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Multi-robot Coordination for Energy-Efficient Exploration

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Abstract

This paper investigates the problem of multi-robot exploration in unknown environment situations. In order to build a coherent representation of the environment, a decentralized coordination approach is proposed to minimize the exploration time while considering the total motion energy saving of the mobile robots. The exploration target is defined as a segment of the environment including the frontiers between the unknown and the explored areas. Each robot evaluates its relative rank among the other robots of the team regarding energy consumption to reach this exploration target. As a result, the robot is assigned to the segment for which it has the lowest rank. An implementation on real robots and tests in simulation as well as a comparison with some existing approaches have been performed. The obtained results demonstrate the validity and the efficiency of the proposed method.

Keywords Autonomous exploration · Multi-robot coordination · Multi-robot task allocation · Distributed robot systems · Mobile robot teams

1 Introduction

One of the most challenging problems of autonomous mobile robotics is the exploration of unknown areas using multiple robots. The main idea behind the multi-robot exploration problem is to coordinate the actions of robots to obtain the greatest amount of information while reducing the time needed to completely build a map of the environment. For this reason, multi-robot exploration algorithms become necessary in many real-world situations like oceanic and planetary exploration (Ropero et al. 2019), or simply applications such as cleaning (Altshuler et al. 2018).

This paper is designed to investigate a new approach in order to coordinate a team of mobile robots for reducing both the overall exploration time and the total motion energy consumption of robots; specifically to explore as many unknown areas of the environment as possible. The use of a multi-robot system is motivated by its ability to perform rapidly complex tasks while being more tolerant to the failure or loss of robots. However, the challenge is the choice of an appropriate coordination strategy that assigns each robot to a specific target while reducing the risk of collision between members of the team.

As solutions to the multi-robot exploration problem, Yamauchi (1998) proposed a decentralized coordination approach in which each robot moves to the closest frontier defined as the limit between uncharted and explored accessible areas. The drawback is that some robots may waste time by navigating to the same frontier. In order to avoid redundant work, Zlot et al. (2002) presented a method based on a market economy that guides the exploration process. In this approach, the potential targets are provided by the robots which negotiate their assignments to them. This auction-based coordination strategy was extended by Hawley and Butler (2013) for coalition formation when the number of robots is more than the exploration targets.

Burgard et al. (2005) performed an approach that explicitly coordinates the robots by considering the estimated path cost to reach a frontier while evaluating its utility corresponding to the expected gain in information from it. Their work also considers the problem of limited communication between robots. In the context of simultaneous localization and mapping (SLAM) (Dissanayake et al. 2001), Stachniss

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et al. (2005) used a Rao-Blackwellized particle filter (RBPF) to present a strategy in which the next locations to visit are selected in order to maximize the size of the explored area while minimizing the uncertainty on the map as well as that on the robot location. In order to improve the overall performance, later approaches considered the use of semantic information for allocating robots to the appropriate targets (Calisi et al. 2009; Li et al. 2016). Some recent work has leveraged distributed inference techniques to coordinate the exploration using visual features (Strom et al. 2015) or simulated laser scans (Smith and Hollinger 2018).

Regarding the cooperation between heterogeneous robots, Wurm et al. (2013) applied a temporal symbolic planning approach to coordinate heterogeneous teams of robots in exploration and transport tasks. Their work was an extension to the one in which the path planning for exploration using marsupial robots was investigated (Wurm et al. 2010).

Alternative coordination strategies exploited techniques based on the segmentation of the environment. Wurm et al. (2008) divided the map into segments using a Voronoi graph (VG) (Beeson et al. 2005). These segments represent individual rooms or parts of a large corridor. The assignment of robots to the segments is done by applying a Hungarian method. The approach presented by Puig et al. (2011) used the K-*means* algorithm to obtain the same number of segments as the robots used for the exploration. Even if these segmentation-based approaches significantly reduce the exploration time compared to the frontier-based approaches, their performance is limited to environments that can be divided into reasonably large and separated segments. Otherwise, if the environments are small and crowded with large teams of robots, other methods could generate better results.

