Collaborative Active SLAM and Distributed Navigation Strategies for High Precision Relative Localization in Heterogeneous Fleets of Ground and Aerial Vehicles

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CENTRALE NANTES

Laboratoire des Sciences du Numérique de Nantes

Outline

Introduction

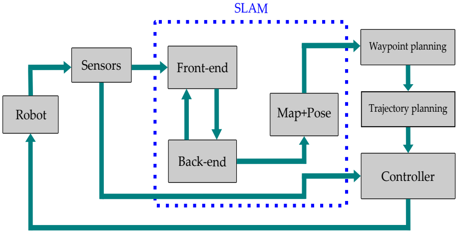
Utility Function Exploiting Path Entropy

Efficient Frontier Management

ACSLAM Using ORB Features

Conclusion

Simultaneous Localization And Mapping (SLAM)




Universidad Zaragoza

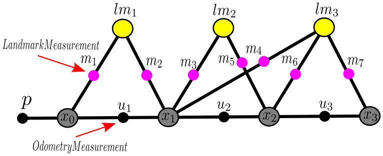
Instituto Universitario de Investigación en Ingeniería de Aragón Universidad Zaragoza

ORB-SLAM2: an Open-Source SLAM System for Monocular, Stereo and RGB-D Cameras

Raúl Mur-Artal and Juan D. Tardós

raulmur@unizar.es tardos@unizar.es

Raúl Mur-Artal and Juan D. Tardós. ORB-SLAM2: an Open-Source SLAM System for Monocular, Stereo and RGB-D Cameras. IEEE Transactions on Robotics, vol. 33, no. 5, pp. 1255-1262, 2017



What is Active SLAM (A-SLAM) problem?

- Active SLAM
  - Autonomous exploration
  - Planning and control
  - Uncertainty reduction
  - Efficient mapping and localization

- Application areas
  - Autonomous vehicles
  - Search and rescue
  - Environment monitoring
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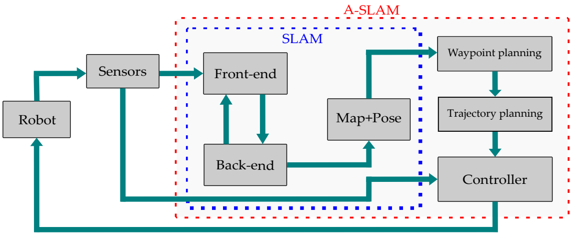

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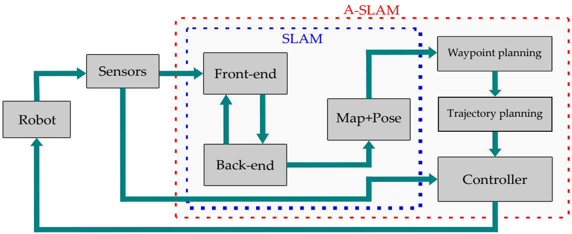

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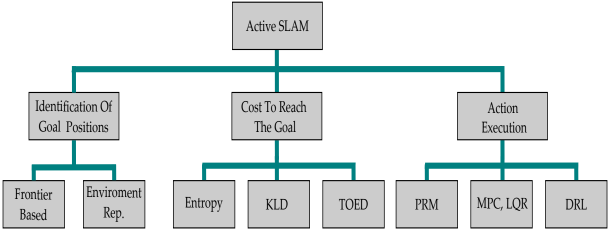

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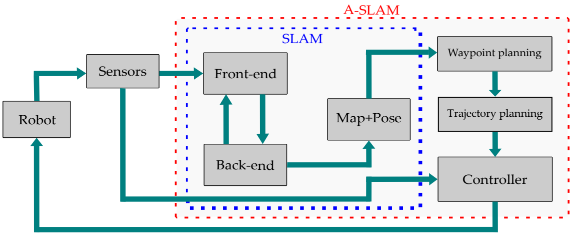

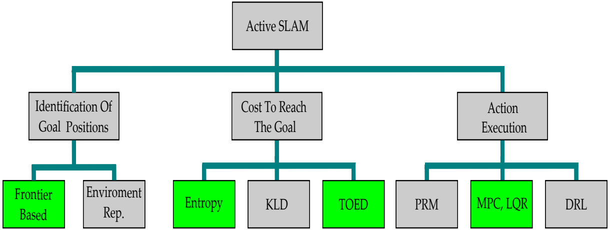

Contributions

1. Review of state-of-the-art [1]
   - Identifying the limitations
   - Proposing future research directions
2. Utility function
   - Path entropy and the modern D-optimality criterion for exploration
   - Considering SLAM uncertainty and map entropy
3. Multi agent ACSLAM framework
   - Filtering frontiers
   - Spread of agents into the environment
4. Active Visual SLAM framework
   - Frontier filtering using IoU map
   - Re-localization scheme to favor loop closure

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Introduction

- We build our approach on Autonomous Graph SLAM (AGS) [2].
- The proposed utility function[3] takes into account the path entropy and Euclidean distance

AWS Small house[4]

Frontier detection and O.G mapping

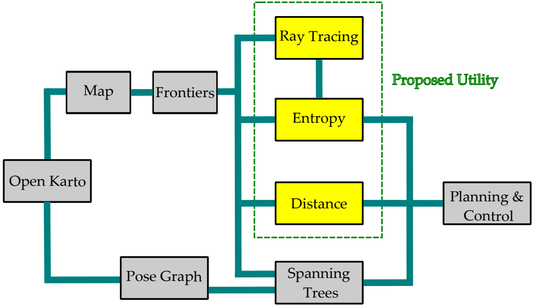
[2] Placed, J.A. et al. "Fast Autonomous Robotic Exploration Using the Underlying Graph Structure". IROS, 2021

[3] Ahmed, M.F., Frémont, V., Fantoni, I., "Active SLAM Utility Function Exploiting Path Entropy." IEEE SOLI, 2023

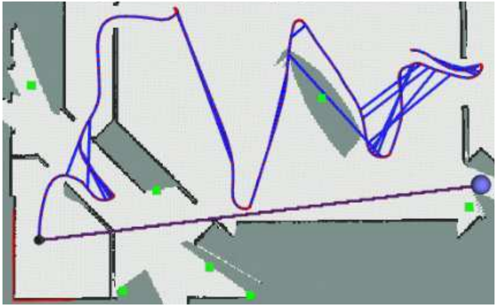
[4] https://github.com/aws-robotics/.

Proposed approach

- Ray Tracing using Bresenham's line algorithm
- Path Entropy, distance



Proposed Approach Single Robot



Proposed utility function ROS implementation

Proposed utility

1. The path entropy is computed as:

$$E^n = E^n[p(m)]_{m \in G^n} \tag{1}$$

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$$\gamma^n = \exp^{-(\lambda * dist(R,n))} \tag{3}$$

$$U_2^n = (1 - E^n/K^n) * \rho^n + \gamma^n \tag{4}$$

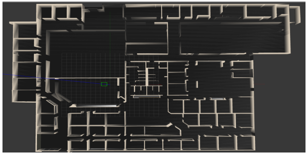
3.

$$U_1^n = \text{Spann}(L_w^n)^5 \tag{5}$$

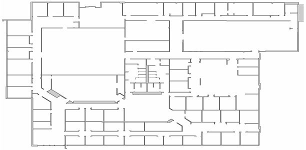
$$U_{tot} = \max(U_1^n + U_2^n) \tag{6}$$

[5] Placed, J.A. et al"Fast Autonomous Robotic Exploration Using the Underlying Graph Structure", IROS, 2021

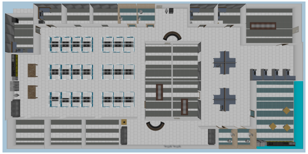
Simulation environment



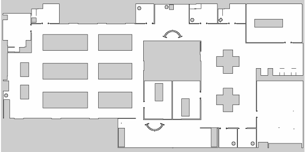
Willow Garage modified $2072m^2$



Occupancy grid map[6]



AWS Office modified $741m^2$ [7]



Occupancy grid map

[6] https://github.com/marinaKollmitz/gazebo
[7] https://github.com/aws-robotics/

Performance metrics

- Graph connectivity metrics debating on the spectral graph theory [8]
  1. Algebraic Connectivity (A.C)
  2. Average Degree of Graph ($\bar{d}$)
  3. Normalized Tree connectivity ($\hat{\tau}(\mathcal{G})$)
- Edge D-optimality

$$\text{D-Opti} = \exp\left(\frac{1}{n}\sum_{i=1}^{m} \ln(\zeta_i)\right) \tag{7}$$

- Area coverage, percentage of uncertainty reduction [%R], map quality as SSIM and RMSE.

