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Multi Robot Surveillance and Planning in Limited Communication Environments

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Abstract: Distributed robots that survey and assist with search & rescue operations usually deal with unknown environments with limited communication. This paper focuses on distributed & cooperative multi-robot area coverage strategies of unknown environments, having constrained communication. Due to restricted communication there is performance loss for the multi-robot team, in terms of increased number of steps to cover an area. From simulation results, it is shown that enabling partial communication amongst robots can recover a significant amount of performance by decreasing the number of steps required for area coverage. Additionally it is found that partially communicating robots that predict the paths of peers do not perform significantly different from robots that are only partially communicating. This is found due to predictions spreading the robots away from one another, which reduces meeting times and instances of inter-robot data sharing.

1 INTRODUCTION

When multiple robots or agents are deployed to survey or map an indoor disaster zone, the area to be mapped or covered is often unknown and has restricted communication. Figure 1 shows such a situation where a fleet of aerial robots navigate and map a previously unknown environment that is cluttered, radio-hampered and GPS-denied. Such a setting leads to reduced inter-robot data sharing, a decrease in cooperative behaviour and a possible increase in redundant area coverage, with the same sub-region of the environment being covered by multiple robots. An increase in redundant coverage increases survey time which leads to delay in search, rescue and disaster containment efforts. To deal with the problem of redundant area coverage, many researchers have used communication to synchronize robot knowledge/data. However, as described this may not always be available in disaster environments.

Thus, the goal of this paper is to evaluate the performance of area coverage algorithms and techniques that deal with unknown limited communication environments. To do this, a distributed multi-robot team is simulated on different communication scenarios to perform surveillance or area coverage. First, agents are simulated in a full communication scenario where the Monte Carlo Tree Search (MCTS) algorithm used in (Hyatt et al., 2020) is used for multi-robot area coverage. Following this, No Communication is simulated where agents have no possibility for communication. The third scenario is partial communication, where robots can communicate when within a communication range. In the fourth scenario, in addition to partial communication robots can predict the paths of peers using a heuristic that is inspired by (Claes et al., 2017). By following this approach, the contributions made by this work are to extend the study on Coverage Path Planning by (Hyatt et al., 2020) to an environment of limited communication and extend the heuristic prediction model introduced by (Claes et al., 2017) to robotic area coverage and where the global state of the environment is unknown.

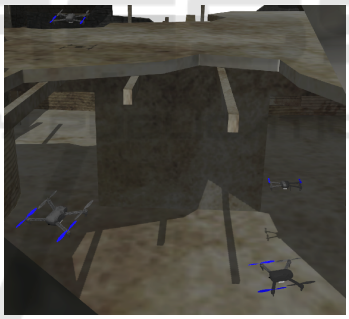

Figure 1: Four aerial robots surveying an environment that has restricted communication.

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The rest of the paper is organised as follows. Section 2 mentions relevant methods used previously to perform multi-robot area coverage and introduces the method used to perform the same in this paper. Section 3 elaborates on the main approach taken in this paper. Following this, Section 4 presents experimental results. Section 5 draws important inferences and also reflects on the limitations of the approach taken. Finally, Section 6 draws key conclusions and provides directions for future work.

2 RELATED WORK

Prior literature/methods have been considered to select a suitable baseline for the approach and experiments. One of the earliest methods in multi-robot area coverage is robots dispersing in the environment (Howard et al., 2002), (Damer et al., 2006), (Pang et al., 2019). The methods following this approach however do not allow robots to share data and work together, thereby reducing cooperation. Frontier based area coverage utilised in (Umari and Mukhopadhyay, 2017), (Nair and Givigi, 2019), (Dadvar et al., 2020), (Bautin et al., 2012), (Benavides et al., 2016) aims at directing robots to positions at the boundaries of known and unknown regions. Most methods however are either centralised or assume unrestricted communication to exist in the environment, where robots can share information with one another, irrespective of physical limitations. Environment partitioning utilised by (Lopez-Perez et al., 2018), (Jain et al., 2020) attempts to reduce redundant coverage by dividing the region amongst robots. However, this approach too assumes unrestricted communication. Game theory based multi-robot mapping in (Meng, 2008), (Ni et al., 2020) attempts to find suitable positions for agents based on the computation of a Nash Equilibrium using a predefined utility measure. This approach however assumes some prior information of the environment as well as unrestricted communication.