This is the case of Bautin et al. (2012) who have proposed a new algorithm so-called MinPos (for Minimum Positions) based on the frontier concept. This approach takes into account the rank of the robot toward its target, which is defined as the number of robots closer to the frontier than the considered one. The rank is evaluated on the basis of the path distance needed for the robot to reach the frontier. The advantage of this approach is its ability to separate the robots in different directions which allows covering effectively the environment and so that reducing the overall exploration time. However, in the very distinct situations where several robots have the same rank toward the same target, the algorithm introduces redundancy in the assignment of robots caused mainly by the limited communication between them. In this context, significant efforts focused on multi-robot exploration under communication constraints (Amigoni et al. 2017). Nestmeyer et al. (2017) presented a role-based distributed algorithm able to guarantee the exploration task by multiple robots while maintaining a continuous connection between them. Otte (2018) demonstrated the ability to train a collective neural network across a swarm of robots with limited communication. Recently, Amigoni et al. (2019) presented a multi-robot system that learns and updates a communication graph in order to improve the exploration of unknown environments considering connectivity constraints. Additionally, Otte et al. (2019) compared several auction algorithms considering unreliable communication.

The approaches discussed above typically use the distance to each exploration target and its expected information gain to assign the robots without considering their energy state. Indeed, even if a robot is closest to an exploration target, this does not guarantee its ability to reach it. As a result, some robots of the team may stop exploring their environment due to lack of energy and could be left with empty batteries in the field. From another point of view, reducing the motion energy consumption of robots keeps them running as long as possible to cover more unknown areas, which is relevant for an exploration task.

The contribution of this paper is a new coordination approach that uses the segmentation of the already explored area (Wurm et al. 2008) and introduces the energy state and consumption of each individual robot as the main criterion for their assignment to their exploration target. The latter is defined as a segment of the environment including the frontiers between the unknown and explored areas. The proposed assignment strategy takes into account the rank of a robot toward a target (Bautin et al. 2012), which is defined as the number of robots that should consume less energy to reach this target.

This work is an improved version of the one previously presented in Benkrid et al. (2016) by using an energy-efficient motion planner[1] to compute the energy consumption needed to the robot for reaching the selected exploration target, as well as to generate the path between them. In addition to the simulation experiments, the implementation and tests on real robots show that the proposed approach distributes effectively the robots over the unknown areas allowing to explore wider environments compared to the existing approaches while maintaining a high performance in terms of reducing the overall exploration time.

The remainder of this paper is outlined as follows. Section 2 contains some preliminaries while introducing the problem posed by the exploration of unknown environments using multiple robots. In Sect. 3, we present our coordination strategy based on the motion energy consumption for a team of mobile robots. In addition to the real-world experiments, we compare in Sect. 4 the performance of the proposed approach to some existing methods through a series of experiments carried out in simulation. Section 5 is a conclusion.

[1] Which explicitly takes into account the energy consumption of the robot rotation.

2 Preliminaries and Problem Formulation

In the present work, we consider the environment to explore as a finite space in which multiple homogeneous robots are deployed, each of them is equipped with sensors that allow building a local map and localizing the robot in it using a SLAM algorithm. To limit the extent of the problem, we consider that all robots can communicate among themselves wherever they are. In addition, the produced map is represented by an occupancy grid in which the targets to explore are identified. Thus, we focus in this paper on the coordination of robots by giving each of them the appropriate target to reach considering its energy state and consumption in order to explore the environment within a minimal time while reducing the total motion energy consumption of the robot team.

The distribution of the robots over the targets can be considered as an optimization problem where the number of possible assignments is equal to the number of permutations without repetition. Considering the fact that solving this problem optimally is intractable for large teams of robots, we propose a new distributed approach that deals with the following criteria:

- During the exploration process, new targets can potentially be discovered. Therefore, no robot should be left without an assignment.
- The deployment of robots in the environment consists of assigning to each robot from the team a specific target to explore.
- Regardless of their number, the robots used for the exploration should be distributed in different directions toward the targets for covering a maximum of unknown areas.
- The distribution of robots over the targets involves considering the energy ability of each robot to reach its assigned exploration target and return to the starting point of the exploration task, from where it can be recovered.
- The total energy consumed during the exploration is the sum of the energies consumed by the members of the robot team to reach the set of targets. The optimization problem is, therefore, the minimization of the energy consumption of each robot of the team to reach a target.
- The time for all assigned targets to be explored is determined by the maximum exploration time among all targets (Bautin et al. 2012).
- Since no information about what is behind the targets is available, the impact of a given assignment on the global system performance cannot be determined. Therefore, the assignment process must be performed in each iteration or extension of the map representing the environment.

