

CBGL: Fast Monte Carlo Passive Global Localisation of 2D LIDAR Sensor

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ΑΡΙΣΤΟΤΕΛΕΙΟ
ΠΑΝΕΠΙΣΤΗΜΙΟ
ΘΕΣΣΑΛΟΝΙΚΗΣ

Summary

Given

- a single 2D LIDAR measurement
- the map of the sensor's environment

CBGL \Rightarrow global localisation ~ 1.0 sec / 100m²

Summary

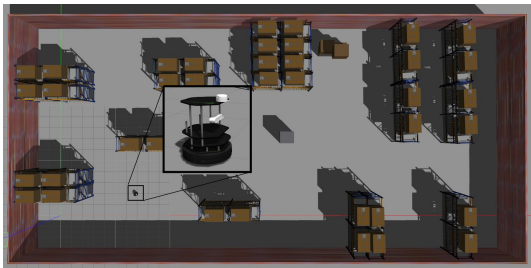
Given

- a single 2D LIDAR measurement
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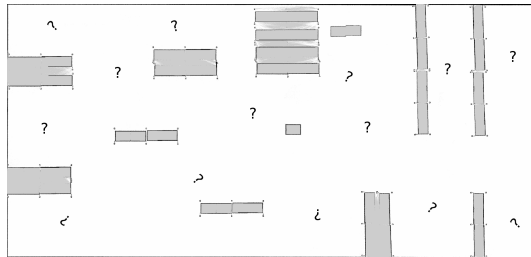
CBGL \Rightarrow global localisation ~ 1.0 sec /100m², robust to

- varying maximum sensor range
- varying field of view
- sensor & map noise
- similar surroundings

Global Localisation

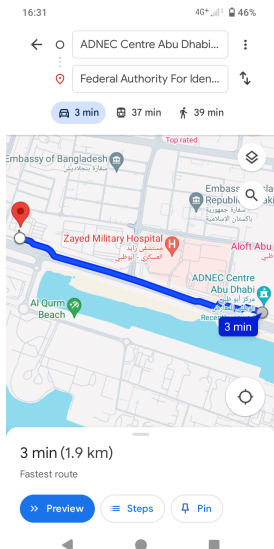


(a) Environment + robot

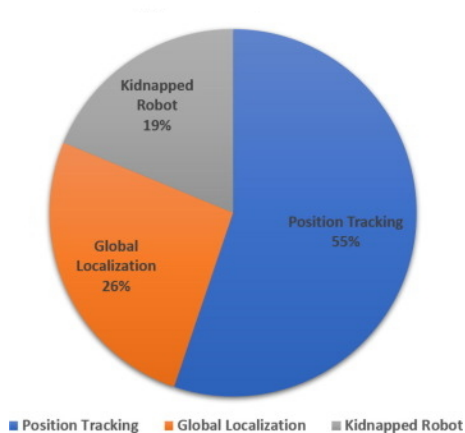


(b) Map of environment

Global Localisation



Localisation problems in mobile robotics



Prabin Kumar Panigrahi, Sukant Kishoro Bisoy, "Localization strategies for autonomous mobile robots: A review" *Journal of King Saud University - Computer and Information Sciences*, 2022

Why global localisation in the first place?

Need for observer-based localisation due to:

- Indoors are GPS/GNSS-denied
- MoCap systems N/A

Contributions of this paper

- Fastest Monte Carlo method for 2D LIDAR/map
(Cumulative Absolute Error per Ray (CAER) $\sim \mathcal{O}(N)$ [1])

[1] A. Filotheou, G. D. Sergiadis and A. G. Dimitriou, "FSM: Correspondenceless scan-matching of panoramic 2D range scans," *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, Kyoto, Japan, 2022