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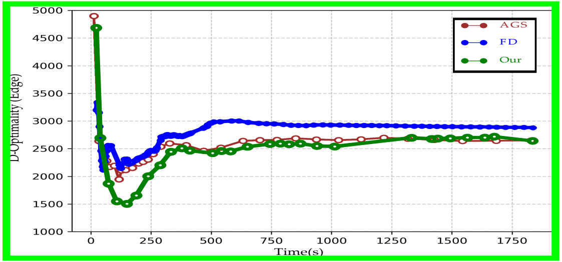
Simulation Results

Env.	Meth.	A.C	$\bar{d}$	$\hat{\tau}(\mathcal{G})$	SSIM	RMSE
W.G	FD	0.104	**3.290**	1.016	0.05	0.70
	AGS	0.426	2.907	1.139	0.05	0.64
	Our	**0.845**	2.925	**1.205**	**0.08**	**0.60**
Office	FD	3.061	**3.179**	1.229	0.09	0.83
	AGS	5.740	2.742	1.312	0.07	0.80
	Our	**9.617**	2.612	**1.941**	**0.11**	**0.77**

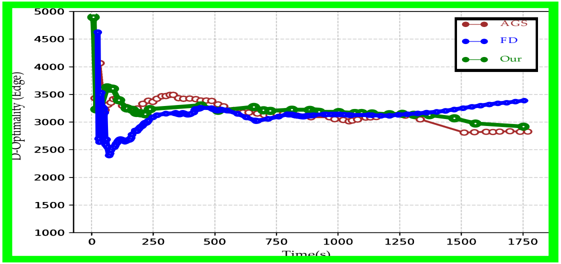
Average graph connectivity and map quality comparison of 15 simulations.

Env.	Method	D-Opti(Max&Min)	Diff	%R
W.G	FD	3700&2900	800	20
	AGS	4800&2600	2200	**45**
	Our	4700&2600	2100	44
Office	FD	4600&3400	1200	26
	AGS	4100&2700	1400	34
	Our	4900&2900	2000	**40**

Uncertainty reduction (%R) comparison



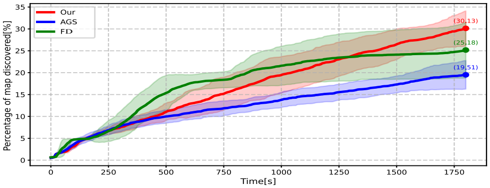
Uncertainty evolution (W.G)



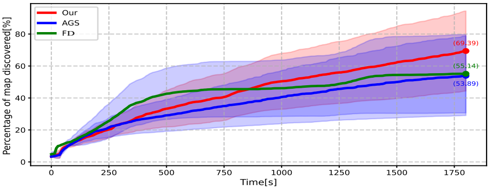
Uncertainty evolution (AWS Office)

Simulation results

- 15 simulations of 30 minutes, FD[9] (green), AGS (blue), Our (red)



Comparison of evolution of map discovered (W.G)



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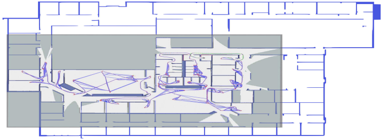
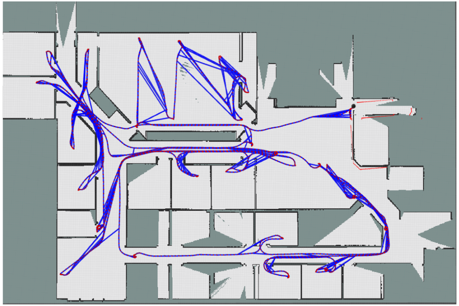


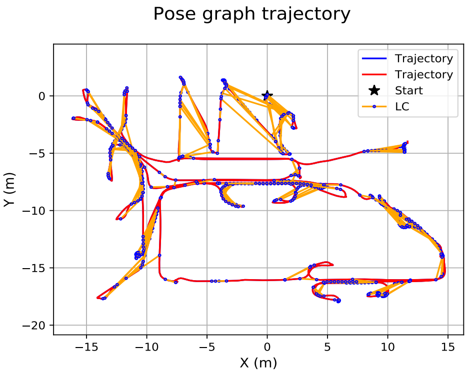
Obtained pose graphs using Our approach W.G

Obtained pose graphs using Our approach AWS Office

[9] Yamauchi, B."A frontier-based approach for autonomous exploration", IEEE CIRA'97, 1997

Simulation results





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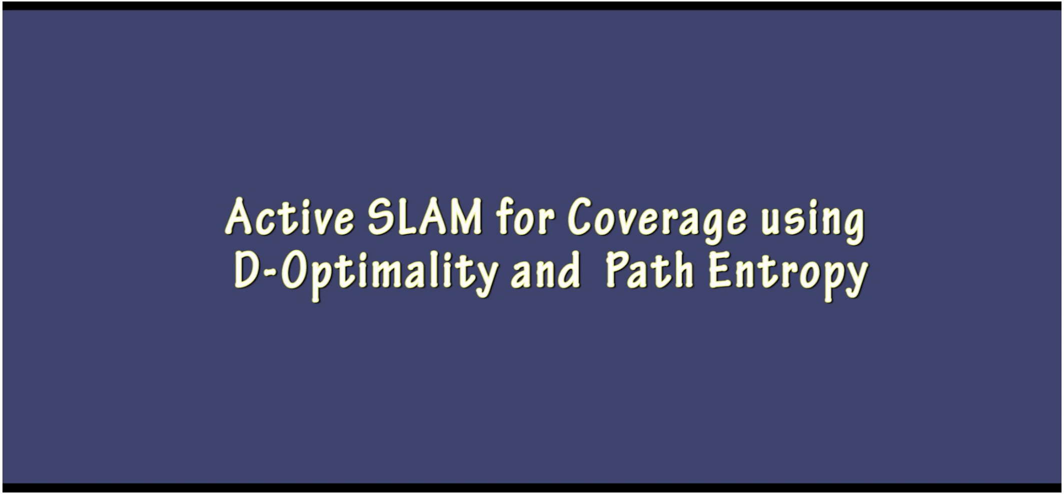
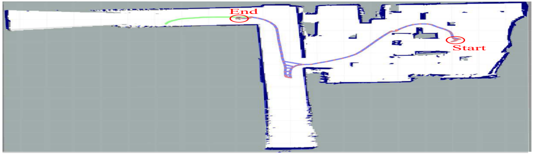
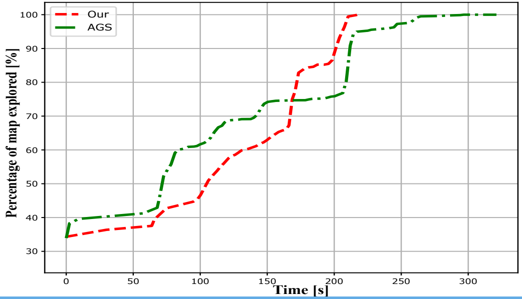


Experimental results

RosBot 2



Mapped environment



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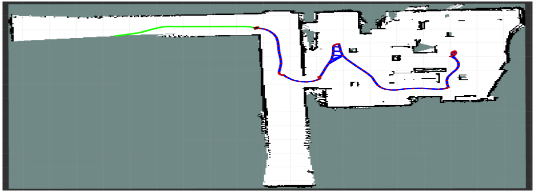
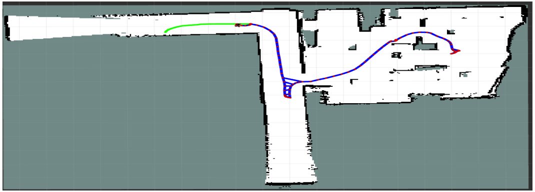
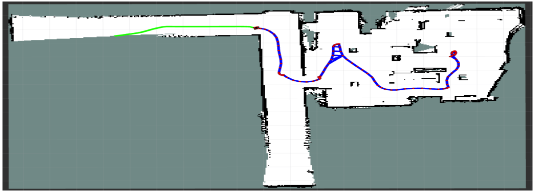