3 Proposed Coordination Approach

3.1 Robot's Motion Energy Consumption

For an exploration task, a mobile robot has limited energy needed for different uses such as motion, communication, sensing and computation. As the motion is the major consumer of the robot's energy (Yan and Mostofi 2013), saving the motion energy of mobile robots allows covering more unknown areas.

In our study, an energy-efficient motion planner detailed in Mei et al. (2006)[2] is used to find the path allowing each robot of the team to reach an exploration target with the lowest energy consumption. In order to compute the robot's motion energy consumption, a directed graph is generated from the grid cell map by considering the free cells as vertices. Each vertex of the graph should represent the robot's state including both location and direction. All neighboring vertices are connected by edges, each edge between two vertices has a weight representing the robot's energy consumption to move from one state to another. If the robot's direction changes between the states, its energy consumption for stops and turns is considered. Thereby, the energy-efficient motion planner attempts to find the energy-efficient path for which there is a minimum of edges and changes of direction between the states.

During the exploration process, each robot of the team computes its energy consumption to reach the target using the energy-efficient motion planner cited above. Thus, the motion energy consumption $\mathrm{Ec_r}$ of a robot r from a starting point A to the desired point B is the energy needed for traveling the energy-efficient path connecting A to B. Considering that the latter consists of N edges and K states where the robot has to change its direction, the robot motion energy consumption $\mathrm{Ec_r}$ is thus given by

$$\mathrm{Ec_r} = \sum_{i=1}^{N} \mathrm{Ec}_{\mathrm{edge}_i} + \sum_{j=1}^{K} \left(\mathrm{Ec_{stop}} + \mathrm{Ec}_{\theta_j}\right), \tag{1}$$

where $\mathrm{Ec}_{\mathrm{edge}_i}$ is the weight of the i-th edge and represents the energy needed for the robot to move between two states, $\mathrm{Ec_{stop}}$ is the energy needed for the robot to stop at the j-th state and Ec_{θ_j} is the energy needed for the robot to turn at the same state with an angle θ_j.

In order to consider the robot's ability to explore its environment, the energy remaining in its battery $\mathrm{Eb_r}$ is compared with the sum of the energy consumed to reach the target Ec_r^t and that needed to return toward the starting position $\mathrm{Ec}_\mathrm{r}^{\mathrm{str}}$. If

[2] Their work has been applied to a single robot and extended in this paper to multi-robot exploration tasks.

this sum is greater, a new energy consumption[3] is used. The latter is defined as

$$\mathrm{Ec_r} = \begin{cases} \mathrm{Ec_r^{\mathit{t}}} & \text{if } \mathrm{Ec_r^{\mathit{t}}} + \mathrm{Ec_r^{str}} \le \mathrm{Eb_r} \\ \infty & \text{otherwise} \end{cases} \quad (2)$$

Thus, considering the case where the energy stored in the battery of a robot is less than its expected energy consumption to reach the target and return to the starting position, this robot will not be considered at the assignment of robots to the targets and should return to the starting position in order to be recovered.

3.2 Robots Assignment Strategy

Our multi-robot coordination strategy aims to reduce both the overall exploration time and the total motion energy consumption of robots to cover a maximum number of accessible areas in an unknown environment. For this purpose, the proposed method uses an assignment algorithm based on the motion energy consumption of each robot to compute its rank toward an exploration target. This rank represents the number of robots that can consume less energy to reach a target than the considered one. As a consequence, each robot is assigned to the target for which it has the lowest rank. Considering P_{rt} the rank of a robot r from the set of all robots R toward a target t from the set of targets T such as:

$$P_{rt} = \mathrm{Card}(R'), \quad (3)$$

where R' is a subset of R including all robots $r' \neq r$ for which their energy consumption $\mathrm{Ec}_{\mathrm{r}'}^{t}$ needed to reach a target t is less than the energy consumption $\mathrm{Ec}_{\mathrm{r}}^{t}$ of the robot r to reach the same target t.

Using the notion of rank, algorithm 1 allows an appropriate target t' to be assigned to a specific robot r, based on its motion energy consumption. This algorithm improves the spatial distribution of robots in the environment to be explored by separating them in different directions toward the targets. Furthermore, this algorithm has low complexity [$O(NM')$ with N: number of robots and M' number of targets (Bautin et al. 2012)], allowing it to be used with robots which are limited in their computational capabilities.

