

A Hybrid Approach for Multiple-robot SLAM with Particle Filtering

Sajad Saeedi*, Michael Trentini**, and Howard Li*

The authors would like to thank **Julian Straub** and **Liam Paull** for their help in presenting the paper.

* University of New Brunswick, Fredericton, NB Canada

** Defence Research and Development Canada-Suffield, Medicine Hat, AB Canada

Outline

- Introduction
- Background of Research and Problem Statement
- Proposed Method
- Experimental Results
- Conclusion

Introduction

- Simultaneous localization and mapping (SLAM)
 - Multiple robot SLAM
 - Problems:
 - unknown relative poses,
 - uncertainty of the relative poses,
 - updating maps and trajectories,
 - communication,
 - Scalability, ... [1]
- This paper:
 - Integrates particle filtering with map merging:
 - Propagating the uncertainty of the relative poses
 - Updating maps and poses

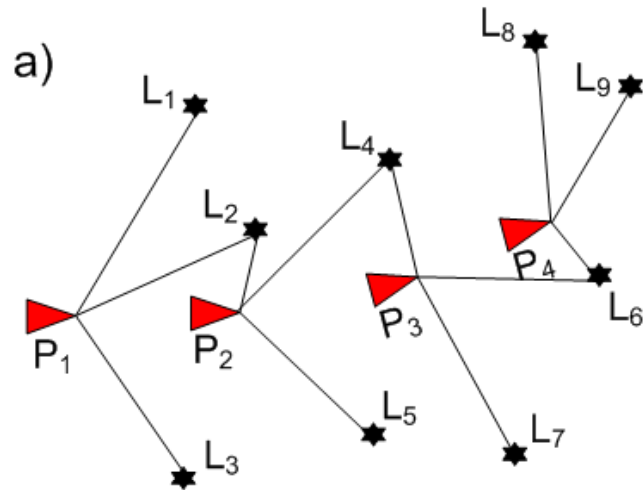
[1] Sajad Saedi, Michael Trentini, Mae Seto, and Howard Li, “Multiple-robot Simultaneous Localization and Mapping - A Review”, *Journal of Field Robotics*, pp. 1-44, 2015.

Outline

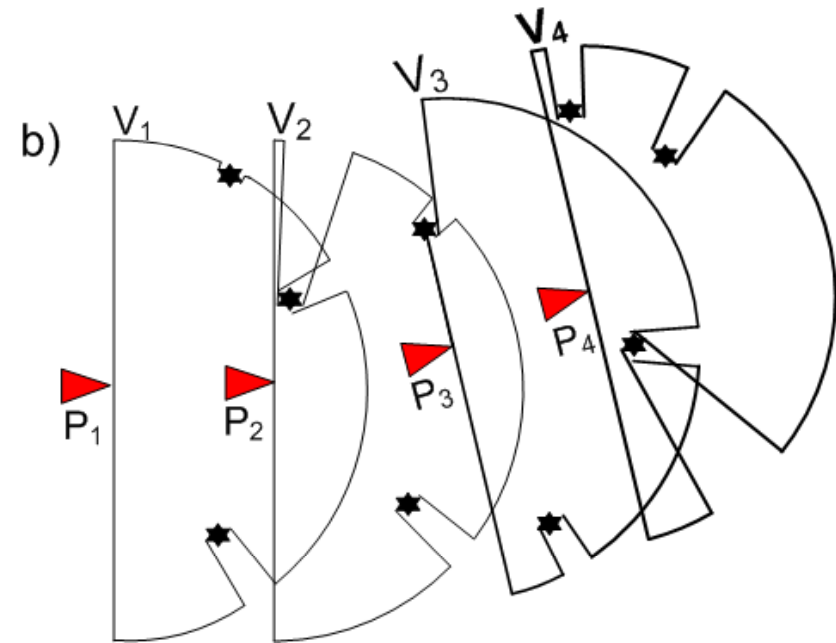
- Introduction
- Background of Research and Problem Statement
- Proposed Method
- Experimental Results
- Conclusion

Background of Research

- Feature-based SLAM and view-based SLAM



feature-based SLAM



View-based SLAM

Background of Research

- Particle filtering algorithms:
 - S. Thrun (IJRR 1901)
 - A. Howard (IJRR 1906)
 - L. Carlone et al. (ICRA 1910)
 - ...
- Particle filter
 - Main advantage: models nonlinearity of the system
 - Main disadvantage: space complexity

