

Active Collaborative Visual SLAM exploiting ORB Features

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Abstract—In autonomous robotics, a significant challenge involves devising robust solutions for Active Collaborative SLAM (AC-SLAM). This process requires multiple robots to cooperatively explore and map an unknown environment by intelligently coordinating their movements and sensor data acquisition. In this article, we present an efficient visual AC-SLAM method using aerial and ground robots for environment exploration and mapping. We propose an efficient frontiers filtering method that takes into account the common IoU map frontiers and reduces the frontiers for each robot. Additionally, we present an approach to guide robots to previously visited goal positions to promote loop closure and reduce SLAM uncertainty. The proposed method is implemented in ROS and evaluated through simulations on publicly available datasets and similar methods, achieving an accumulative average of 59% increase in area coverage.

I. INTRODUCTION

Current research increasingly focuses on Active Collaborative SLAM (AC-SLAM), which leverages multiple robots working in unison. This collaborative method offers significant advantages, such as faster terrain mapping and robust operation in dynamic scenarios. However, the deployment of multiple robots introduces challenges like coordination, resource management, and sensor data integration. Moreover, merging individual robot contributions into a unified map poses complex computational and algorithmic challenges. Here, we propose implementing a visual AC-SLAM algorithm using heterogeneous agents and extend the work in [1] to a multi-agent system, where a team of ground robots and aerial robots (UAVs) collaboratively map and explore the environment. To achieve this aim, we propose a method that exploits ORB [2] feature information from different viewpoints of UAVs and ground robots into a common merged map, we detect frontiers in local and overlapped ground robot maps and propose a frontier filtering method that encourages the spread of agents and exploration of the environment. Additionally, we also present a re-localization scheme to guide robots to previously visited goal positions to favor loop closure.

The subsequent sections are organized as follows: Section II provides a review of related work, Section III explains the methodology of the proposed approach, Section IV shows the simulation results, we conclude Section V summarizing

our contributions and prospects for future work. Throughout this article, we will use the words *robots* or *agents* interchangeably, and the same applies to *frontiers* and *points*, as they imply the same meaning in the context.

II. RELATED WORK

A. Active Collaborative SLAM

In AC-SLAM, the frontier detection and uncertainty quantification approaches debated in A-SLAM [3] also apply with additional constraints of managing computational and communication resources, and the ability to recover from network failure. The exchanged parameters are entropy [4], localization info [5], visual features [6], and frontier points. The authors of [7], incorporate these multirobot constraints by adding the future robot paths while minimizing the optimal control function which considers the future steps and observations minimizing the robot state and map uncertainty and adding them into the belief space (assumed to be Gaussian).

[8] presents a decentralized method for a long-planning horizon of actions for exploration and maintains estimation uncertainties at a certain threshold. The active path planner uses a modified version of RRT* and selects the action that best minimizes the entropy change per distance traveled. The major advantage of this approach is that it maintains good pose estimation and encourages loop-closure trajectories. An interesting solution is given by a similar approach to the method proposed by [9] using a Relative Entropy (RE) optimization method which integrates motion planning with robot localization and selects trajectories that minimize the localization error and associated uncertainty bound. A planning-cost function is computed, which includes the uncertainty in the state in addition to the state and control cost.

B. Frontiers-based exploration

Frontiers play a pivotal role in augmenting the precision of robot localization by enabling intelligent exploration and data acquisition strategies, reducing uncertainty, and enhancing the map building and localization processes. In [10] each frontier is segmented, a trajectory is planned for each segment, and the trajectory with the highest map segment covariance is selected from the global cost map. The work presented in [4] uses frontier exploration for autonomous exploration a utility function based on Shannon's and Renyi entropy is used for the computation of the utility of paths. The method described by [11] uses a cost function that is somewhat similar to [5], it takes into consideration the discovery of the target area of a robot by another member

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of the swarm and switches from a frontier to a distance based navigation function to guide the robot toward the goal frontier.

Frontiers-based coverage approaches in [12] divide the perception task into a broad exploration layer and a detailed mapping layer, making use of heterogeneous robots to carry out the two tasks while solving a Fixed Start Open Traveling Salesman Problem (FSOTSP). Once a frontier has been identified, the robot can use path planning algorithms to reach it and maximize the exploration while minimizing its SLAM uncertainty. In [13] the authors present a decentralized autonomous exploration method that considers frontiers detected by other agents and inter robot exchange of frontiers. This method uses distance and information gain matrices for frontier utility computation.