During an exploration task, each of the team's robots repeatedly and independently performs the following steps: first, it shares its position, the energy remaining in its battery and its local map built from its perceptions and merged with the broadcasted maps of the other robots. The generated partial map of the environment is then segmented to a set S of segments following the method described in Wurm et al. (2008). This map is also used to identify the sets of frontiers F_s which are affiliated to the segments that include them. Thus, the motion energy consumption matrix Ec_R^S is calculated using the positions of all robots and their energy autonomy. This matrix holds the expected energy consumption Ec_r^s of each robot r of the team R to reach the closest frontier included in each segment s from the set S. Considering the situation in which a robot is already in a segment, its motion energy consumption is reduced by a constant factor β[4] in order to keep it in its assigned segment until the total exploration of the latter. The motion energy consumption matrix Ec_R^S is then used to assign the specific robot r' to the appropriate segment s' using algorithm 1. This algorithm is also used to assign the same robot r' to the appropriate frontier $f'_{s'}$ inside the previously determined segments s' using the motion energy consumption matrix $\mathrm{Ec}_R^{F_{s'}}$ calculated from each robot r to reach all the frontiers $f_{s'}$ included in this segment. All the steps previously cited for the target assignment are summarized in Algorithm 2.

Algorithm 1: Motion Energy Consumption-Based Target Assignment

Require: The robot $r \in R$ to be assigned and the matrix of motion energy consumption Ec_R^T
1. **foreach** $t \in T$ **do** calculate P_{rt};
2. Assign the robot r to the appropriate target t' with: $t' \in T \wedge t' = \underset{\forall t \in T}{arg\,min}(P_{rt})$;
3. **if** *there is equality* **then** choose a target for which the motion energy consumption is minimum among $arg\,min(P_{rt})$;

Return : The assignment of robot r to the target t'

4 Experimental Results

4.1 Simulation Experiments

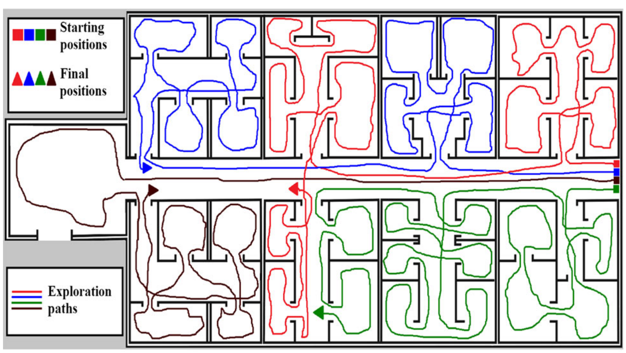
In order to evaluate our approach over previous techniques, some simulation experiments have been performed on MATLAB software using Robotics Toolbox from Corke (2011). Figure 1 depicts two maps of a real office environment used for the simulations, the first map represents its structured and large configuration without any fitting out (see Fig. 1a) unlike the second map which refers to the same environment cluttered with objects and obstacles (see Fig. 1b). The state space is discretized using an occupancy grid based representation, each cell of this grid is considered as a unit that can be classified in one of the following states: **free** (for explored cell cleared from obstacle); **occupied** (for explored cell occupied

[3] This energy consumption will be used to assign the robots to their appropriate exploration targets.

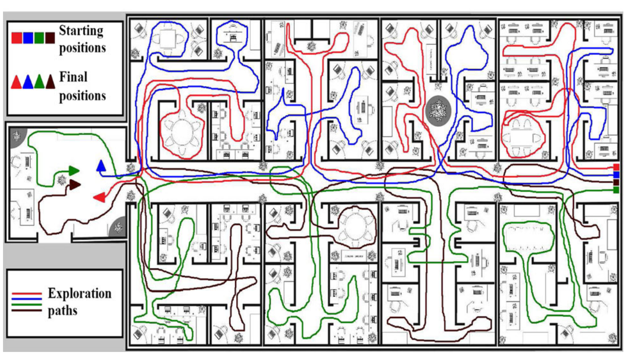
[4] The experiments showed that the value of β should be within the interval [0.3, 0.7].