Exp 1 Our method



Exp 2 Our method

Experimental results



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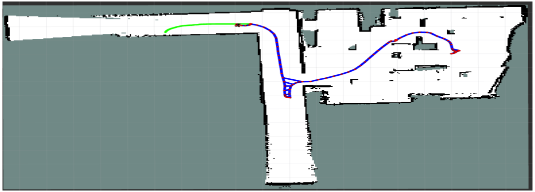

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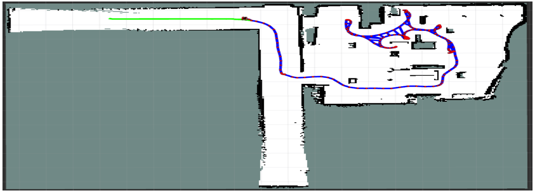
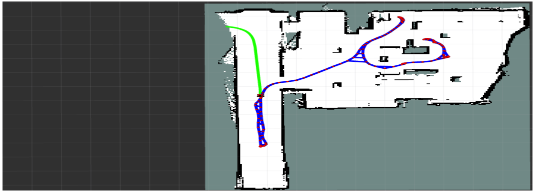


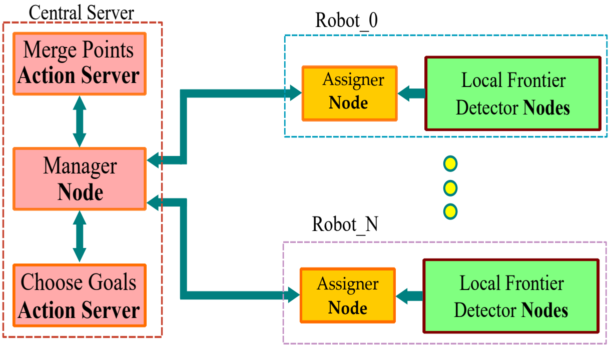
Exp 1 AGS method



Exp 2 AGS method

Proposed approach [10].

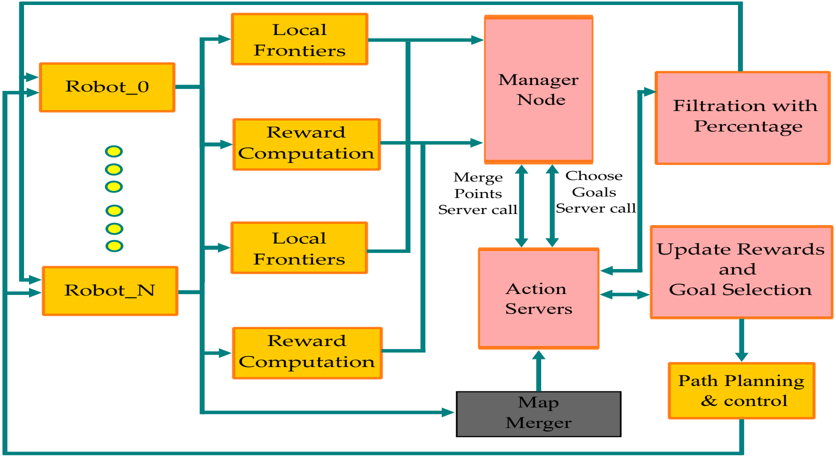
- Minimization of frontiers by using reward, distance-based, and merged map information gain metrics



Overview of the proposed method. Central server, and local nodes communication

[10] Ahmed, M.F., Maragliano, M., Frémont, V., Recchiuto, C.T., Sgorbissa, A., "Efficient Frontier Management for Collaborative Active SLAM". IEEE MFI, 2024.

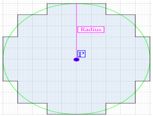
Proposed approach

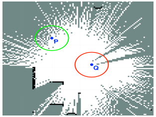


Detailed architecture of the proposed method

Proposed approach

1. *Frontiers Management (Filtration with percentage server)*





2. For a set of frontiers $F = \{f_0, f_1, \ldots, f_N\} \subset \mathbb{R}^2$, where $\forall i \in 0, 1, \ldots, N$, $f_i = (x_i, y_i)$, each robot computes a matrix of rewards $H = \{r_0, r_1, ...r_N\} \in \mathbb{R}$

$$H = \begin{bmatrix} \text{Reward} & \text{X} & \text{Y} \\ \hline r_0 & x_0 & y_0 \\ \vdots & \vdots & \vdots \\ r_N & x_N & y_N \end{bmatrix} \tag{8}$$

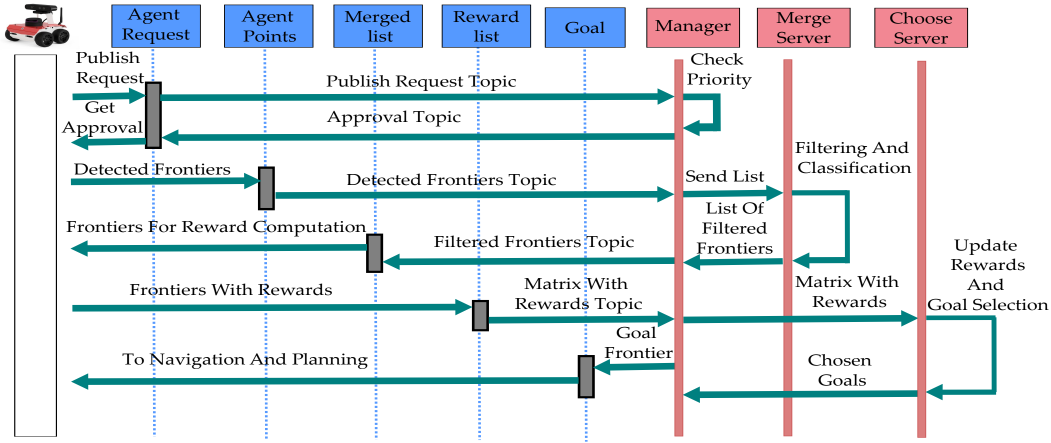
3. *Spread Policy (update rewards and goal selection)*

$$K = \frac{\texttt{max reward}}{\texttt{number of targets assigned}} \tag{9}$$

$$k = \frac{K}{d^2} \tag{10}$$

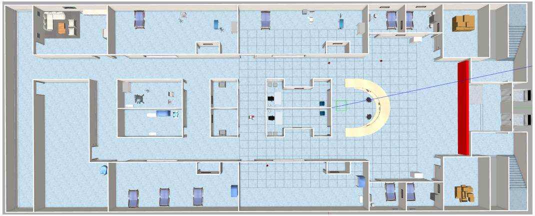
$$R_{new} = R_{old} - k \tag{11}$$

Proposed approach (sequence diagram)

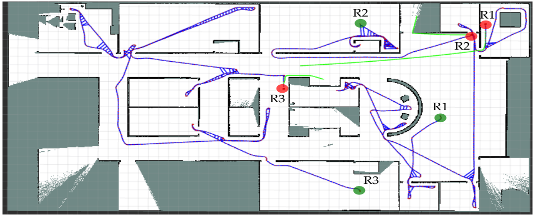


Sequence diagram. Local nodes of each robot (blue) and Server (red)

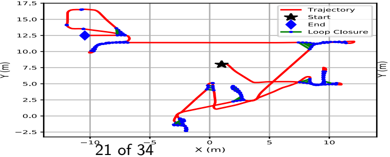
Simulation environment



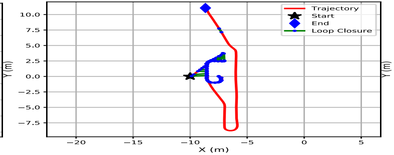
AWS Hospital $1243m^2$



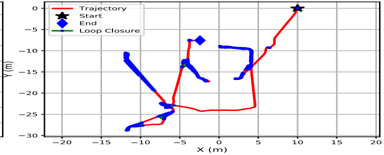
Computed OG map with pose graphs



Pose graph of Robot 1 (R1)

