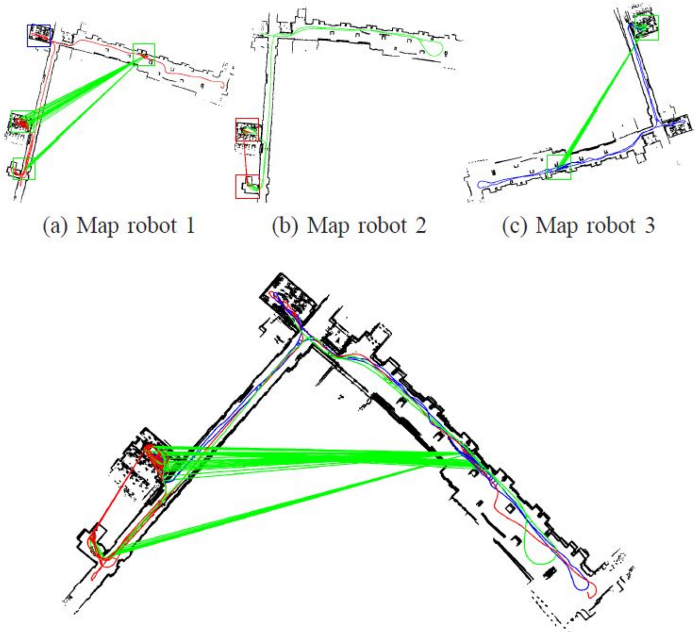


(d) Final global map

Results

- Real experiments

Ada Byron building, Univ. Zaragoza.



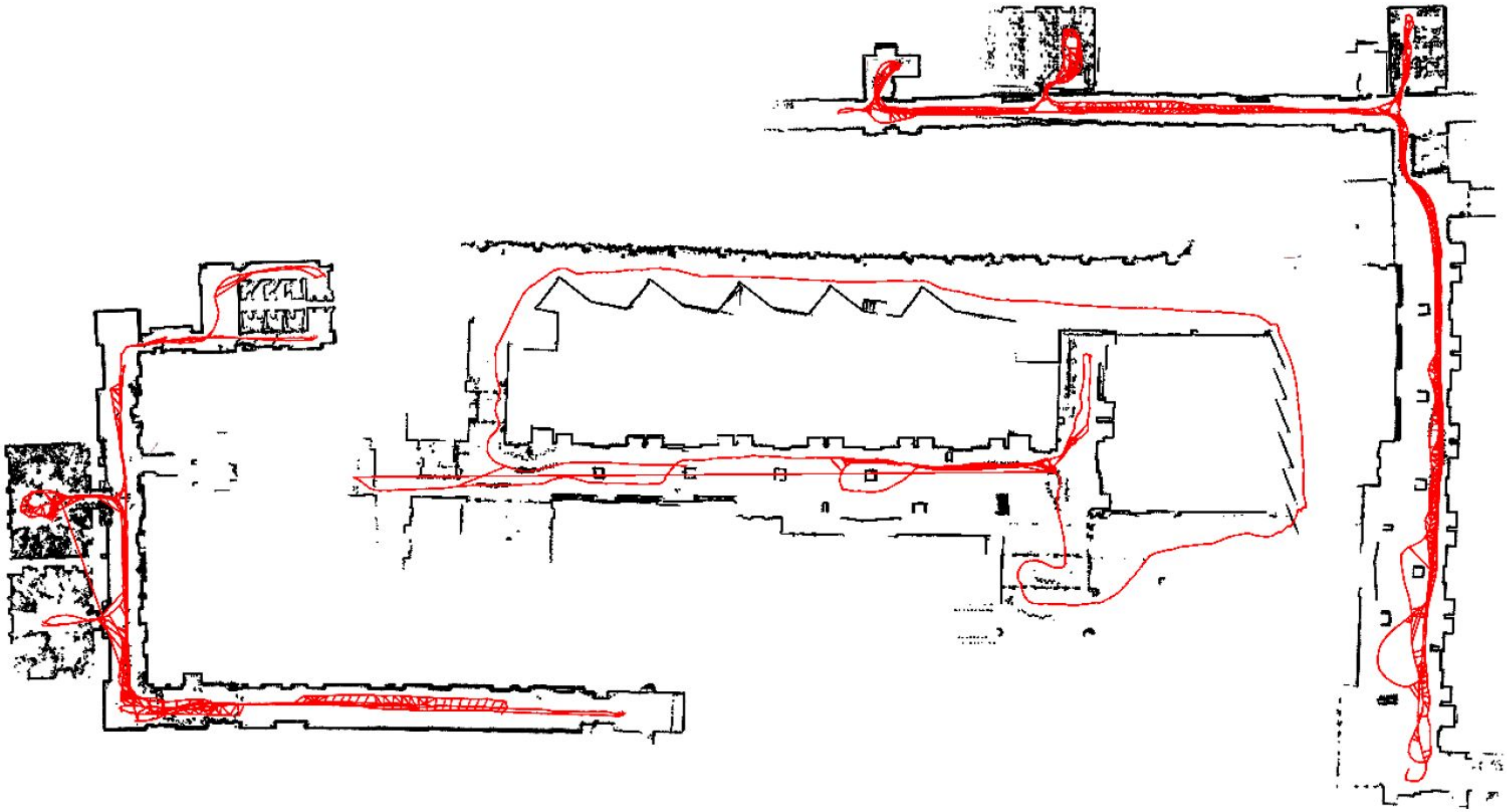
(a) Map robot 1 (b) Map robot 2 (c) Map robot 3

(d) Global map

DIAG basement, Sapienza Univ. Rome

Results

- Post processing



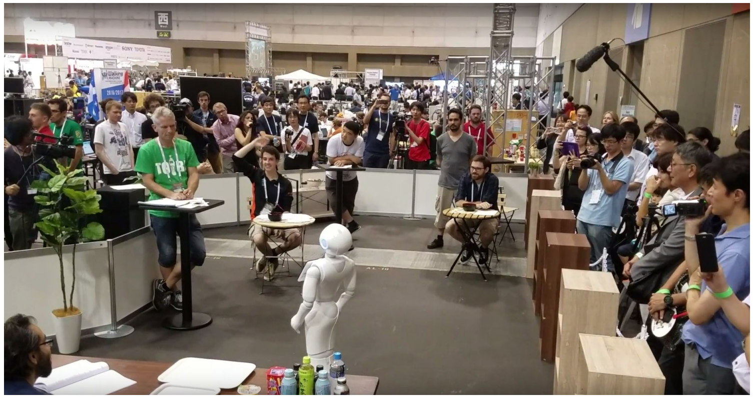
Future work

- Fix misalignments online by sharing portions of the map where the robots did not meet physically in time.
  - Simplified skeleton of the graph
- Active MR-SLAM: SLAM + exploration
  - Robots decide where to go to improve their maps
  - Robots plan future “meeting points” to share information
- Multi-session SLAM
  - Map is acquired at different times, days,...
  - Similarities to MR-SLAM
    - Graph management
    - Data storage
  - Active switch from SLAM to Localization-only modalities

Thanks: Alberto Soragna

RoboCup@Home

- Application in a domestic setting
  - Navigation in known environment
  - Navigation in unknown environment
  - People detection and tracking
  - Speech understanding
  - Human-robot interaction
- SPQReL team
  - RoCoCo Lab at Sapienza
  - L-CAS, University of Lincoln, UK
  - https://sites.google.com/dis.uniroma1.it/spqrel/



Thanks for your attention!

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