III. METHODOLOGY

While many research works have been focused on collaborative strategies for SLAM, or single-robot active-SLAM, only a few works have dealt with AC-SLAM. However, these approaches present common limitations: a) they have high computational costs associated with the number of frontiers processed. b) They fail to encourage the spread of robots into the environment by not taking into account the common frontier points from the agents. c) A scalar mapping quantifies the uncertainty of the entire pose graph covariance matrix, which can become very large, especially in landmark-based SLAM methods, thereby increasing the computational cost. d) In the case of SLAM failure or high uncertainty, there is no re-localization method. Furthermore, they do not explicitly implement strategies for efficient management of frontiers to speed up map discovery and robot localization. In this work, we propose a visual AC-SLAM approach that deals with overcoming these limitations using a fleet of ground and aerial robots and exploiting visual features from different viewpoints of both heterogeneous robots. Our proposed method outlines a strategy aimed at reducing the number of frontiers for reward computation and distributing robots within the environment, thereby facilitating exploration and mapping. Furthermore, we also present a re-localization method quantifying the SLAM pose graph edge covariance matrix hereby allowing the robots to visit already visited goal positions for re-localization and uncertainty reduction for a better SLAM estimate. We leverage a combination of reward metrics, common map points, and merged map information gain to refine the goal selection. In single robot A-SLAM the work of [1] uses the ORBSLAM2[14] as SLAM Backend and proposes a modern D-Optimality criterion for utility function reward computation as the maximum number of spanning trees in the weighted graph Laplacian.

We expand the method of [1] to a multi-robot AC-SLAM and incorporate the utility function from our previous work in [15] which considers frontier path entropy to exploit map uncertainty for utility computation. Using the Intersection over Union (IoU) overlapping map information, the number of frontiers is significantly reduced for efficient frontier sharing and exploration. Utilizing edge D-Optimality as an

uncertainty metric, we propose a re-localization scheme to encourage loop closure and reduce uncertainty. In Figure 1 we show the resultant architecture of the proposed system implemented in ROS Noetic using actionlib¹ library for UAV and ground robots (Robot_0... Robot_N).

Each robot/UAV runs its own instance of ORBSLAM2 using onboard RGBD sensors. The resultant ORB features are converted to a 3D voxel map (Octomap) [16] for efficient representation using Octo and Grid Mapper module². For each of the ground robot and drone, we limit the maximum and minimum height of the Octomap to 0.5 and 1 meters (m) respectively, thus limiting the ground robots to ignore ORB features above $0.5m$ high and for drones to ignore them of less than $1m$. We then project this Octomap to a 2D Occupancy Grid (O.G) map and apply frontier detection methods using OpenCV and RRT-exploration from [1] to detect local frontiers in each robot's local map. The MapMerger module merges the offline drone O.G maps with those of ground robots with world reference frame set to that of Robot_0.

The IoU mapper computes the overlapped O.G map between two robots and detects frontiers and penalizes each robot's local frontiers thus reducing them. Section III-A elaborates this process. Once the frontiers have been filtered they are passed to the frontier management and reward computation server as discussed in Section III-B which performs further reduction and updates the rewards before finally assigning goal frontiers to the local controller nodes of robots. In the following sections, we describe the functionality of these modules.

A. IoU frontiers Management

The local frontiers from each agent are reduced by comparing them with IoU map frontiers using distance based metrics before sending them to the manager node for reward computation. IoU mapper module computes the map using Algorithm 1 which takes the O.G maps from Robot_0 and Robot_1 as $M1$, $M2$ and returns the IoU map. From Algorithm 1, after the identification of overlapping map coordinates we populate the map occupancy values according to the known free and obstacle information as 0 and 100 respectively. This map is passed to the IoU frontiers module which uses OpenCV frontier detector incorporating Canny edge detection [17] to detect local frontiers. The frontier filter module takes into account the local frontiers and reduces them by comparing them with those of the IoU map. Algorithm 2 shows an example for Robot_0 but can be generalized to Robot_N. It takes as input Robot_0 local points as 2D map points $M1_pts$, IoU map points IoU_pts and a inter point distance threshold $DIST_THRSH$ parameter adjusted at runtime for penalizing local points which are too close to those of IoU map.