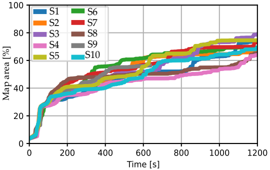


Pose graph of Robot 2 (R2)

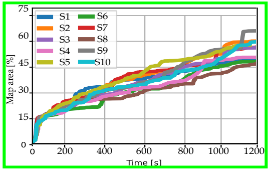


Pose graph of Robot 3 (R3)

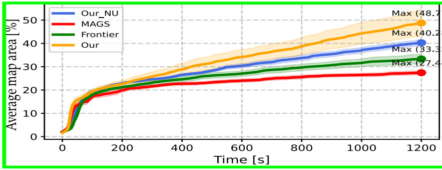
Simulation results



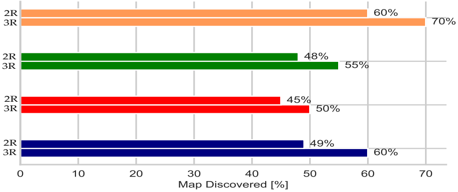
[%] of map coverage in AWS hospital



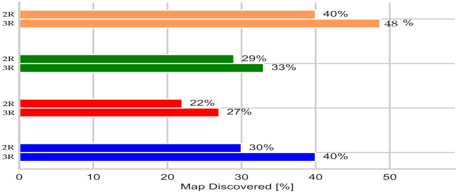
[%] of map coverage in W.G



Average [%] of map coverage W.G



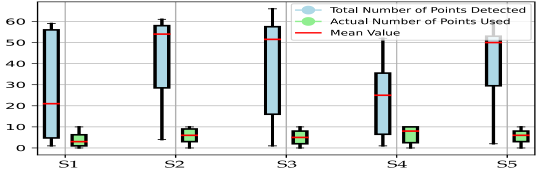
Average [%] map coverage AWS hospital



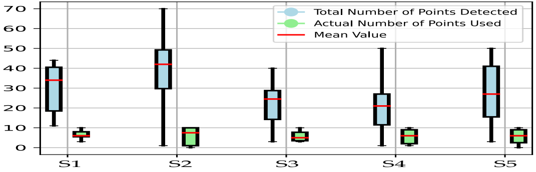
Average [%] map coverage in W.G

Simulation results

- Performance metrics
  - Area coverage
  - Average points reduction
  - `PER_UNK` and `RAD`
  - Map quality using SSIM, RMSE and AE



Number of points reduction in AWS Hospital



Number of points reduction in W.G

Simulation results

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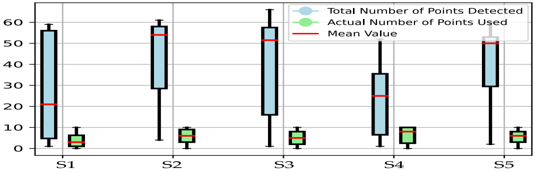
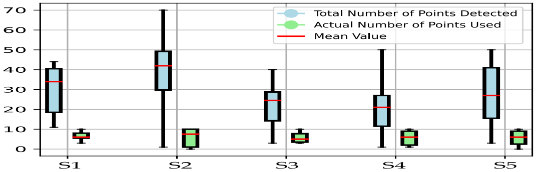


Number of points reduction in AWS Hospital



Number of points reduction in W.G

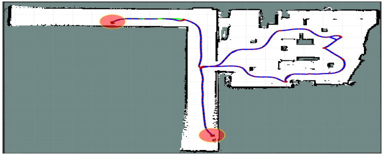
Env.	PER_UNK[%]	Used[%]	RAD[m]	Used[%]
W.G	60 %	34.5 %	1.00	**87.0 %**
	50 %	1.4 %	1.25	1.8%
	$\leq$ 40 %	**64.0 %**	$\geq$ 1.50	9.7%
HOS	60 %	**67.3**	1.00	**76.2 %**
	50 %	4.3	1.25	5.1 %
	$\leq$ 40 %	28.2 %	$\geq$ 1.50	8.5 %

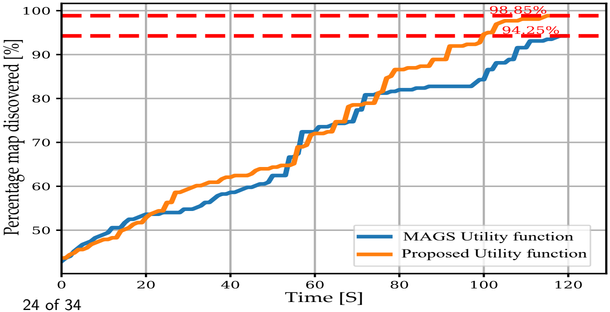
PER_UNK and RAD usage

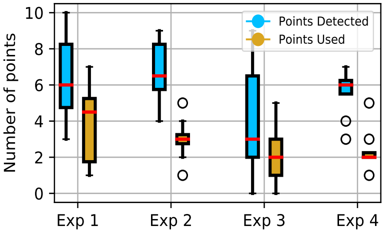
Env	Method	SSIM	RMSE	AE
W.G	Our	0.74	5.43	25.68
W.G	MAGS	**0.86**	6.34	28.39
W.G	Frontier	*0.20*	**10.04**	**40.89**
HOS	Our	**0.74**	4.89	25.39
HOS	MAGS	0.72	6.39	29.98
HOS	Frontier	0.35	**12.67**	**42.89**

Map quality metrices.

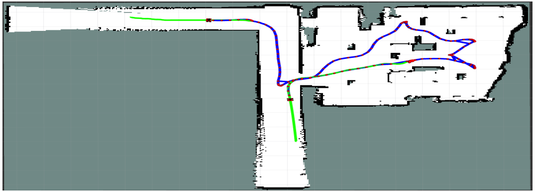
Experimental results



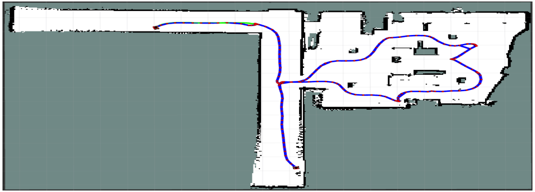




Experimental results

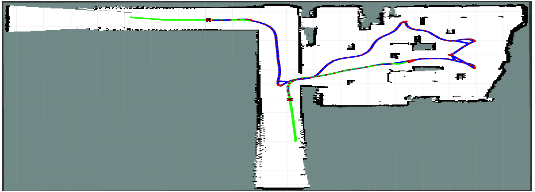


Exp 1 Our method

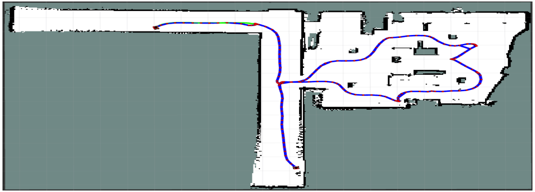


Exp 2 Our method

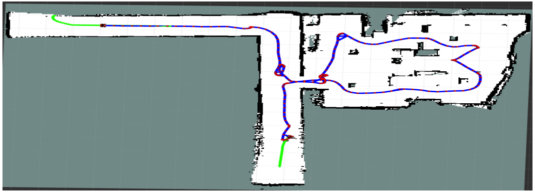
Experimental results



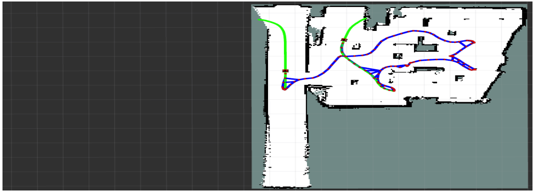
Exp 1 Our method



Exp 2 Our method



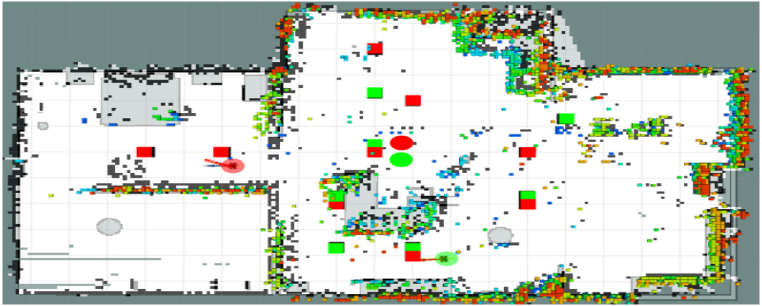
Exp 1 AGS method



Exp 2 AGS method

Introduction

- We extend Explorb-slam[11] to a multi-agent system
- Frontier filtering method that encourages the spread of agents and exploration
- Re-localization to favor loop closure