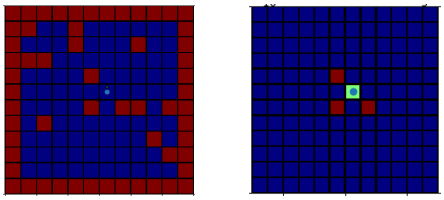
In comparison to these methods, the Monte Carlo Tree Search (MCTS) algorithm used by Hyatt et al (Hyatt et al., 2020) allows robots to simulate the paths of peers, which brings in cooperation and reduces redundant coverage. The algorithm also plans an action based on future rewards, which helps robots avoid getting stuck in cluttered regions. One drawback however is that the approach assumes an unrestricted communication environment. However, as the approach is distributed, cooperative and can explore unknown maps by looking ahead, it has been chosen as the baseline. Apart from robot area coverage, MCTS has also been used for other multi-robot applications like warehouse commissioning, (Li et al., 2019), (Czechowski and Oliehoek, 2020), (Claes et al., 2017) and active object recognition (Best et al., 2019). In (Claes et al., 2017), robots additionally have the capability to predict the paths of peers, which could also be useful in a limited communication setting.

3 APPROACH

The experiments of this paper are based on an area coverage setting with multiple cooperative robots. The setting is modelled by a simulation where robots are represented as software agents that can communicate with one another according to set rules of communication. Based on the level of communication between agents, four different settings or communication scenarios are created and described further in 3.3.1 to 3.3.4. The first setting implemented is the Full Communication scenario, where agents have no restrictions on their communication capability. Following this is the No Communication scenario where agents cannot communicate with one another. In the third setting of Partial Communication, agents can share information when within a predefined communication range. Agents are also given the capability to predict the paths of peers in the fourth setting of Partial Communication with Prediction. Compared to the first (baseline) setting, the remaining settings are expected to take larger time-steps for area coverage. This increase in time-steps is referred to as performance loss in this work. The goal of the partial communication setting variants are to recover this loss.

3.1 Simulation Environment

In each communication scenario, every agent only knows the size of the region that the entire team is required to cover and the number of agents in the team. Each agent divides the region into grid-cells that can take one of the values of $\{Covered, Unexplored, Obstacle\}$. Initially, all grid-cells are assumed to be $Unexplored$. A grid-cell transitions from $Unexplored$ to $Covered$ when an agent moves over it. Agents can also only observe their local surroundings. This can be understood by considering Figure 2 where the agent's environment position can be seen in subfigure 2a, while what the agent perceives of the environment can be seen in subfigure 2b. Further, each agent can take up positions in the grid-world which is represented as a tuple (x, y, yaw). The position (x, y) refers to the x and y coordinates in the grid-world, while yaw refers to



(a) Agent's Environment Position (b) Agent's Environment Belief

Figure 2: Local observability - The colours $\{Green, Blue, Red\}$ correspond to $\{Covered, Unexplored, Obstacle\}$ respectively.

the heading angle of the agent with respect to the horizontal axis. Each agent can execute one of the actions $\{FORWARD, RIGHT, LEFT\}$, where the action $FORWARD$ moves an agent one grid-cell ahead based on the *yaw* value, while $RIGHT$ and $LEFT$ actions only rotate the agent by 90°.

3.2 Algorithm

Algorithm 1: MCTS for Area Coverage.

Ensure: Area Coverage by N Agents $(A_1, A_2..A_N)$

1: **while** *CoverageGoal* is Not Met **do**
2: **for** $i \leftarrow 1, .., N$ **do**
3: $A_i.Map \leftarrow A_i.Sensing$
4: $\boxed{DataSharing()}$
5: $A_i.Action \leftarrow A_i.MCTSPlanning$
6: **end for**
7: $ActionExecution(A_1, A_2..A_N)$
8: **end while**

Algorithm 1 describes the steps that are common to all settings. The approach consists of each agent sequentially executing four major steps of Environment Sensing, Data Sharing (if possible), MCTS Path Planning and Action Execution. These steps are executed until a predefined *CoverageGoal* is achieved by the whole team. In every setting, each agent of the team first senses the environment to update its knowledge/map about the environment. Following this is the Data Sharing step which differs in every setting and thus indicated in a box. In the Prediction scenario, there is additionally the function of peer prediction at this step. Utilising information obtained from sensing & sharing or by prediction, an agent begins the path planning step where it utilises MCTS to plan the next action from the action set $\{FORWARD, RIGHT, LEFT\}$. The above steps are performed by each agent, after which the planned action of every agent of the team is executed.