B. Frontier and reward management Server

This section incorporates the *central server* in our previous work of [3] and will be briefly described here. The *central*

¹<http://wiki.ros.org/actionlib>

²http://wiki.ros.org/octomap_server

To maintain the D-Opti and reduce the SLAM uncertainty, we propose a method to re-localize the robot by guiding it to a previously visited goal point to favor loop closure and improve localization. As shown in Algorithm 3 and implemented in *controller node*. Algorithm 3 takes input the saved goal list as SG_list, ORBSLAM2 status, D-Opti, D_MAX is maximum allowed D-Opti value set at runtime and the current robot position R_pos. Whenever the agent loses localization (ORBSLAM2 status=lost) or D-Opti is greater than D_MAX, the robot is guided to revisit already visited goal points by weighing them with path entropy as computed in our previous work in [15]. The robot is assigned the goal point with the largest path entropy and re-localization counter *reloc* is incremented.

Algorithm 3 Saved Goal Selection Based on Entropy

Require: SG_list, ORB_Stat, D-Opti, D_MAX, R_pos

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1: if (ORB_Stat is lost)  $\vee$  (D-Opti > D_MAX) then
2:   for all item in SG_list do
3:      $ent \leftarrow \text{entropy}(item_x, item_y, R\_pos)$ 
4:      $egoal\_list \leftarrow (1 - ent)$ 
5:   end for
6:    $win_{x,y} \leftarrow \text{Max. value in } egoal\_list,$ 
7:   send  $win_{x,y}$  to robot
8: end if
9:  $reloc \leftarrow reloc + 1, SG\_list \leftarrow win_{x,y}$ 

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IV. SIMULATION RESULTS

The simulations were carried out on ROS Noetic, Ubuntu 20.04 (LTS) on Intel Core i7[®], with a system RAM of 32GB and NVIDIA RTX 1000 GPU. The video demonstration¹ and source code is available². As described earlier, we modified the approach of [1] to multi-robot and implemented the proposed approach as mentioned in Section III using ORBSLAM2 [14] backend, RosBot³ equipped with RGBD sensor, LiDAR, and using Timed Elastic Band (TEB) and A* as local and global planners respectively from the ROS navigation stack. We used open-source modified House Environment (H.E) and Warehouse Environment (W.E) from Gazebo simulator⁴ measuring $157m^2$ and $260m^2$ respectively. Figure 2 shows the Gazebo images masked on top of the resulting O.G maps from UAV by flying it at 5m height in a lawn mover pattern and the final map of H.E. From the O.G maps in Figure 2a and 2b we can observe a difference in obstacle area as both environments have different nature of obstacles contributing to more ORB features for W.E. Figure 2c shows the resulting merged map from Robot_0, Robot_1 and UAV, and indicating the initial, final robot positions alongside their filtered frontiers. The ground truth O.G maps for local and global planners were generated using the Gazebo 2D Map plugin⁵ which uses wavefront exploration.

¹<https://www.youtube.com/watch?v=6j3VBdnVcO8>

²https://github.com/MF-Ahmed/ExplORBSLAM_multi

³<https://husarion.com/>.

⁴<https://github.com/aws-robotics>

⁵<https://github.com/marinaKollmitz/gazebo>

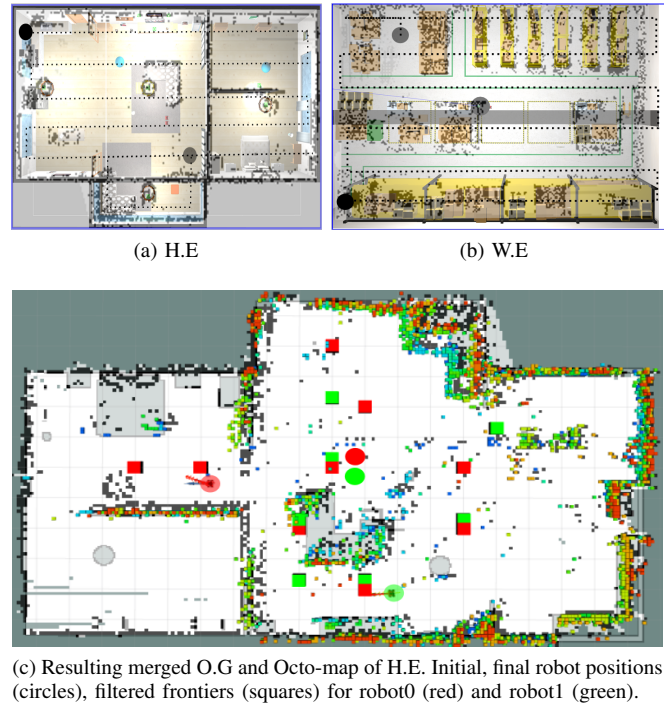


Fig. 2: 2a and 2b environments used and the overlapped resulting O.G map from UAV indicating path (black dots), start(black circle), end (gray circle) positions. 2c showing resulting merged O.G and Octo-map of the H.E.