Rviz visualization of the proposed approach

[11] J. A. Placed et al."Explorb-slam: Active visual slam exploiting the pose-graph topology", ROBOT2022, 2023

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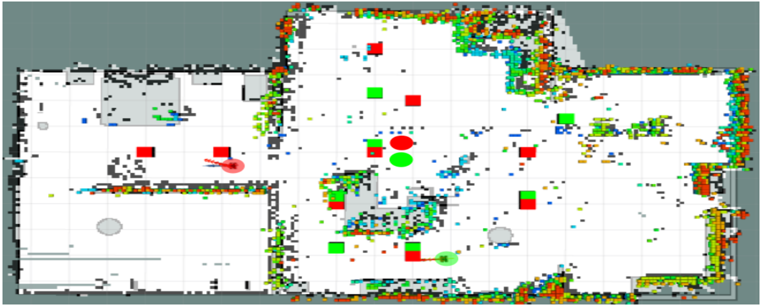

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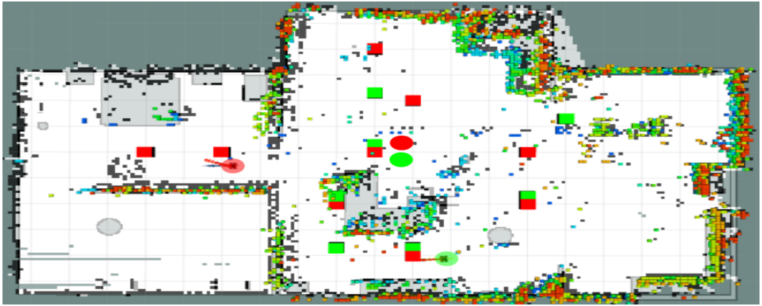

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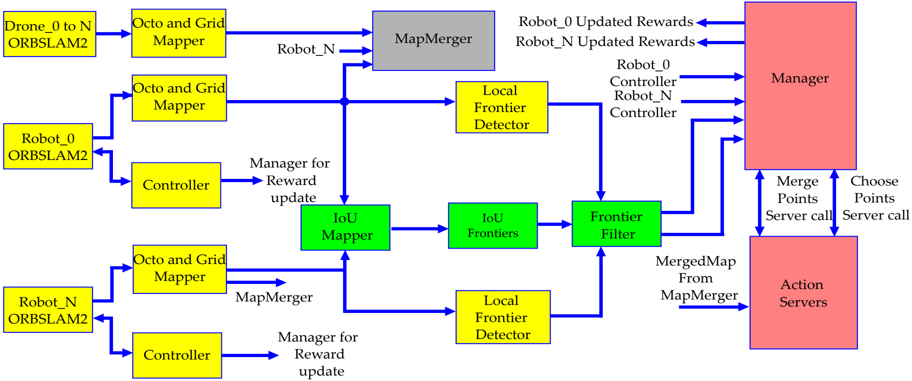
Proposed approach[12]



Central server, and local nodes communication

[12] Ahmed, M.F., Frémont, V., Fantoni, I. "Active Collaborative Visual SLAM exploiting ORB Features". **Accepted** in IEEE ICARCV 2024 conference.

Proposed approach

Algorithm 1: Frontier Filter

Input: M1_pts, IoU_pts, DIST_THRESH
Output: filtered_pts

```
all_pts ← M1_pts + IoU_pts;
filtered_pts ← ∅;
forall p in all_pts do
    too_close ← False;
    forall fp in filtered_pts do
        if dist(p, fp) < DIST_THRESH then
            too_close ← True;
            break;
    if not too_close then
        add p to filtered_pts;
return filtered_pts;
```

Algorithm 2: Saved Goal Selection Based on Entropy

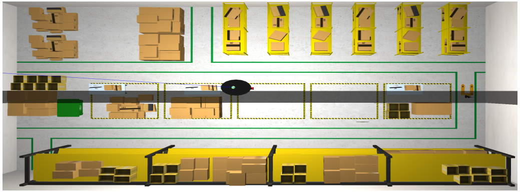
Input: SG_list, ORB_Stat, D-Opti, D_MAX, R_pos
Output: win_goal

```
if (ORB_Stat is lost) ∨ (D-Opti > D_MAX) then
    foreach item in SG_list do
        ent ← entropy(item_x, item_y, R_pos);
        egoal_list ← (1 − ent);
    win_{x,y} ← Max. value in egoal_list;
    send win_{x,y} to robot;
reloc ← reloc + 1; SG_list ← win_{x,y};
```

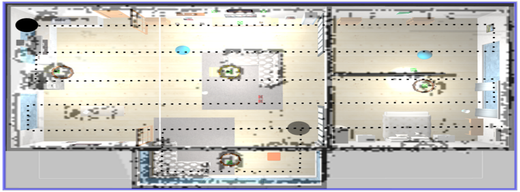
$$\text{D-Opti} = \exp\left(\frac{1}{n}\sum_{i=1}^{m}\ln(\zeta_i)\right) \quad (12)$$

Simulation Environment

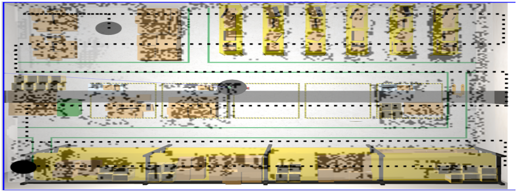
House Environment (H.E), $157M^2$



Warehouse Environment (W.E), $260M^2$



H.E drone path and map

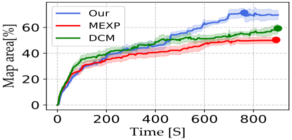


W.E drone path and map

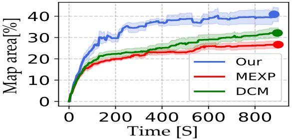
Simulation video

Simulation results

- We conducted 10 simulations of 15 minutes, comparing with MEXP[13] (red), DCM [14] (green), and Our (blue) methods
- Performance metrics
  - Average points reduction
  - Edge D-optimality
  - Spread of goals
  - SSIM, MSE, NCC, and CS



% area in H.E.



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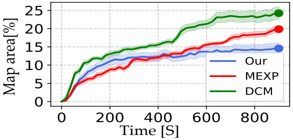
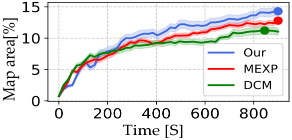


% of IoU area in H.E.



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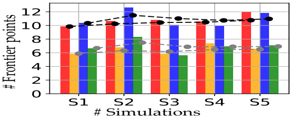
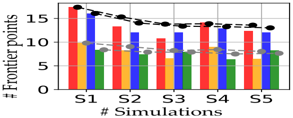


Filtered points in H.G.



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[13] J. A. Placed et al."Explorb-slam: Active visual slam exploiting the pose-graph topology", ROBOT2022, 2023
[14] Anna B. et al "Decentralized strategy for cooperative multi-robot exploration and mapping", IFAC-PapersOnLine, 2020

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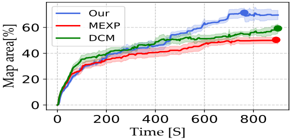

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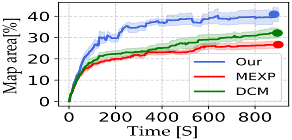

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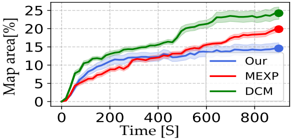
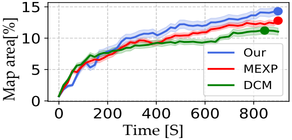


% of IoU area in H.E.