Algorithm 2: Energy Based Multi-Robot Exploration

Determine the set of map segments S ;
Determine the set of frontiers F_s for each segment $s \in S$;
Set the matrix of motion energy consumption Ec_R^S to 0;
foreach $r \in R$ **do**
  foreach $s \in S$ **do**
    Compute the motion energy consumption Ec_r^s ;
    if *the robot r is already in the segment s* **then** Reduce Ec_r^s according to $Ec_r^s \leftarrow \beta Ec_r^s$;
    Update Ec_R^S according to: $Ec_R^S(r, s) \leftarrow Ec_r^s$;
Assign the determined robot $r' \in R$ to the appropriate segment $s' \in S$ using Algorithm 1 ;
Set the matrix of motion energy consumption $Ec_R^{F_{s'}}$ to 0;
foreach $r \in R$ **do**
  foreach $f_{s'} \in F_{s'}$ **do**
    Compute the motion energy consumption $Ec_r^{f_{s'}}$;
    Update $Ec_R^{F_{s'}}$ according to: $Ec_R^{F_{s'}}(r, f_{s'}) \leftarrow Ec_r^{f_{s'}}$;
Assign the determined robot $r' \in R$ to the appropriate frontier $f'_{s'} \in F_{s'}$ using Algorithm 1 ;



(a) The structured and large configuration



(b) The crowded configuration

Fig. 1 The simulated environment with the starting and final positions as well as the exploration paths (successive assignments) of four robots using our coordination approach

by obstacle); **unknown** (for unexplored cell) and **frontier** (for explored free cell neighboring of an unknown cell).

The simulated robots are assumed to be identical, and their dimension is set as the size of a grid cell. Based on the energy measurements taken from our mobile robots used in the real-world experiments, the following values were used in the simulation tests: for one unit of distance, each robot consumes 1.14 unit of energy; the energy consumption for $\sqrt{2}$ unit of distance is fixed to 1.56 unit; each stop consumes 0.75 unit of energy; a turn of 45° takes 0.55 unit of energy; turns of 90°, 135°, 180° take, respectively, 0.85, 1.15, 1.35 unit of energy. Furthermore, we can assume that all robots use sensors that allow them to scan their neighborhood at 360° field of view with a parameterized range fixed in our experimental simulation to 5 units.[5] The inaccuracies during the robot localization and the map generation are not considered. The position of each robot is shared with the energy remaining in its battery as well as its local generated map to the other robots through a simulated communication network covering all areas of the environment.

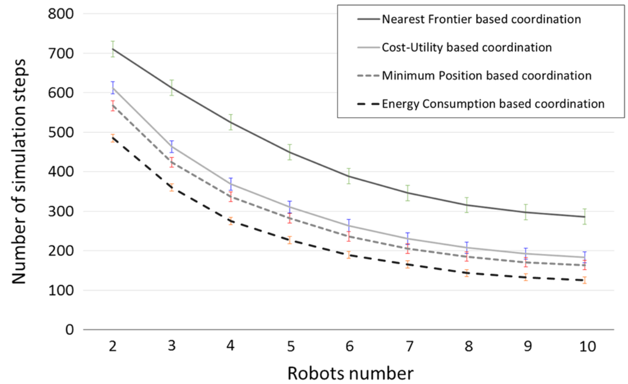
Regarding the reduction of the overall exploration time and the total motion energy consumption of robots, the proposed coordination approach is compared to three different methods[6]: the nearest frontier introduced by Yamauchi (1998), the cost-utility based approach performed by Burgard et al. (2005) and MinPos algorithm proposed by Bautin et al. (2012). In order to eliminate influences from the segmentation technique on our coordination method, the segmented maps of the simulated environment are supposed to be given.

In the first part of our study, we supposed unlimited energy for all robots of the team. For each coordination strategy, we performed several experiments while varying the size of the simulated team from two to ten robots with the same random starting position. The objective was to compare the exploration time needed to cover all unknown areas of the environment. Figure 2 presents the results (provided in simulation steps) according to the map of the environment used for the simulation. These results represent an average of 50 runs of each method with a given amount of robots. The error bars in the plots indicate 95% confidence intervals.