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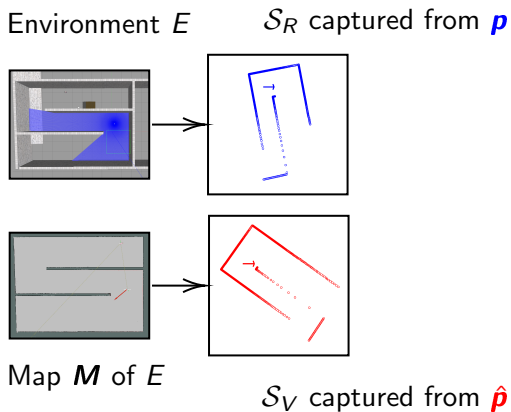
- Fastest Monte Carlo method for 2D LIDAR/map
(Cumulative Absolute Error per Ray (CAER) $\sim \mathcal{O}(N)$ [1])
- Higher discovery rates
- Extension and validation of pose-estimate-hierarchy-extraction-logic from CAER values [2]

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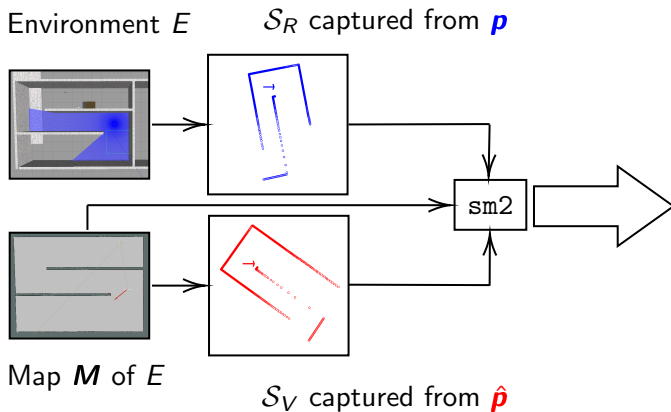
[2] A. Filotheou, A. L. Symeonidis, G. D. Sergiadis, and A. G. Dimitriou, "Correspondenceless scan-to-map-scan matching of 2D panoramic range scans", *Array*, 2023

Background (0/3)

Background (1/3): Map-scan



Background (2/3): Scan-to-map-scan matching (sm2)



Background (3/3): Cumulative Absolute Error per Ray (CAER)

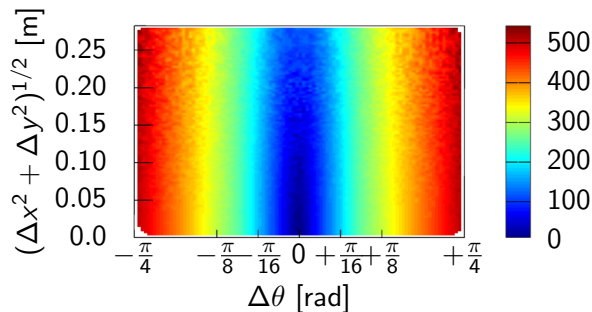
$$\psi(\mathcal{S}_R(\mathbf{p}), \mathcal{S}_V(\hat{\mathbf{p}})) = \sum_{n=0}^{N_s-1} \left| \mathcal{S}_R[\theta_n] - \mathcal{S}_V[\theta_n] \right|, \text{ where}$$

$$\theta_n = -\frac{\lambda}{2} + n \cdot \frac{\lambda}{N_s}, n = 0, 1, \dots, N_s - 1$$

Background (3/3): Cumulative Absolute Error per Ray (CAER)

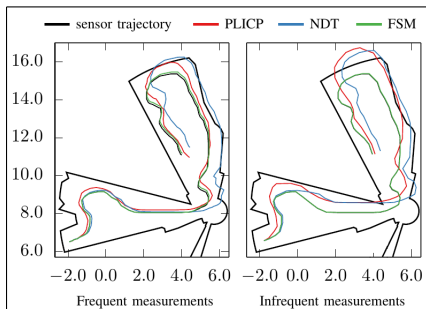
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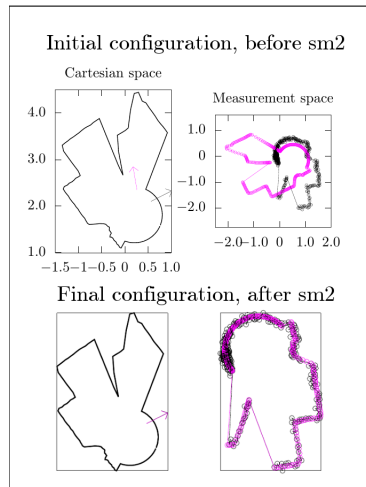
CAER uses so far