We compared our proposed approach against 1) the approach of [13] namely DCM which uses inter and intra-agent frontier distance based information gain metrics for frontier utility computation using a decentralized frontier management approach for exploration and mapping. This method does not consider SLAM uncertainty quantification nor does it use any frontier reduction method alongside IoU map consideration. 2) And that of [1] by converting it into a multi-robot system namely MEXP without any frontier reduction, reward update, or IoU map consideration as presented in Section III. For environment exploration we compare metrics of percentage of area covered, IoU map area, frontiers reduction, edge D-Optimality, and number of re-localization efforts. Regarding map quality, we compared metrics measuring Structural Similarity Index Measurement (SSIM) $\in \{0, 1\}$, Mean Square Error (MSE) $\in \mathbb{R}$, Normalized Cross Covariance (NCC) $\in \{0, 1\}$ and Cosine Similarity (CS) $\in \{0, 1\}$ with reference to ground truth maps. These metrics debate over the pixel values, intensity, and structure of the resulting map then compared to the ground truth map. We conducted 10 simulations of 15 minutes each using 2 robots and 1 UAV for both H.G. and W.E. using Our, MEXP, and DCM methods rendering a total simulation time of 15 hours. The runtime parameters of PER_UNK, RAD, MIN_PTS, MAX_PTS, DIST_THRESH and D_MAX were initialized to 60%, 1m, 0, 5, 1m and 1.5 respectively. Figure 3 shows the average percentage of maps discovered along

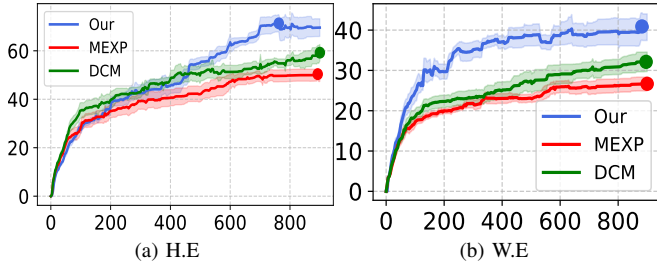


Fig. 3: % area of map in H.G and W.E environments.

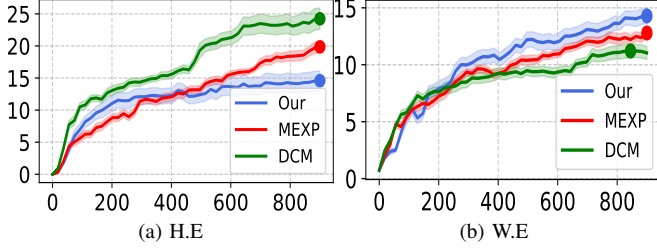


Fig. 4: Area of IoU map in H.E and W.E environments.

with the Standard Deviation (SD) using our, MEXP, and DCM approaches with reference to time in seconds (time[s]). From Figure 3a it can be observed that our approach covers 20% and 12% more area in H.E when compared to MEXP and DCM approaches. While in Figure 3b Our approach covers 16% and 11% more area than MEXP and DCM due to efficient frontiers filtering and utility function. We can also observe that DCM performs better (with more coverage) than MEXP because of the reduced computational time resulting in no uncertainty quantification and its dependence on frontiers information only. Figure 4 shows the average IoU map area and SD explored in both environments with reference to time[s]. From both Figure 4a and 4b we can conclude that our approach effectively bounds the IoU map area to $15m^2$ for both environments effectively spreading the robots for exploration.

Figure 5 displays the comparison of frontier points reduction in H.E and W.E using our approach along with the

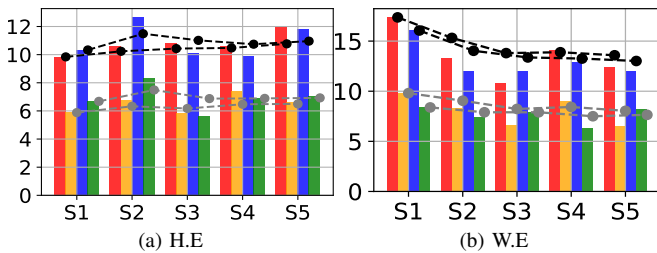


Fig. 5: Robot_0 all points (red), Robot_1 all points (blue), Robot_0 points after IoU filtering (orange), Robot_1 points after IoU filtering (green), running average all points (black dots), running average IoU filtered points (gray dots).