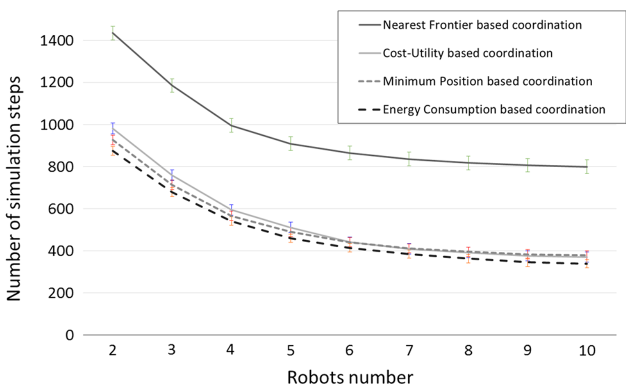
According to the results, the proposed coordination approach may allow exploring the structured and large configuration of the environment in less time compared to the three other methods, regardless of the number of robots used for the exploration (see Fig. 2a). This performance is justified by the use of the segmentation technique that divides the environment into separate regions representing the segments as targets for the robots assignment. In the crowded configuration of the environment, the performance of our approach decreases significantly but remains slightly better than the three other methods, regardless of the number of robots (see Fig. 2b). This small advantage is mainly due to the use of the energy-efficient motion planner that allows finding the

[5] This value is approximately derived from the range measurement of the Kinect sensor used for the real-world experiments.

[6] These approaches are purely distance-based for robot assignment.

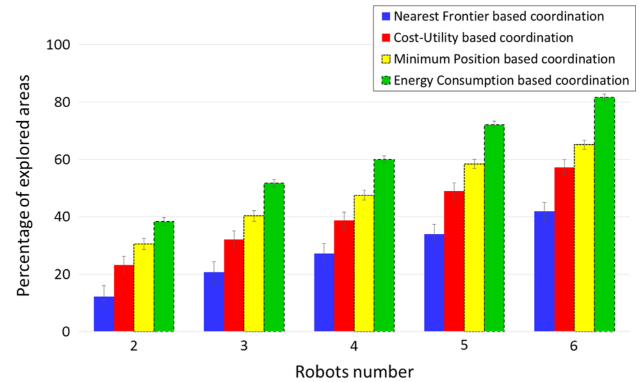


(a) The structured and large configuration

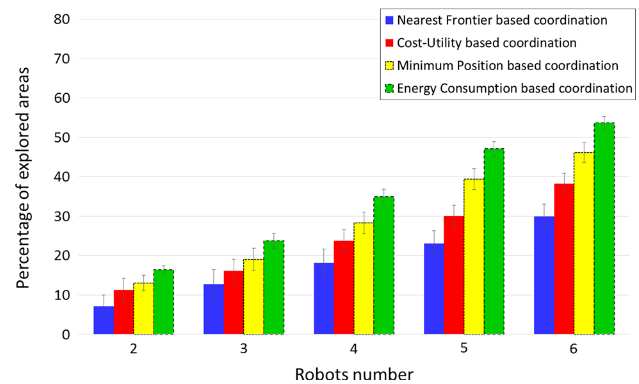


(b) The crowded configuration

Fig. 2 Exploration results according to the configuration of the simulated environment



(a) The structured and large configuration



(b) The crowded configuration

Fig. 3 Percentage of explored areas according to the configuration of the simulated environment

energy-efficient paths with a minimum of stops and turns for the robots.

The second part of our study was carried out to compare the motion energy consumption of the robot team using each of the four coordination approaches in our simulation experiments. The energy stored in the batteries of the robots has been initially fixed.[7] The aim was that none of the coordination methods should allow to fully exploring the simulated environment. At the end of the exploration process (when all the robots have consumed the energy stored in their batteries), we measured in percentage the surface of the environment explored by the robots. Figure 3 shows the results that represent an average of 50 runs of each method with a given size of the simulated team (which has been varied from two to six robots for the two configurations of the environment). The error bars in the plots indicate the 95% confidence level.

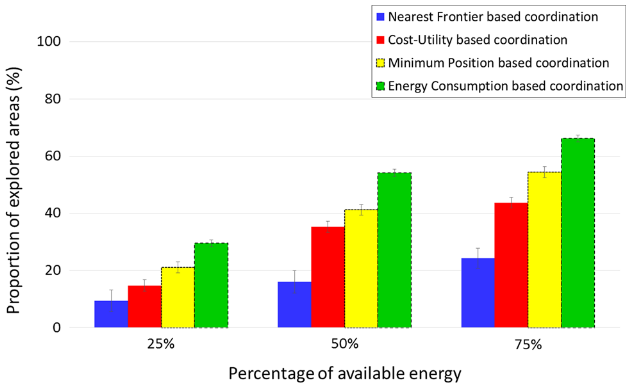
The main observation that can be made is the efficiency of our coordination approach to cover more unknown areas and thus to reduce the total motion energy consumption of robots compared to the three other methods in the two configurations of the simulated environment. In addition, we can observe the impact of the segmentation technique on the performance of our coordination approach. The latter is less effective in the crowded configuration of the environment where the segmentation of the map has little effects.