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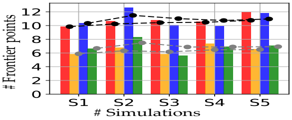

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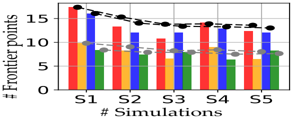

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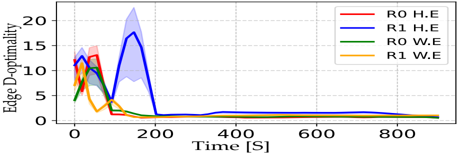
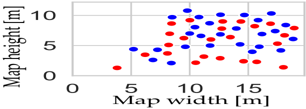
Simulation results



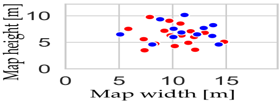
Uncertainty evolution in both environments.

House Environment										
Robot	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**	**S10**
R0	4	0	3	2	0	0	2	0	0	0
R1	0	3	1	3	0	0	0	3	6	0
Total	4	3	4	5	0	0	2	3	6	0
Warehouse Environment										
R0	4	0	1	2	1	2	1	0	0	2
R1	1	2	0	0	1	3	2	0	0	0
Total	5	2	1	2	2	5	3	0	0	2

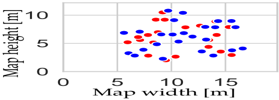
Number of re-localization efforts.



Goal points Our in H.E.



Goal points MEXP in H.E.

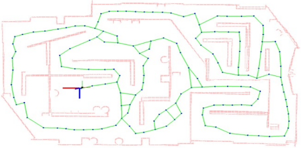


Goal points DCM in H.E.

Env	**Method**	**MSE**	**SSIM**	**NCC**	**CS**
H.E	Our	**7544.238**	**0.386**	**0.426**	**0.455**
H.E	MEXP	7673.455	0.308	0.228	0.214
H.E	DCM	8695.255	0.198	0.125	0.155
W.E	Our	**8753.571**	**0.352**	**0.415**	**0.347**
W.E	MEXP	10160.746	0.265	0.344	0.262
W.E	DCM	11059.335	0.139	0.117	0.061

Perspective

- **Environment representation (map)**

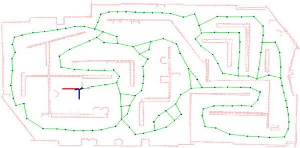


Topological (Xue et al, 2020)

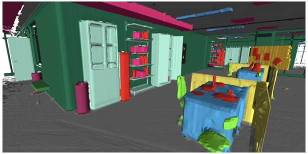
- **Uncertainty quantification**
- **Path planning**

Perspective

- **Environment representation (map)**



Topological (Xue et al, 2020)

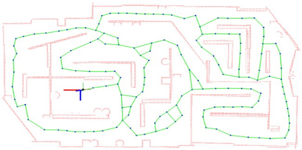


Metric-Semantic, (Rosinol et al, 2019)

- **Uncertainty quantification**
- **Path planning**

Perspective

- **Environment representation (map)**



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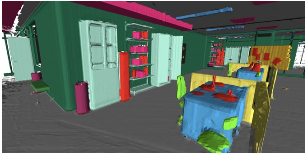

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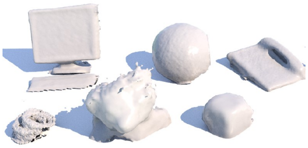
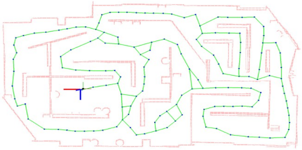


Hybrid and Hierarchical, (McCormac et al, 2018)

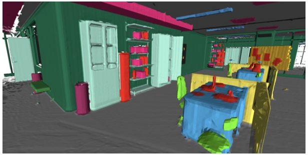
- **Uncertainty quantification**
- **Path planning**

Perspective

- **Environment representation (map)**



Topological (Xue et al, 2020)



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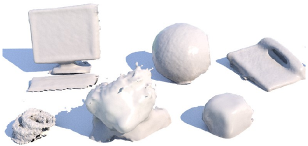

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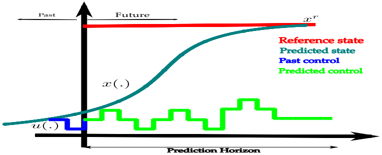
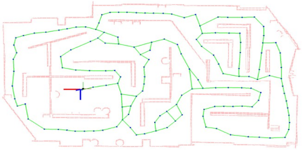


Model Predictive Control (MPC)

Perspective

- **Environment representation (map)**



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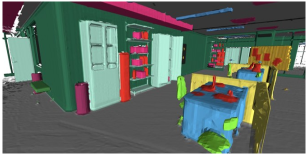

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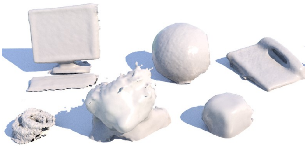

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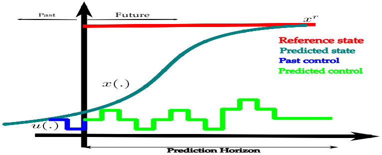
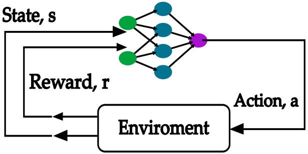


Model Predictive Control (MPC)



Deep Reinforcement Learning (DRL)

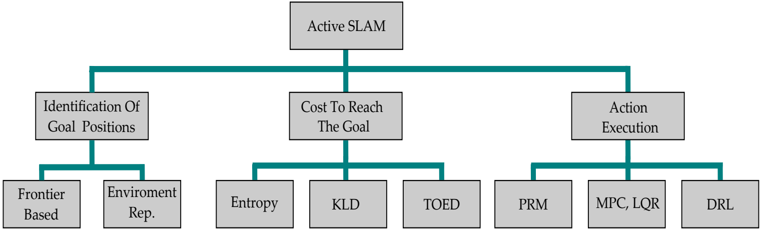
Thank you for your attention!

- Classical POMDP formulation is defined as a 7 tuple $(\mathcal{X}, \mathcal{A}, \mathcal{O}, \mathcal{T}, \rho_o, \beta, \gamma)$

$$T(x, a, x^{'}) = p(x^{'} \mid x, a) \qquad (13)$$

$$\rho_o(x, a, o) = p(o \mid x^{'}, a) \qquad (14)$$

$$\alpha^* = \underset{t}{\mathrm{argmax}} \sum_{t=0}^{\infty} \mathbb{E}\gamma^t \beta(x_t, a_t) \qquad (15)$$



ASLAM sub-modules

What Is The Active SLAM (A-SLAM) problem?

- Uncertainty quantification. IT and TOED methods.
  - *Entropy*

$$
\boxed{
\begin{aligned}
\mathcal{H}[p(x)] &= \tfrac{n}{2}(1+\log(2\pi)+\tfrac{1}{2}\log(det\Omega)) \\
\mathcal{H}[p(m)] &= -\textstyle\sum_{i,j}(p(m_{i,j})log(p(m_{i,j})) \\
&\quad + (1-p(m_{i,j}))log(1-p(m_{i,j}))
\end{aligned}
}
$$

  - Theory Of Optimal Experimantal Design (TOED)

$$\boxed{\begin{gathered} A-Optimality \\ \triangleq \tfrac{1}{n}(\textstyle\sum_{k==1}^{n}\zeta_k) \end{gathered}}$$

$$\boxed{\begin{gathered} D-Optimality \\ \triangleq exp(\tfrac{1}{n}\textstyle\sum_{k=1}^{n}log(\zeta_k)) \end{gathered}}$$

$$\boxed{\begin{gathered} E-Optimality \\ min_{1\leq i\leq n}(\zeta_i) \end{gathered}}$$

- Action execution.