3.2.1 Data Sharing

The data sharing step is required for each agent to share its grid-world position, its surveyed map and its most recently computed plans. This data is shared only with a selection of agents, based on the setting. Using surveyed map information of peer agents, an agent updates its own knowledge of the overall region to explore. The computed plans of peer agents are then executed on this updated knowledge map during the MCTS planning step, as will be explained further. By using the updated knowledge map, an agent can plan paths away from already covered environment portions, which minimises redundant coverage plans and reduces the number of coverage steps by the team.

3.2.2 MCTS Planning

The planning step utilises MCTS to plan an action. In the search method, an agent uses Monte Carlo Simulations to construct a tree of future states of the environment. The tree consists of nodes that represents the state of the environment and branches which correspond to actions $\{FORWARD, RIGHT, LEFT\}$. A single iteration of MCTS planning consists of four parts (Browne et al., 2012). The first part is where the tree is traversed using a tree policy (selection). A new action is sampled and a new node is created based on the resulting environment state (expansion). A heuristic policy/ default policy is then executed for a predefined number of time-steps (roll-out). Finally, a reward is computed which is stored in the visited nodes (back-propagation). This is also the technique followed by (Hyatt et al., 2020). While the Tree Policy used is the same as this work (Upper confidence bound for trees, UCT1), there are modifications made in the Default Policy. The Default Policy utilised by (Hyatt et al., 2020) does not handle the case of being completely surrounded by *Covered* grid-cells. The Default Policy implemented here considers this and directs planning towards one of the *Covered* grid-cells in a semi-random manner.

The Reward function is the $TotalReward$ which is given by,

$$TotalReward = w_{LR} \times LocalReward + w_{GR} \times GlobalReward \quad (1)$$

w_{GR} and w_{LR} are the weights given to the global and local rewards respectively. In the above equation $GlobalReward$ is given by the relation:

$$GlobalReward = -\frac{N(UnexploredCells)}{N(TotalCells)} \quad (2)$$

In the above equation $N(UnexploredCells)$ refers to the number of unexplored grid-cells in the gridmap

and $N(TotalCells)$ refers to the total number of grid-cells present in the gridmap. The *LocalReward* is given by equation 3,

$$LocalReward = \sum_{t=1}^{T} \left[\frac{1}{(t+1)^2} (C_{cov} - C_{hit}) \right] \quad (3)$$

In the above equation C_{cov} and C_{hit} are hyper-parameters that determine the simulation result. $C_{cov} > 0$ if the robot lands up on a newly discovered grid cell at time step t and "covers" it, else $C_{cov} = 0$. $C_{hit} > 0$ if the robot encounters an obstacle or another robot at time step t, else it remains 0. The normalisation using the $(t+1)^2$ term is used to decay the reward overtime.

Overall, in every MCTS algorithm iteration the agent first simulates the plans of peer agents on its own simulator/knowledge map of the environment. This simulation is only possible if the agent has information obtained via Data Sharing or through prediction. During rollout, the agent simulates its own plan using the default policy and computes the *LocalReward* for a predefined number of time-steps (T). The *GlobalReward* and *TotalReward* are then computed, which is back-propagated until the root of the tree. This process is repeated for a predefined number of iterations. The root of the tree represents the starting of the planning and the action that results in the largest accumulated reward at the root is executed. Thus, while planning happens for the future T time-steps, only the one action that gives the highest *TotalReward* is executed.

3.3 Communication Scenarios

As seen in algorithm 1, each setting differs in the Data Sharing step. This will be discussed below.

3.3.1 Full Communication (FULLCOMM or FC)

Algorithm 2: FC Data Sharing for Agent i (A_i).

for $j \leftarrow 1,..,N$ and $j \neq i$ **do**
  $A_i.Map \leftarrow MapMerge(A_i.Map, A_j.Map)$
  $A_i.Position_{A_j} \leftarrow A_j.Position$
  $A_i.PathPlan_{A_j} \leftarrow A_j.PathPlan$
end for

Algorithm 2 shows the specific portion of data sharing for an Agent i (A_i) during the FULLCOMM scenario. As there is unrestricted data sharing, A_i shares and receives information from every peer of the team of size N at anytime. A_i updates its map by merging its current knowledge of the world with map information from peers. The current position and most recent path plans or the best path plans in the previous time-step of all peers is also recorded (Hyatt et al., 2020). This is used in the subsequent step of MCTS Planning in Algorithm 1. As agents know the positions and plans of peers at all times in FULLCOMM, there is reduced redundant coverage. This leads to the least area coverage time amongst the four settings.