Outline

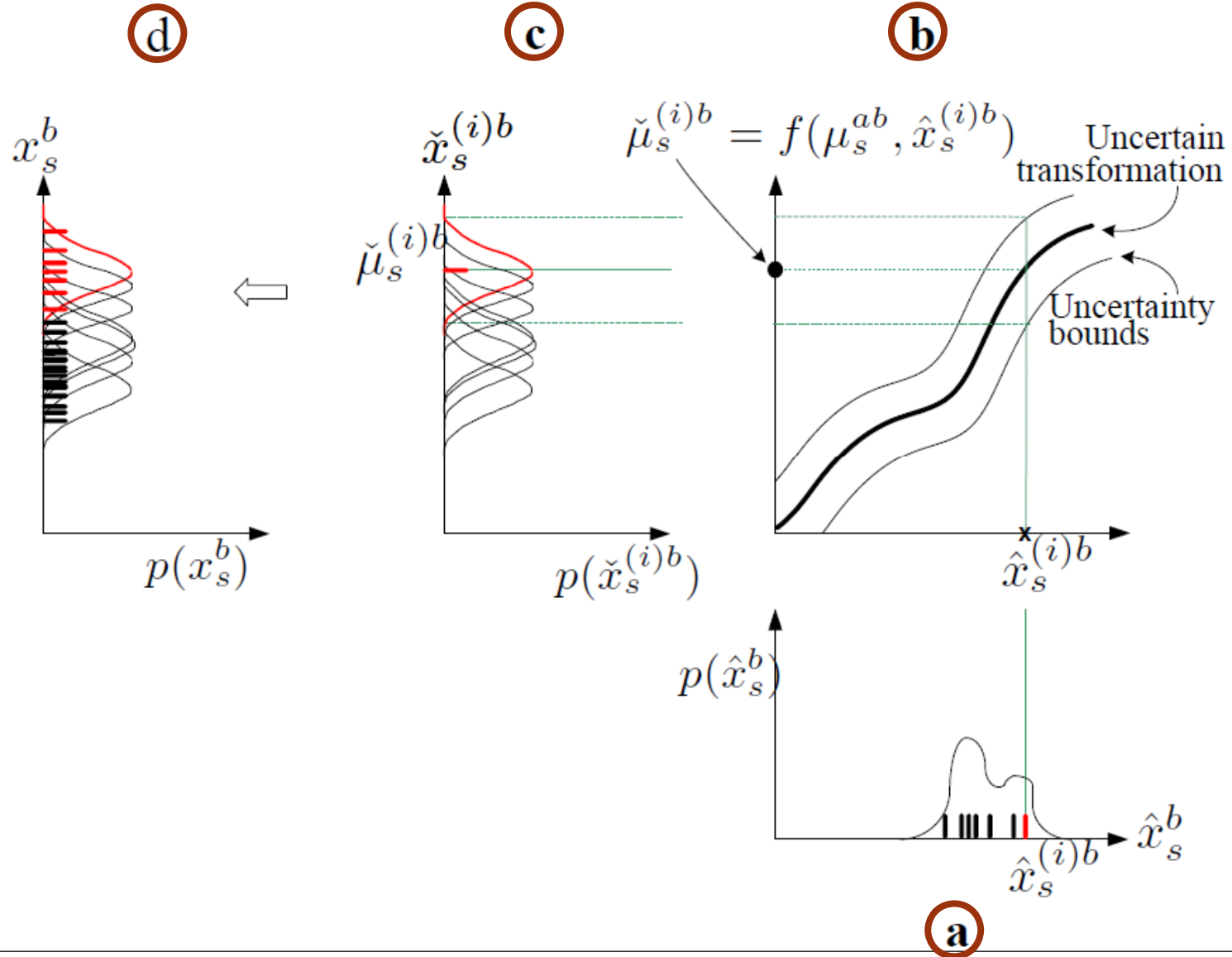
- Introduction
- Background of Research and Problem Statement
- *Proposed Method*
- Experimental Results
- Conclusion

Proposed Method

- **Before relative pose are known**
- **After relative pose are known**
- **Batch Integration:**
 - the integration of the information, maps and poses, from multiple robots prior to the time that the relative poses were known.
 - Batch integration is done in two steps:
 - **particle regeneration:** deals with uncertainty of the relative pose
 - **batch update:** deals with fast update of the past information

Proposed Method

- **Batch Integration** \rightarrow particle regeneration



Proposed Method

Algorithm 1 Particle regeneration:

$S_s^b = \text{particleRegeneration}(\hat{S}_s^b, \delta_s^{ab})$

Require: set of particles of posterior before the transformation at time s : \hat{S}_s^b ,
uncertain transformation between robots a and b at time s : δ_s^{ab} .