Scan-matching



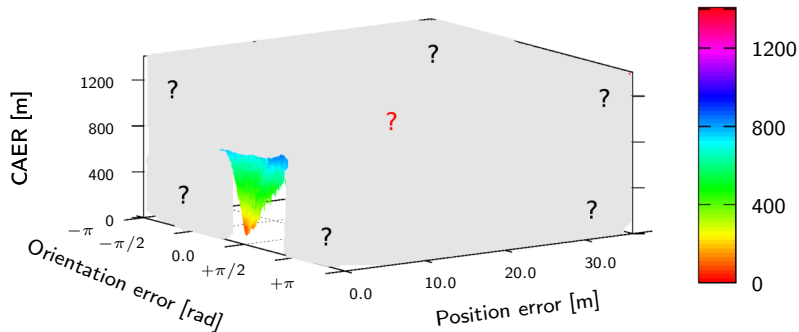
(a) A. Filotheou, G. D. Sergiadis and A. G. Dimitriou, "FSM: Correspondenceless scan-matching of panoramic 2D range scans," 2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Kyoto, Japan, 2022

Scan-to-map-scan matching

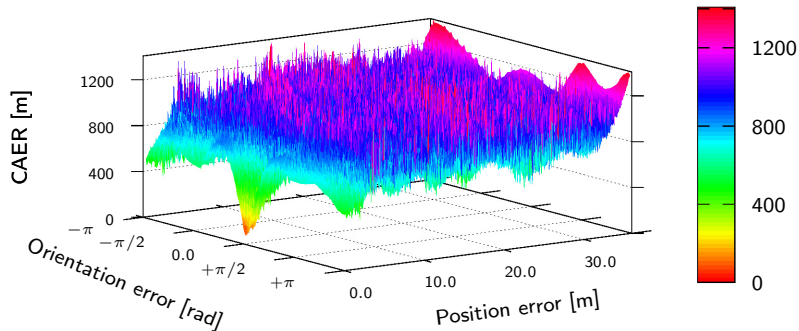


(b) A. Filotheou, A. L. Symeonidis, G. D. Sergiadis, and A. G. Dimitriou, "Correspondenceless scan-to-map-scan matching of 2D panoramic range scans", Array, 2023

CAER far from sensor pose?



CAER far from sensor pose



CAER-Based Global Localisation: CBGL

Algorithm CBGL

Require: $S_R, \lambda, \mathbf{M}, (d_l, d_\alpha), k$

Ensure: Pose estimate of sensor measuring S_R

```
1:  $A \leftarrow \text{calculate\_area}(\text{free}(\mathbf{M}))$ 
2:  $\mathcal{H}, \mathcal{H}_1, \mathcal{H}_2 \leftarrow \{\emptyset\}$ 
3: for  $i \leftarrow 0, 1, \dots, d_l \cdot A - 1$  do
4:    $(\hat{x}, \hat{y}, \hat{\theta}) \leftarrow \text{disperse\_dense\_pose}(\text{free}(\mathbf{M}), \hat{\theta} \in [0, 2\pi))$ 
    $\mathcal{H} \leftarrow \text{hypotheses\_cloud\_into\_map's\_traversable\_area}(\hat{x}, \hat{y}, \hat{\theta})$ 
5:   for  $j \leftarrow 0, 1, \dots, d_\alpha - 1$  do
6:      $\mathcal{H} \leftarrow \{\mathcal{H}, (\hat{x}, \hat{y}, \hat{\theta} + j \cdot 2\pi/d_\alpha)\}$ 
7:   end for
8: end for
9:  $\mathcal{H}_1 \leftarrow \text{bottom\_k\_poses}(S_R, \mathbf{M}, \mathcal{H}, k, \lambda)$  (Alg. 2)
10: for  $i \leftarrow 0, 1, \dots, |\mathcal{H}_1| - 1$  do
11:    $\mathcal{H}_2 \leftarrow \{\mathcal{H}_2, \text{scan\_to\_map\_scan}(\text{match}(\mathcal{H}_1[i], S_R))\}$  (Alg. 1)
12: end for
13: return  $\text{bottom\_k\_poses}(S_R, \mathbf{M}, \mathcal{H}_2, 1, \lambda)$ 
```