3.3.2 No Communication (NOCOMM or NC)

During NOCOMM, A_i has no possibility for communication and the data sharing step in algorithm 1 is skipped. When calculating plans, A_i only simulates its own actions but still computes *TotalReward*. As the agents of the team make plans without taking into account the plans of one another, redundant coverage is the highest and area coverage takes the maximum number of steps.

3.3.3 Partial Communication (PARCOMM or PC)

Algorithm 3: PC Data Sharing for Agent i (A_i).

$A_i.Neighbours \leftarrow A_i.CommRangeSensing$
for $j \leftarrow 1,..,A_i.Neighbours$ **do**
  $A_i.Map \leftarrow MapMerge(A_i.Map, A_j.Map)$
  $A_i.Position_{A_j} \leftarrow A_j.Position$
  $A_i.PathPlan_{A_j} \leftarrow A_j.PathPlan$
end for

Algorithm 3 explains data sharing in the partial communication scenario where A_i shares data with neighbouring peers that are within a predefined communication range. The list of neighbouring peers ($A_i.Neighbours$) is obtained via the step of sensing peers that are within a pre-defined communication range ($A_i.CommRangeSensing$). The data shared between A_i with neighbours is the same as FULLCOMM. During MCTS planning, A_i simulates the path of neighbouring peers and subsequently computes the *TotalReward*. As there is some amount of sharing in PARCOMM, agents can avoid redundant coverage at several instances of time, resulting in area coverage steps lying in between NOCOMM and FULLCOMM.

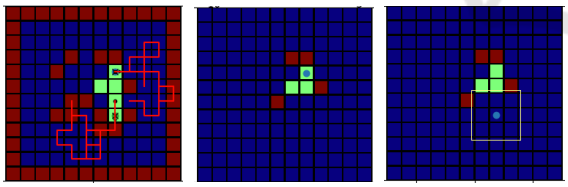
3.3.4 Partial Communication with Prediction (PARCOMM_PRED or PCPD)

Algorithm 4 illustrates PARCOMM_PRED that builds over PARCOMM. In this, A_i predicts the paths of agents outside communication range. As A_i knows the total number of team members, it can extract

Algorithm 4: PARCOMM_PRED Data Sharing and Prediction for Agent i (A_i).

$A_i.Neighbours \leftarrow A_i.CommRangeSensing$
for $j \leftarrow 1,..,N$ and $j \neq i$ **do**
  if A_j in $A_i.Neighbours$ **then**
    $A_i.Map \leftarrow MapMerge(A_i.Map, A_j.Map)$
    $A_i.Position_{A_j} \leftarrow A_j.Position$
    $A_i.PathPlan_{A_j} \leftarrow A_j.PathPlan$
  else
    $A_i.PathPlan_{A_j} \leftarrow A_i.PeerPrediction(A_j)$
  end if
end for

agents that are not present in $A_i.Neighbours$ (Non-Neighbours). To make predictions, A_i uses the most recent plans that it knows about Non-Neighbours. The plan obtained by A_i ($A_i.PathPlan_{A_j}$) is a finite list of actions that a peer agent executes, for a predefined number of time steps in the default policy of MCTS. When this list gets exhausted, A_i predicts the path of peer agents using a Coverage-by-Step Heuristic metric. This metric is used for any instance in the list $A_i.PathPlan_{A_j}$ that is unknown. In this metric, A_i predicts the actions of peer agents by computing the reward for the eight grid-cells around the predicted/last seen position of the peer agent. This can be understood by considering the scenario of Figure 3. In the scenario, Agent 0 computes a heuristic for each of the eight neighbouring grid-cells (within the yellow box in subfigure 3c) of Agent 1 in order to predict its next position and action.



(a) Environment (b) Agent Position (c) Peer Belief

Figure 3: Coverage-by-Step Heuristic Computation - Amongst the two agents in subfigure 3a, Agent 0 (top) predicts the next action of Agent 1 (bottom) using a heuristic reward of the surrounding eight gridcells as shown in subfigure 3c.