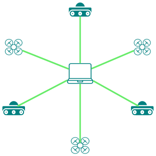
$$l(x,u) = \|x_u - x^r\|_Q^2 + \|u - u^r\|_R^2 \qquad (16)$$

$$\underset{u}{\text{minimize}}\, J_N(x_0,u) = \sum_{k=0}^{N-1} l((x_u(k),u(k))) \qquad (17)$$

$$V_\pi(s_{t_0}) = \sum_{t=t_0}^{\infty}\gamma^t r(s_t,\pi(s_t,a_t)) \qquad (18)$$

Active Collaborative SLAM (ACSLAM)

- Entropy, KLD, localization info, visual features, and frontier points
- Incorporating the multirobot constraints induced by adding the future robot paths and minimizing robot state and map uncertainty.
- Parameters relating to exploration and re-localization
- 3D Mapping info (OctoMap) and relative entropy



Centralized

Active Collaborative SLAM (ACSLAM)

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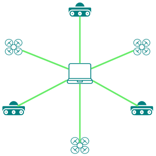
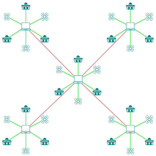


Centralized



Decentralized

Active Collaborative SLAM (ACSLAM)

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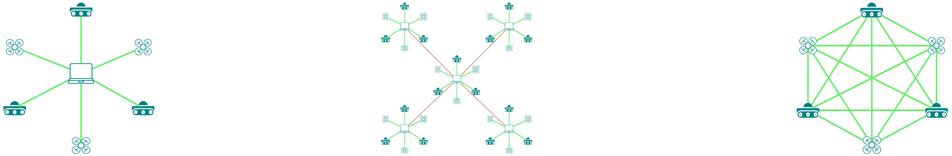
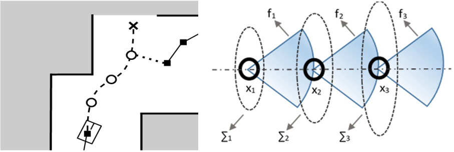


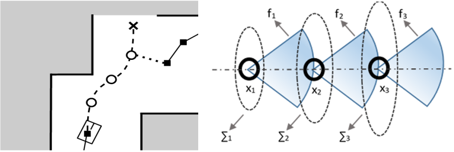
Centralized Decentralized Distributed

Related Work ASLAM



Carrillo H. et al, 2017

Related Work ASLAM



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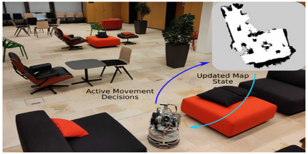
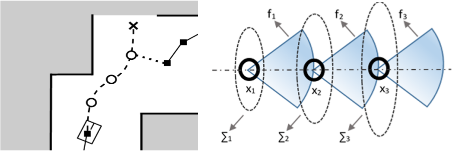


Bonetto E. et al, 2022

Related Work ASLAM



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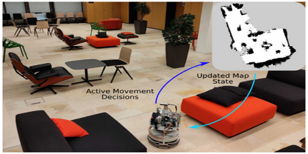

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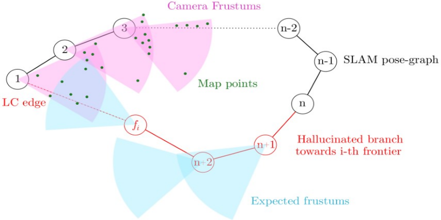

Placid J. et al, 2023

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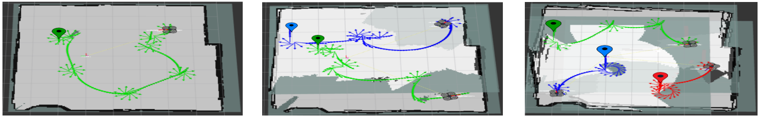

Nesrin et al, 2018

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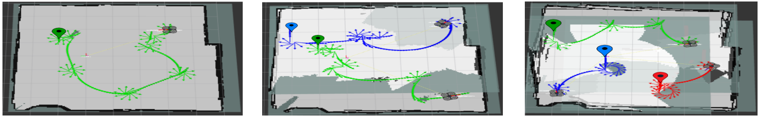

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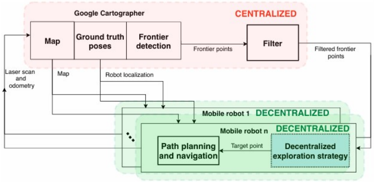

Batinovic, A. et al, 2020

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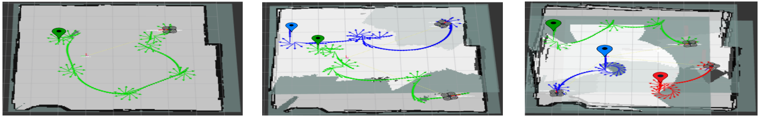

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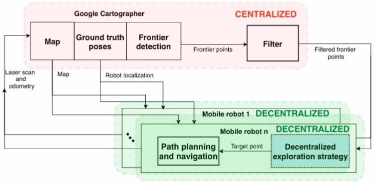

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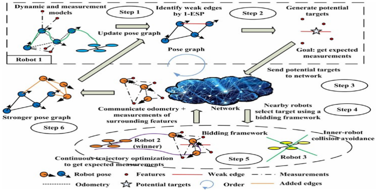
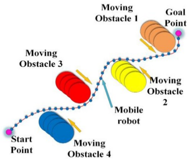


Yuguo C. et al, 2020

Limitations of existing methods[15]



Dynamic obstacles, Chen, C.S. et al, 2022

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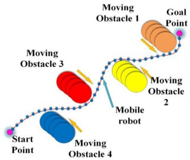

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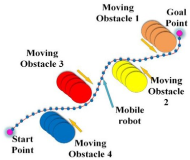

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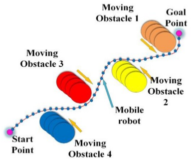

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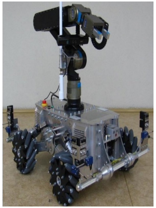

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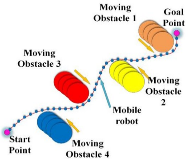

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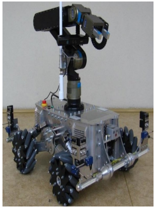

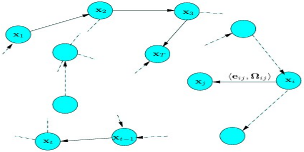

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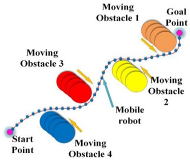

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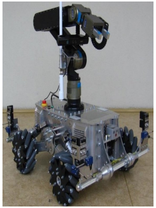

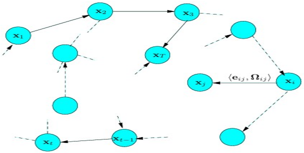

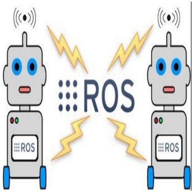

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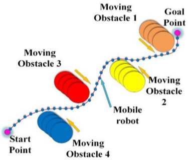

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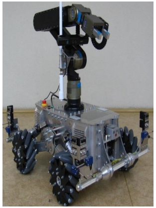

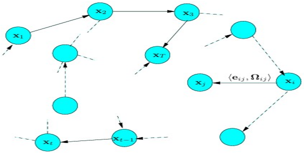

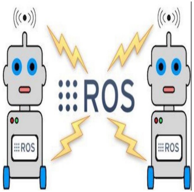

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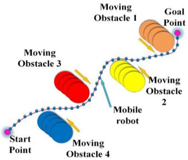

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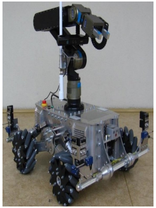

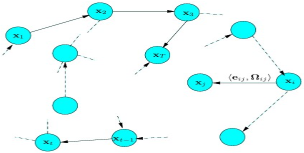

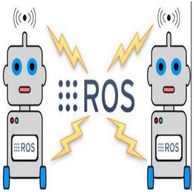

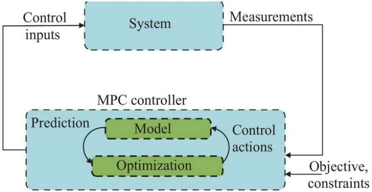

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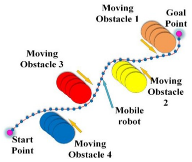

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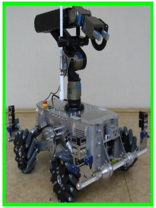

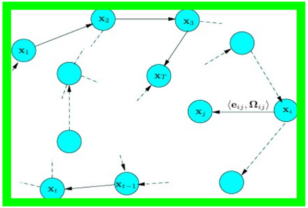

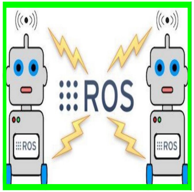

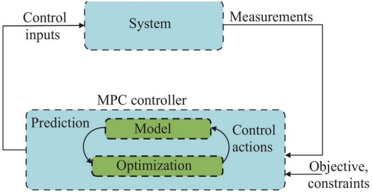

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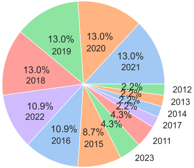
Active SLAM Review Articles Insights [16]



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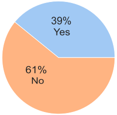

ROS.