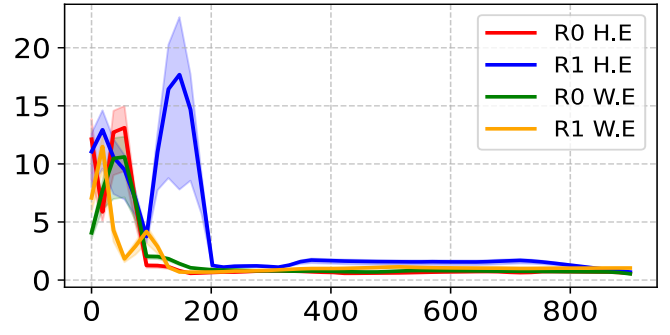


Fig. 6: Evolution of edge D-Optimality in environments for Robot_0 (R0), Robot_1 (R1).

TABLE I: Number Of Re-localization efforts.

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

running average before and after reduction in black and gray lines for five simulations (S1, S2, S3, S4, S5). From Figure 5a we can deduce that for both R0 and R1 the number of points has reduced to 60% for H.E while Figure 5b shows a 66% reduction in W.E. This significant reduction in frontier points consequently reduces the computational cost required by the reward processing on the server side with the adoption of frontier management strategies in Section III-A to limit the number of global frontiers.

When considering the D-Opti and SLAM covariance matrix uncertainty quantification. Figure 6 shows the evolution of edge D-Opti with reference to time[S]. Initially, all the robots have high uncertainty which eventually decreases as robots explore the environment and due to the efforts to maintain the edge D-Opti to $\leq D_{MAX}$ using methods described in Section III-C. We can infer that in both environments our method can effectively bound the uncertainty by re-localizing the robots to previously visited goal positions. Table I shows the number of re-localization efforts performed by each agent in H.E and H.E. We conclude that in H.E, R1 has performed 16 re-localization efforts to reduce the high uncertainty as evident from Figure 6 to finally converge to $\leq D_{MAX}$. In W.E the robots perform fewer re-localization efforts due to the greater environment ORB features from the UAV O.G map, resulting in more obstacle area as compared to H.E.

Figure 7 shows the spread of assigned goal positions with reference to the width and height of H.E map. From Figure 7a when compared to 7b and 7c, we can conclude that due to our efficient frontier management and re-localization policy, we can assign goal positions which support exploration while maintaining efficient SLAM estimate. MEXP in Figure 7b has no frontier management method hence fewer goal

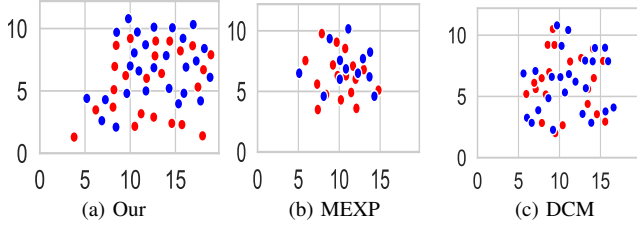


Fig. 7: Spread of final goal positions for H.E R0 (red), R1 (blue).

TABLE II: MAP QUALITY METRICES.

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

positions due to the high computational cost associated with many frontiers. While in Figure 7c, DCM manages to have more goal points but they are very close or overlapped to each other, this is because it does not consider inter goal distance while computing frontier information gain.

Regarding the visual analysis of the maps and debating on map quality metrics in Table II. in almost all cases, using our method rendered reduced MSE and increased SSIM, NCC, and CS as compared to MEXP and DCM methods. We further conclude that the DCM method when compared to MEXP explores the environment more as shown in Figure 3, but has higher MSE and lower SSIM, NCC, and NC.

V. CONCLUSIONS

We proposed a method for the coordination of multiple robots in a collaborative exploration domain performing visual AC-SLAM. We proposed a strategy to efficiently reduce the number of frontiers for the agents to compute their reward functions to reduce the computational cost and to spread the robots into the environment. We also proposed a re-localization method to promote loop closure. We presented extensive simulation analysis on publicly available environments and compared our approach to similar methods and achieved to explore an average of 32% and 27% more area. Possible future works include real robot experiments and exchanging the local pose graphs for collaborative localization and mapping.

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