The heuristic reward ($Reward_{heur}$) is computed for each zone. Equation (4) shows this reward computation, where R_{cov} denotes the coverage reward of the particular zone and N_{min_steps} gives the minimum number of steps that the belief agent is required to move from its current position to the zone position.

$$Reward_{heur} = \frac{R_{cov}}{N_{minsteps}} \tag{4}$$

The value of R_{cov} is given by the equation

$$R_{cov} = \begin{cases} +2, & \text{if zone is } Unexplored \\ +1, & \text{if zone is } Covered \\ 0, & \text{if zone is } Obstacle \end{cases} \tag{5}$$

It is important to note that due to an unknown environment, predictions are not always correct. The number of correct predictions decreases with time since the last meeting between agents. When predictions are correct, agents spread out in the environment that potentially leads to a reduction in the area coverage steps by the team. With wrong predictions however, a particular sub-region may remain unexplored as each agent may assume that the other explores it. This increases the area coverage steps overtime. A method to solve this is inspired by the do-it-yourself (DIY) reward presented by Claes et al in (Claes et al., 2017) where agents have a certain bias to perform tasks on its own. This idea is incorporated into the rollout step of the MCTS planner, where the agent simulates the actions of solely the Neighbour agents before making its own plans. Once the agent has planned its own path, it simulates the plans of Non-Neighbours. This helps override the plans of peers for which it has less information about. To ensure that plans of Non-Neighbours are still considered during MCTS planning, the agent still computes the *GlobalReward*. As PARCOMM_PRED includes the aspect of partial communication, the area coverage steps lies between FULLCOMM & NOCOMM. Compared to PARCOMM however, there is no significant difference in coverage steps, as will be observed and discussed further.

4 EXPERIMENTS

The experiments for each communication scenario were implemented on a simulation environment developed in Python. The experiments involved spawning a team of robots on a gridmap and recording the number of steps taken by the team for area coverage. The experiments were run on 40x40 gridmaps with 10% obstacle density. All experiments were conducted on five different gridmaps for 10 times each, thereby resulting in 50 simulations for each setting. The goal of each simulation was 95% area coverage. 100% area coverage was not considered, due to the high variance of results that was caused when agents would cover far off single grid-cells. By default, the sensor and communication range was set to one. With a sensor range of one, agents could sense the status of nearby eight grid-cells as explained in Figure 2. A communication range of one implied

that agents could share information with those agents present in the eight surrounding grid-cells. Further, simulations terminated when the team of agents completed the area coverage. The hyper-parameters that were utilised are listed in Table 1.

Table 1: Hyper-parameter Values.

Hyper-parameter	Description	Value
C_cov	Coverage Reward	5
C_hit	Collision Penalty	2
lw	Local Reward Weight	1
gw	Global Reward Weight	1
T_horizon	Rollout steps	30
MCTS iter	MCTS Loop Iterations	100
C_p	UCT1 Exploration	0.707

As discussed previously, PARCOMM and PARCOMM_PRED are created to recover the lost performance when moving from FULLCOMM to NOCOMM. In the experiments, this is measured using a recovery performance metric. Equation 6 shows this metric for the PARCOMM case,

$$Recovery_{PC} = \left(\frac{N_{NC} - N_{PC}}{N_{NC} - N_{FC}}\right) \times 100 \qquad (6)$$

In this equation N_{NC}, N_{PC} and N_{FC} are the number steps for area coverage for NOCOMM, PARCOMM and FULLCOMM respectively. Equation 6 measures the recovered number of steps for PARCOMM as a percentage of the original lost performance when moving to NOCOMM. A larger value of $Recovery_{PC}$ indicates a larger difference between NOCOMM & PARCOMM, and PARCOMM moves closer to FULLCOMM performance. A similar computation is also made for PARCOMM_PRED by replacing the numerator with $N_{NC} - N_{PCPD}$, where N_{PCPD} is the number of steps for the PARCOMM_PRED setting.

4.1 Area Coverage v/s Team Size

In this experiment, the number of steps for area coverage is studied for increasing team size and for each communication scenario.

From Figure 4, it can be seen that the performance of both PARCOMM and PARCOMM_PRED lies in between NOCOMM and FULLCOMM. Due to the overlapping confidence intervals, the difference between PARCOMM and PARCOMM_PRED is not significant for any team size. From the values indicated in Table 2, the recovery provided by each setting increases with the increase in team-size. In the 10 agent scenario, recovery increases upto 66% for both PARCOMM and PARCOMM_PRED.

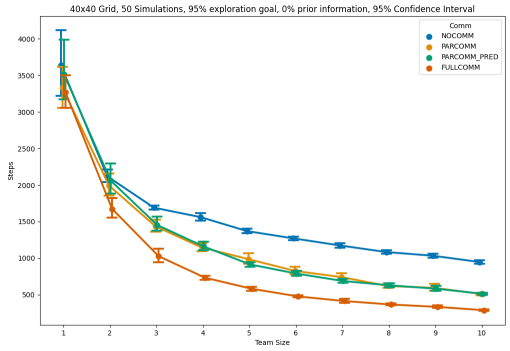


Figure 4: 40x40 Map.