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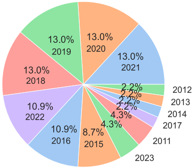

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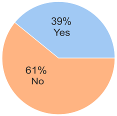

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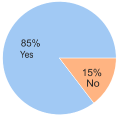

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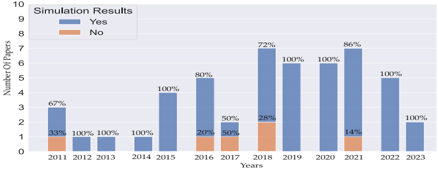

Simulation per annum.

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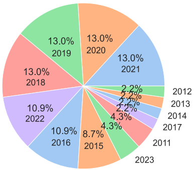
Active SLAM Review Articles Insights [16]



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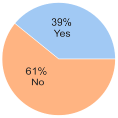

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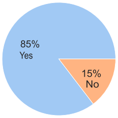

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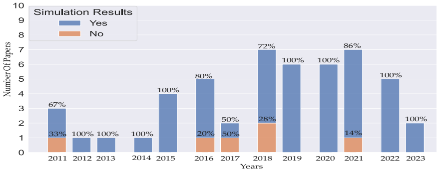

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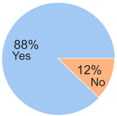

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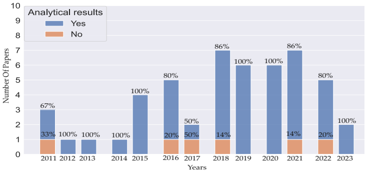

Analytical per annum.

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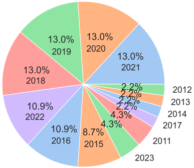
Active SLAM Review Articles Insights [16]



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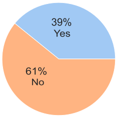

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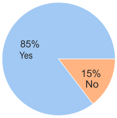

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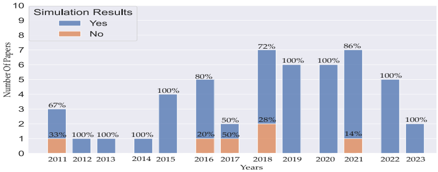

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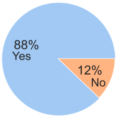

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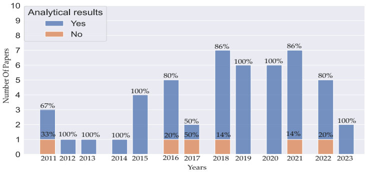

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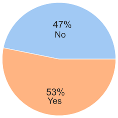
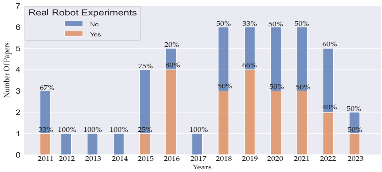


% Robots



Real robots per annum

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Proposed Approach (Flow Charts)

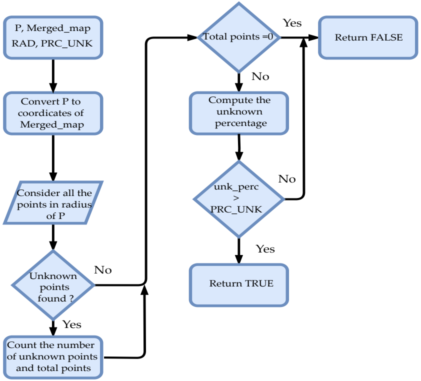
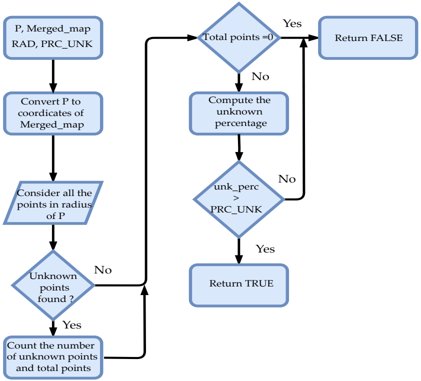


Fig. 1: Check if a Point is Near the Map Border

Proposed Approach (Flow Charts)



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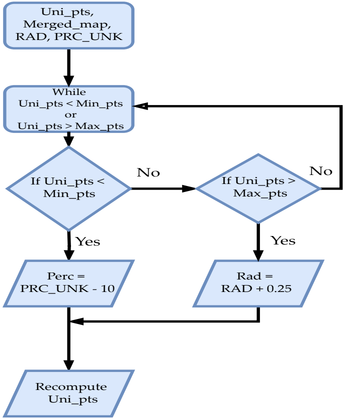


Fig. 2: Check list dimension.

Proposed Approach (Flow Charts contd ...)

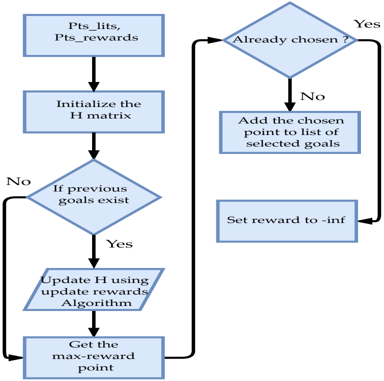
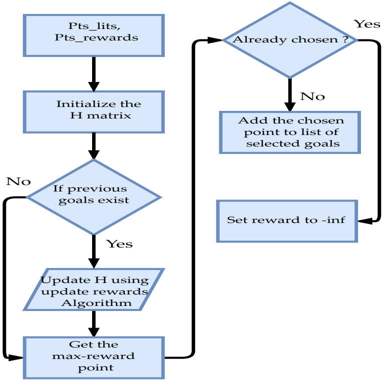


Fig. 3: Select Points.

Proposed Approach (Flow Charts contd ...)



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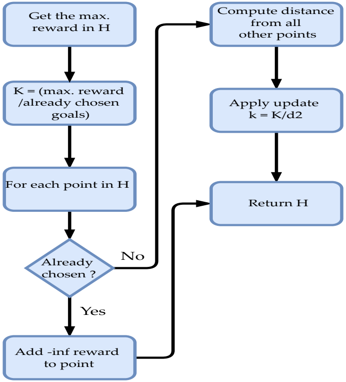

Fig. 4: Update Rewards.

List Of Publications

Type	Citation
Journal	Ahmed, M.F., Masood, K., Frémont, V., Fantoni, I. Active SLAM: A Review on Last Decade. Sensors 2023.
Journal	Ahmed, M.F., Maragliano, M., Frémont, V., Recchiuto, C.T., Entropy Based Multi-robot Active SLAM **Under review** in Journal of Intelligent & Robotic Systems (JIRS).
Conference	Ahmed, M.F., Frémont, V., Fantoni, I., Active SLAM Utility Function Exploiting Path Entropy. IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), 2023 (**Best student paper award**).
Conference	Ahmed, M.F., Maragliano, M., Frémont, V., Recchiuto, C.T., Sgorbissa, A., Efficient Frontier Management for Collaborative Active SLAM. IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI), 2024.
Conference	Ahmed, M.F., Frémont, V., Fantoni, I. Active Collaborative Visual SLAM exploiting ORB Features **Accepted** in IEEE ICARCV 2024 conference.

List of publications during the course of this thesis.