Algorithm bottom_k_poses

Require: $S_R, \mathbf{M}, \mathcal{P}, k, \lambda$

Ensure: Set of k poses of \mathcal{P} with least CAER values, \mathcal{P}_∇

```
1:  $\Psi \leftarrow \{\emptyset\}$ 
2: for  $q \leftarrow 0, 1, \dots, |\mathcal{P}| - 1$  do
3:    $S_V^q \leftarrow S_V^M(\mathcal{P}[q]) = \text{scan\_map}(\mathbf{M}, \mathcal{P}[q], \lambda)$ 
4:    $\Psi \leftarrow \{\Psi, \text{CAER}(S_R, S_V^q)\}$ 
5: end for
6:  $[\Psi_\uparrow, I^*] \leftarrow \text{sort}(\Psi, \text{asc})$ , such that  $\Psi[I^*] = \Psi_\uparrow$ 
7: return  $\mathcal{P}_\nabla = \{\mathcal{P}[I^*[0]], \mathcal{P}[I^*[1]], \dots, \mathcal{P}[I^*[k-1]]\}$ 
```

Experiments

Experiments in real conditions (1/3)

$$r_{\max} = 30.0 \text{ m}$$

$$\lambda = 270 \text{ deg}$$

$$\text{Area} = 180 \text{ m}^2$$

Mean execution time = 1.6 sec

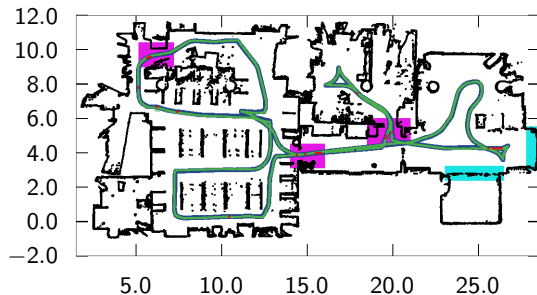


Figure: Trajectory of sensor, estimated locations, locations with error > 0.5 m

Experiments in real conditions (1/3)

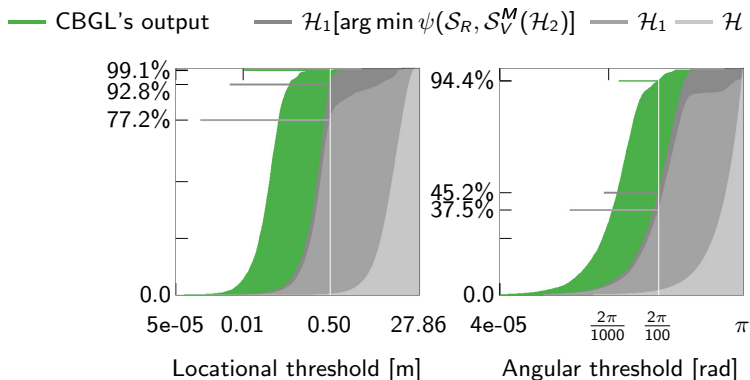


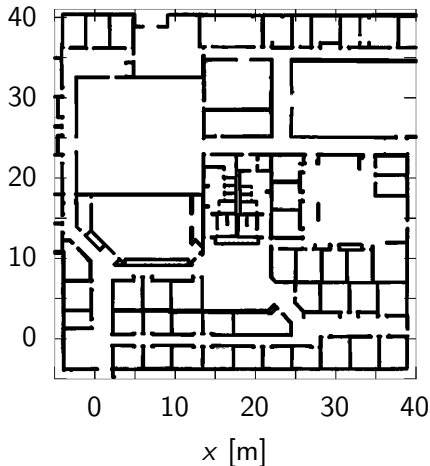
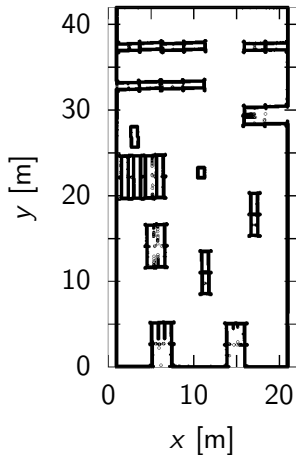
Figure: Proportions of pose estimates whose location and orientation errors are lower than corresponding acceptance thresholds