Table 2: 40x40 Map Data.

Team Size	FC	NC	PC Rec	PCPD Rec
1	3265	3637	83	33
2	1674	2118	28	12
3	1028	1691	38	36
4	733	1562	50	48
5	582	1371	49	58
6	477	1271	56	61
7	414	1174	57	64
8	367	1084	65	63
9	334	1034	63	64
10	289	948	66	66

4.2 Area Coverage v/s Communication Range

In this experiment, a team of three agents is spawned into the arena. The communication range is varied to take one of the values in the set $\{1,2,3,4,5\}$. A communication range of N indicates that an agent can communicate with up-to N grid-cells around it in all directions. Due to the high variance in the case of smaller number of agents, each of the communication scenarios are run for 400 simulations (instead of 50) and the recovery provided by the PARCOMM and PARCOMM_PRED is measured using Equation 6.

Table 3: Area Coverage v/s Communication Range, 3 agents - Data (NC - 1717, FC - 1077).

Range	PC	PCPD	PC Rec	PCPD Rec
1	1435	1418	44	43
2	1358	1360	47	59
3	1312	1278	62	73
4	1248	1220	73	79
5	1187	1182	77	81

In the case of a smaller number of agents (three in this case) spawned into an arena, it can be seen from Figure 5 that area coverage steps of PARCOMM

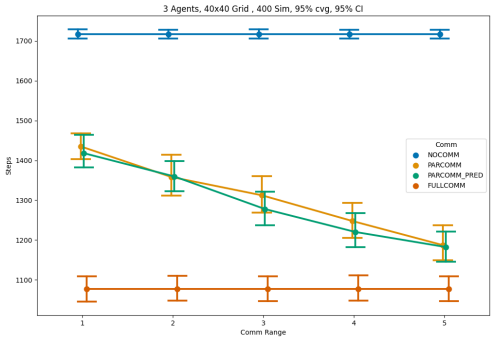


Figure 5: Area Coverage v/s Communication Range, 3 agents - Graph.

& PARCOMM_PRED approach FULLCOMM level with an increase in communication range. The overlapping confidence intervals indicate no significant difference between PARCOMM_PRED and PARCOMM. From Table 3, it can be seen that increasing the communication range from one till five can increase the percentage of recovery to 81% for PARCOMM_PRED and 77% for PARCOMM.

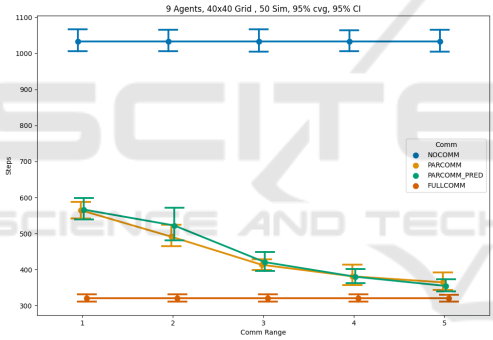


Figure 6: Area Coverage v/s Communication Range, 9 agents - Graph.

Table 4: Area Coverage v/s Communication Range, 9 agents - Data (NC - 1034, FC - 321).

Range	PC	PCPD	PC Rec	PCPD Rec
1	565	567	66	66
2	491	522	76	72
3	413	421	87	86
4	382	380	92	92
5	365	355	94	95

The same experiment was repeated with larger number of agents (nine) for 50 simulations and the coverage performance was studied. Figure 6 shows overlap in the confidence intervals of PARCOMM and PARCOMM_PRED, indicating no significant difference. From Table 4, the percentage recovery in the case of communication range of five is as high as 95%.

4.3 Meeting Time Steps v/s Team Size

In the previous sections, it was observed that there is no statistical significant difference between PARCOMM and PARCOMM_PRED. This experiment aims at providing reasoning to this observed behaviour by studying the number of time steps where agents meet one another for varying team sizes. The number of meeting times is considered as it is the moment when agents can share information, thereby knowing each one's plans and updating its own knowledge about the environment coverage. This is performed for both PARCOMM & PARCOMM_PRED and the meeting time steps metric is the average of the total number of time steps that agents of a team spend in meeting a peer.

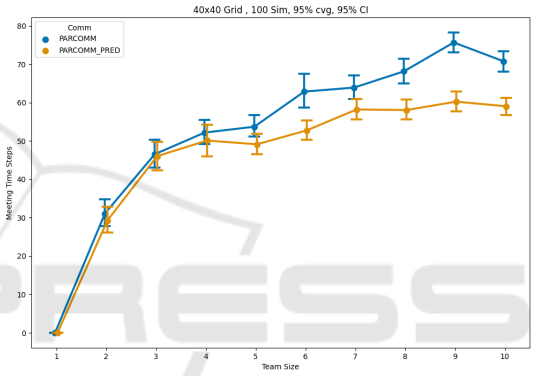


Figure 7: Meeting Time Steps v/s Team Size - Graph.