Ensure: set of particles of posterior after the transformation at time s : S_s^b .

- 1: $S_s^b \leftarrow \emptyset$
- 2: $\mu_s^{ab} \leftarrow \text{mean}(\delta_s^{ab})$
- 3: $\Sigma_s^{ab} \leftarrow \text{cov}(\delta_s^{ab})$
- 4: $\hat{n}^b \leftarrow \|\hat{S}_s^b\|$
- 5: **for** $i = 1 \rightarrow \hat{n}^b$ **do**
- 6: $\langle \hat{x}_s^{b(i)}, \hat{m}_s^{b(i)}, \hat{w}_s^{b(i)} \rangle \leftarrow \hat{S}_s^{b(i)}$
- 7: $\check{\mu}_s^{(i)b} \leftarrow f(\mu_s^{ab}, \hat{x}_s^{(i)b})$
- 8: $\check{\Sigma}_s^{(i)b} \leftarrow F_\delta \Sigma_s^{ab} F_\delta'$
- 9: $p(\check{x}_s^{(i)b}) \sim \mathcal{N}(\check{x}_s^{(i)b}; \check{\mu}_s^{(i)b}, \check{\Sigma}_s^{(i)b})$
- 10: $m_s^{b(i)} \leftarrow \text{lup}(\hat{m}_s^{b(i)}, \mu_s^{ab}, \Sigma_s^{ab})$
- 11: **for** $j = 1 \rightarrow \lceil \frac{n}{\hat{n}^b} \rceil$ **do**
- 12: sample $x_s^{(j)b} \sim p(\check{x}_s^{(i)b})$
- 13: $S_s^b \leftarrow S_s^b \cup \langle x_s^{(j)b}, m_s^{b(i)}, \hat{w}_s^{b(i)} \rangle$
- 14: **end for**
- 15: **end for**
- 16: return S_s^b

Proposed Method

- Fusing maps of the particles, using map merging

Algorithm 2 Batch update: $S_s^{ab} = \text{batchUpdate}(S_s^a, S_s^b)$

Require: set of particles representing posterior at time s : S_s^a ,
set of particles representing posterior at time s : S_s^b .

Ensure: set of particles representing joint posterior at time s :
 S_s^{ab} .

```
1:  $S_s^{ab} \leftarrow \emptyset$ 
2:  $S_s^a \leftarrow \text{populate}(S_s^a, n)$ 
3: for  $i = 1 \rightarrow n$  do
4:    $\langle x_s^{(i)a}, m_s^{(i)a}, w_s^{(i)a} \rangle \leftarrow \text{rand}(S_s^a)$ 
5:    $\langle x_s^{(i)b}, m_s^{(i)b}, w_s^{(i)b} \rangle \leftarrow \text{rand}(S_s^b)$ 
6:    $m_s^{(i)ab} \leftarrow \text{fuse}(m_s^{(i)a}, m_s^{(i)b})$ 
7:    $w_s^{(i)ab} \leftarrow w_s^{(i)a} w_s^{(i)b}$ 
8:    $S_s^{ab} \leftarrow S_s^{ab} \cup \langle x_s^{(i)a}, x_s^{(i)b}, m_s^{(i)ab}, w_s^{(i)ab} \rangle$ 
9: end for
10:  $S_s^{ab} \leftarrow \text{normalize}(S_s^{ab})$ 
11: return  $S_s^{ab}$ 
```

- Fuse(.) function explained in

[2] Sajad Saeedi, Liam Paull, Michael Trentini, and Howard Li,

“Group Mapping: A Topological Approach to Map Merging for Multiple Robots”,

IEEE Robotics and Automation Magazine, 21(2), pp. 60-72, 2014.