Simulations in large environments (2/3)

$$r_{\max} = 10.0 \text{ m}$$

$$\lambda = 360 \text{ deg}$$

$$\sigma_R = 0.05 \text{ m}$$

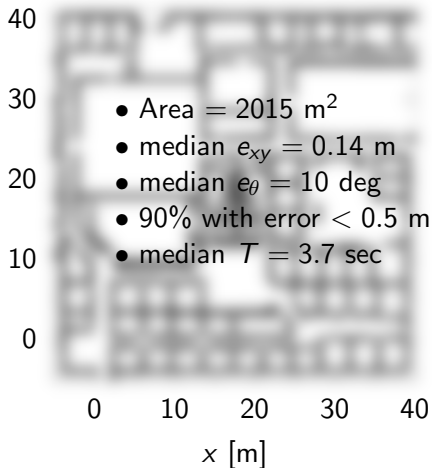
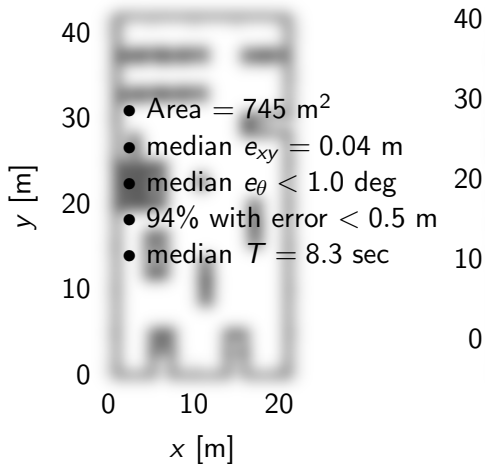


Simulations in large environments (2/3)

$r_{\max} = 10.0$ m

$\lambda = 360$ deg

$\sigma_R = 0.05$ m



Simulations in 45402 environments* (3/3)

$$r_{\max} = \inf$$

$$\lambda = 270/360 \text{ deg}$$

$$\sigma_M = 0.05 \text{ m}$$

$$\sigma_R = 0.03 \text{ m}$$

4 sm2 methods

- $\lambda_{\text{NDT}} = \lambda_{\text{FastGICP}} = \lambda_{\text{FastVGICP}} = 270 \text{ deg}$ but $\lambda_{x1} = 360 \text{ deg}$
- $\overline{e_{\mathcal{H}_1}}(\text{NDT}) \simeq \overline{e_{\mathcal{H}_1}}(\text{FastGICP}) \simeq \overline{e_{\mathcal{H}_1}}(\text{FastVGICP}) \simeq \overline{e_{\mathcal{H}_1}}(x1)$
- Execution time $\sim 1.0 \text{ sec} / 100 \text{ m}^2 @ 1 \text{ ray/deg}$

* Courtesy of the Department of Computer Science, University of Freiburg, <http://ais.informatik.uni-freiburg.de/slamevaluation/datasets.php>

Limitations

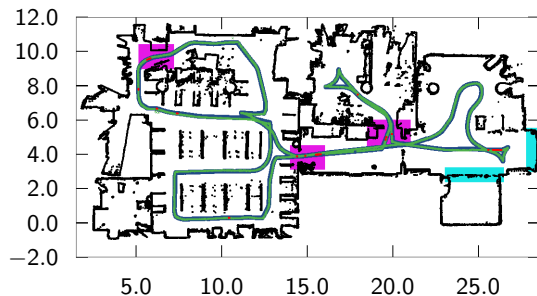


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- small k in `bottom_k_poses`

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Thank you for your attention

- Code is available at github.com/li9i/cbgl
- Presentation at github.com/li9i/cbgl_presentation_iros24