Table 5: Meeting Time Steps v/s Team Size - Data.

Team Size	PC	PCPD	p_val	Sig?
2	31	29	0.46	No
3	47	46	0.85	No
4	52	50	0.44	No
5	54	49	0.02	Yes
6	63	53	0	Yes
7	64	58	0.01	Yes
8	68	58	0	Yes
9	76	60	0	Yes
10	71	59	0	Yes

From Figure 7, it can be seen that agents under PARCOMM_PRED meet less often as compared to PARCOMM. From Table 5 this difference is found to be statistically significant (using t-tests) for team sizes greater than five.

5 DISCUSSION

From the experiments conducted, it is seen that partial communication results in high performance recovery. This recovery increases with increase in team size and communication range, which indicates the benefit of increased meeting times and information sharing amongst agents for the overall exploration performance. It is also found that enabling agents to predict the plans of peers does not provide additional benefit to area coverage, due to reduced number of meeting times. We discuss these inferences in more detail here.

5.1 Merit of Information Sharing

The strategy that each agent follows is sensing, information sharing and MCTS planning. Sharing of information is observed to be highly beneficial for overall region exploration. Subsections 4.1 & 4.2 indicate this, where increasing team size and communication range decreases the area coverage steps. After an agent obtains shared information, it first simulates the plans of peers and then plans its own path. This leads to paths that can avoid redundant coverage. Subsection 4.3 also shows information sharing benefit. Even though PARCOMM_PRED spreads robots away, the coverage steps is similiar to PARCOMM due to the increase in redundant coverage, resulting from reduced information sharing.

5.2 Large Partial Communication Recovery

Subsections 4.1 and 4.2 indicate that increasing team size and communication range can increase the performance recovery of PARCOMM. The performance recovery with nine agents in PARCOMM is as high as 63% and raising the communication range to five grid-cells further increases this recovery to 94%. This can be attributed to increased information sharing instances. It is also important to note that in the physical world, communication range is not as tightly controlled with gridcells and robots can communicate through a larger range. Thus when deployed in realistic situations, PARCOMM is likely to further be closer to the performance of FULLCOMM. This indicates that certain multi-robot coverage algorithms that rely on unrestricted communication, can be deployed into limited communication environments and possibly achieve almost unchanged performance levels.

5.3 Limited Benefit of Peer Prediction

PARCOMM and PARCOMM_PRED perform in a similar manner as seen from subsections 4.1 and 4.2. Predictions causes a robot to spread away from peers and reduces data sharing instances, where robots share important map coverage information. This information enables an agent avoid already covered regions. Thus, reducing meeting times results in higher chances of redundant area coverage. Subsection 4.3 also shows the effect where the difference in the meetings between agents in PARCOMM_PRED and PARCOMM is significant for large team sizes. This is due to increased number of misprediction corrections for robots in larger team sizes. When this occurs, correct predictions about peer paths increases which leads to further dispersion and reduced meeting times.

5.4 Limitations

While the approach and experiments do provide results that can be translated to a real-world setting, there are some limitations. One limitation is the map, where grid-cells are of the same size as the robot. While grid-cells do provide a rough estimate of obstacles, they may not always be coarse enough to model every obstacle. In terms of the MCTS algorithm, due to the finite amount of computation, 100% coverage of the area is difficult and additional mechanisms to handle isolated far off unexplored grid-cells are required. In the experiments, currently termination occurs when the whole team covers the grid and not when each individual agent senses termination. This leads to a type of centralised termination which is not desirable, especially if robots are expected to return to the base station after they are done mapping.

6 CONCLUSIONS

In this work, strategies that enable multi-robot surveying or area coverage in unknown limited communication environments have been studied. An existing baseline method that used Monte Carlo Tree Search (Hyatt et al., 2020) was implemented first. The communication dependency of this work was completely removed and strategies to recover the lost efficiency were studied. As seen from the experiments, providing robots the ability to communicate when within a communication range can regain a significantly high percentage of lost efficiency. By increasing the communication range this percentage can be further increased. It is also found that peer predictions can spread out robots in the arena, but do not significantly

reduce area coverage time due to the reduced number of information sharing instances. Some directions for future work are strategies on ensuring less varying 100% area coverage and experiments avoiding centralised termination.