Proposed Method

- Integration of Particle regeneration(9)
And
Batch update (10)

Algorithm 3 Hybrid method:

$(P_t, mode) = \text{hybrid}(u_t^a, u_t^b, z_t^a, z_t^b, P_{t-1}, mode)$

```
1: if  $mode = \text{singleRobotSLAM}$  then
2:    $(S_{t-1}^a, S_{t-1}^b) \leftarrow P_{t-1}$ 
3:    $S_t^a = \text{singleRobotSLAM}(S_{t-1}^a, u_t^a, z_t^a)$ 
4:    $S_t^b = \text{singleRobotSLAM}(S_{t-1}^b, u_t^b, z_t^b)$ 
5:    $(\delta_t^{ab}, success) \leftarrow \text{relativePose}(S_t^a, S_t^b)$ 
6:   if  $success = \text{false}$  then
7:      $P_t \leftarrow (S_t^a, S_t^b)$ 
8:   else
9:      $S_t^b = \text{particleRegeneration}(S_t^b, \delta_t^{ab})$ 
10:     $S_t^{ab} = \text{batchUpdate}(S_t^a, S_t^b)$ 
11:     $mode = \text{multipleRobotSLAM}$ 
12:     $P_t \leftarrow S_t^{ab}$ 
13:   end if
14:   return  $(P_t, mode)$ 
15: else
16:    $S_{t-1}^{ab} \leftarrow P_{t-1}$ 
17:    $S_t^{ab} = \text{multipleRobotSLAM}(S_{t-1}^{ab}, u_t^a, u_t^b, z_t^a, z_t^b)$ 
18:    $P_t \leftarrow S_t^{ab}$ 
19:   return  $(P_t, mode)$ 
20: end if
```

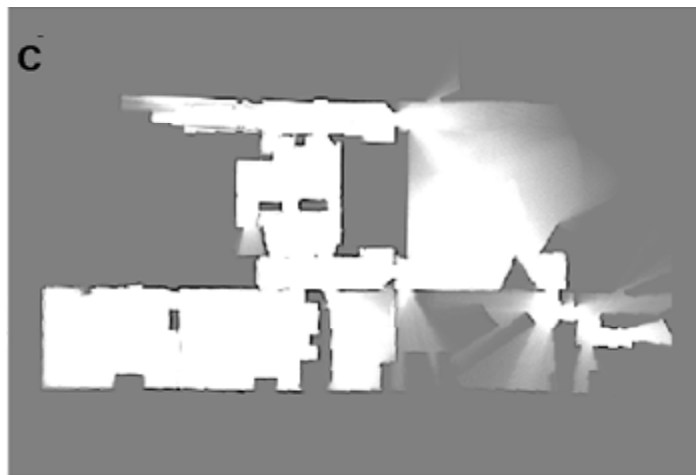
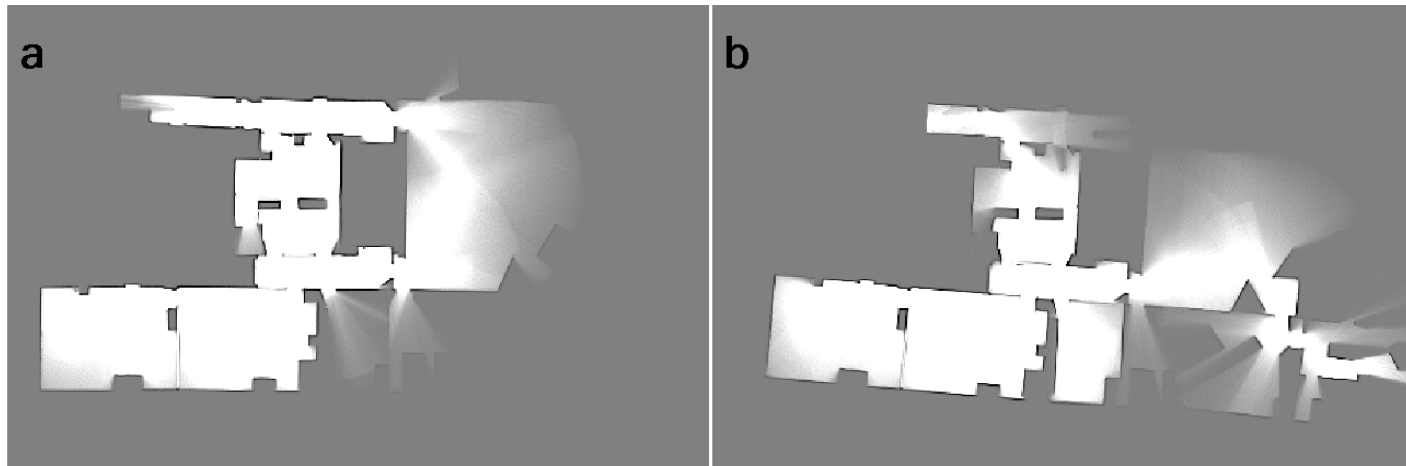
[3] Sajad Saeedi, Liam Paull, Michael Trentini, Mae Seto, and Howard Li, “Map Merging for Multiple Robots Using Hough Peak Matching”,
Robotics and Autonomous Systems, 62(10), pp. 1408-1424, 2014