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REFERENCES

Bautin, A., Simonin, O., and Charpillet, F. (2012). Minpos : A novel frontier allocation algorithm for multi-robot exploration. In Su, C.-Y., Rakheja, S., and Liu, H., editors, *Intelligent Robotics and Applications*, pages 496–508.

Benavides, F., Monzón, P., Carvalho Chanel, C. P., and Grampín, E. (2016). Multi-robot cooperative systems for exploration: Advances in dealing with constrained communication environments. In *2016 XIII Latin American Robotics Symposium and IV Brazilian Robotics Symposium (LARS/SBR)*, pages 181–186.

Best, G., Cliff, O. M., Patten, T., Mettu, R. R., and Fitch, R. (2019). Dec-mcts: Decentralized planning for multi-robot active perception. *Int. J. Robotics Res.*, 38(2-3).

Browne, C., Powley, E., Whitehouse, D., Lucas, S., Cowling, P., Rohlfshagen, P., Tavener, S., Perez Liebana, D., Samothrakis, S., and Colton, S. (2012). A survey of monte carlo tree search methods. *IEEE Transactions on Computational Intelligence and AI in Games*, 4:1:1–43.

Claes, D., Oliehoek, F., Baier, H., and Tuyls, K. (2017). Decentralised online planning for multi-robot warehouse commissioning. In *Proceedings of the 16th Conference on Autonomous Agents and MultiAgent Systems*, AAMAS '17, page 492–500, Richland, SC. International Foundation for Autonomous Agents and Multiagent Systems.

Czechowski, A. and Oliehoek, F. A. (2020). Decentralized mcts via learned teammate models. *Proceedings of the Twenty-Ninth International Joint Conference on Artificial Intelligence*.

Dadvar, M., Moazami, S., Myler, H. R., and Zargarzadeh, H. (2020). Exploration and coordination of complementary multi-robot teams in a hunter and gatherer scenario. https://arxiv.org/abs/1912.07521.

Damer, S., Ludwig, L., LaPoint, M. A., Gini, M., Papanikolopoulos, N., and Budenske, J. (2006). Dispersion and exploration algorithms for robots in unknown environments. In Gerhart, G. R., Shoemaker, C. M., and Gage, D. W., editors, *Unmanned Systems Technology VIII*, volume 6230, pages 251 – 260. SPIE.

Howard, A., Matarić, M. J., and Sukhatme, G. S. (2002). Mobile sensor network deployment using potential fields: A distributed, scalable solution to the area coverage problem. In *Proceedings of the International Symposium on Distributed Autonomous Robotic Systems*, pages 299–308.

Hyatt, P., Brock, Z., and Killpack, M. D. (2020). A versatile multi-robot monte carlo tree search planner for on-line coverage path planning. https://arxiv.org/abs/2002.04517.

Jain, U., Tiwari, R., and Godfrey, W. (2020). A hybrid evsa approach in clustered search space with ad-hoc partitioning for multi-robot searching. *Evolutionary Intelligence*, 13.

Li, M., Yang, W., Cai, Z., Yang, S., and Wang, J. (2019). Integrating decision sharing with prediction in decentralized planning for multi-agent coordination under uncertainty. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19*, pages 450–456. International Joint Conferences on Artificial Intelligence Organization.

Lopez-Perez, J., Hernandez-Belmonte, U., Ramirez-Paredes, J.-P., Contreras-Cruz, M., and Ayala, V. (2018). Distributed multirobot exploration based on scene partitioning and frontier selection. *Mathematical Problems in Engineering*, 2018:1–17.

Meng, Y. (2008). Multi-robot searching using game-theory based approach. *International Journal of Advanced Robotic Systems*, 5(4):44.

Nair, M. and Givigi, S. (2019). The impact of communications considerations in multi-robot systems. In *2019 International Conference on Communications, Signal Processing, and their Applications (ICCSPA)*, pages 1–6.

Ni, J., Tang, G., Mo, Z., Cao, W., and Yang, S. X. (2020). An improved potential game theory based method for multi-uav cooperative search. *IEEE Access*, 8:47787–47796.

Pang, B., Song, Y., Zhang, C., Wang, H., and Yang, R. (2019). A swarm robotic exploration strategy based on an improved random walk method. *J. Robotics*, 2019:6914212:1–6914212:9.

Umari, H. and Mukhopadhyay, S. (2017). Autonomous robotic exploration based on multiple rapidly-exploring randomized trees. In *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 1396–1402.