Outline

- Introduction
- Background of Research and Problem Statement
- Proposed Method
- Experimental Results
- Conclusion

Experimental Results

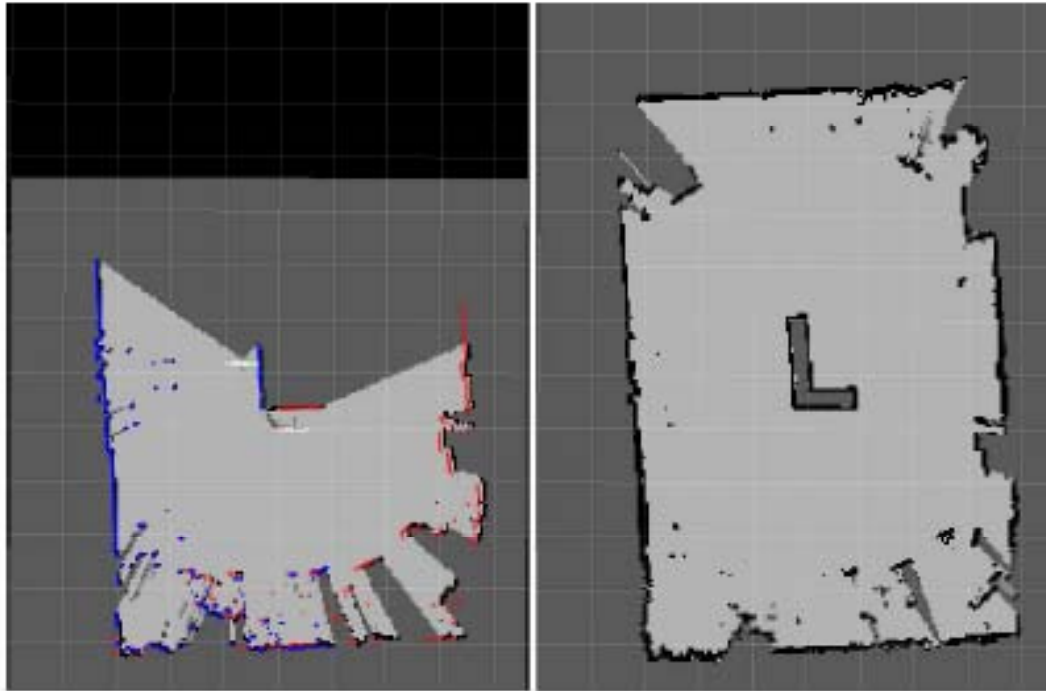
- Experiment 1: RADISH data set, Fort AP Hill





For the real-world experiment, two CoroBot robots were used in a VICON lab.

Experimental Results



Map of the VICON lab at the early stage. Blue and red points are laser beams of the Corobot robots (left). Final map of the VICON lab (right).

The trajectory error of the **Hybrid Algorithm** is **3.5%** less than **A. Howard's** algorithm.

The time required to update the information in the batch mode was \approx **0.25 seconds**

The time required to update the maps using A. Howard's algorithm was \approx **12 seconds**

Outline

- Introduction
- Background of Research and Problem Statement
- Map Merging with Hough Transforms
- Experimental Results
- Conclusion

Conclusions

- The unknown relative poses is addressed by integrating a map merging algorithm with the particle filtering.
- The uncertainty of the relative poses was taken into account using a novel algorithm.
- The integration of the information was performed in a batch mode which reduces the time complexity.

- Future works:
 - Improve time-space complexity

Thank You.

Email: *sajad.saeedi.g@unb.ca*