In order to show the benefit of the proposed approach regarding the total motion energy saving of the robot team, a third part of the simulation experiments was carried out. The number of robots used to explore the simulated environment was fixed to four.[8] The objective was to measure the proportion of the explored area according to the energy stored in the batteries of the robots. This available energy represents, respectively, 25%, 50% and 75% of the total energy needed to fully explore the simulated environment. As shown in Fig. 4, the results are given as a percentage and represent an average of 50 runs of each exploration algorithm. The 95% confidence level is indicated by the error bars in the plots.

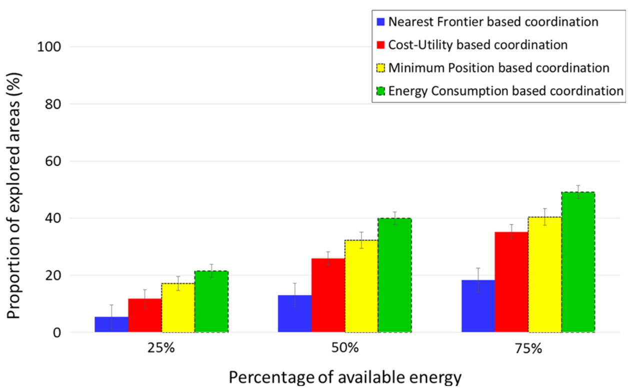
For each configuration of the simulated environment, the proposed strategy can significantly outperforms the three other methods, especially for a high level of available energy

[7] This energy varies from one robot to another, the rate of variation can reach 15%.

[8] The significant results were obtained with four robots for all simulated environments.



(a) The structured and large configuration



(b) The crowded configuration

Fig. 4 Proportion of the area explored according to the energy available in the robots batteries and the configuration of the simulated environment

where the difference between the proportions of the explored areas is approximately 30% more important. These last results strengthen the observation previously done about the ability of our coordination approach to reduce the total motion energy consumption of the robot team which allows exploring more unknown areas.

These last results are justified by the combination of the segmentation technique and the minimum position algorithm based on the motion energy consumed by the robots. The latter are separated in different directions toward the targets following the path determined by the energy-efficient motion planner.

4.2 Real Robots Experiments

The evaluation of our coordination strategy in the real-world experiments has been conducted on two mobile robots specifically designed and built for this study. Each of them uses a National Instruments robot (i.e., NI Robotics Starter Kit 2) as a platform featuring sensors, motors and NI Single-Board RIO hardware for embedded control. In the context of navigation and mapping, a Kinect sensor was mounted on the top

Fig. 5 Front view of the integrated robots used for the real-world experiments

of the platform and used as a $2D$ laser scanner by converting the Kinect's $3D$ depth into $2D$ laser scan-like data based on the technique proposed by Kamarudin et al. (2013). Each platform of both mobile robots has been also connected to a Netbook (embedded on it) using an Ethernet cable. This Netbook consists of a 2.16 GHz Intel Celeron N2840 and 4 GB random access memory (RAM), the whole powered by a 4-cell lithium-prismatic battery. Figure 5 shows a front view of the mobile robots.

As far as the software components are concerned, the Windows 7 operating system was used as a host with Ubuntu 12.04 installed in a virtual machine on each Netbook. The LabVIEW program running on Windows collected the data from the NI platform and allowed calculating the odometry of the robot as well as evaluating the charge state of its battery. The results were sent, with the scan data obtained from the Kinect sensor, to the SLAM algorithm (Gmapping[9] developed by Grisetti et al. (2007)) running on the Robot Operating System (ROS[10]) in a Linux virtual machine. The resulting map was merged with the local map of the other robot shared with its position and energy remaining in its battery[11] through wireless communication.[12] The generated global map was then used by the exploration algorithms for assigning the determined robot to the appropriate target. The communication between the host (i.e., Windows 7) and ROS was assured by the ROSBridge and the TCP/IP protocol.

The first experiment with the two mobile robots was carried out to prove the ability of our coordination approach in order to cover all unknown areas of the environment. The goal of the experiment was to explore two adjacent office rooms connected by a long corridor leading to a hall. The map segmentation technique was used so that each distinct

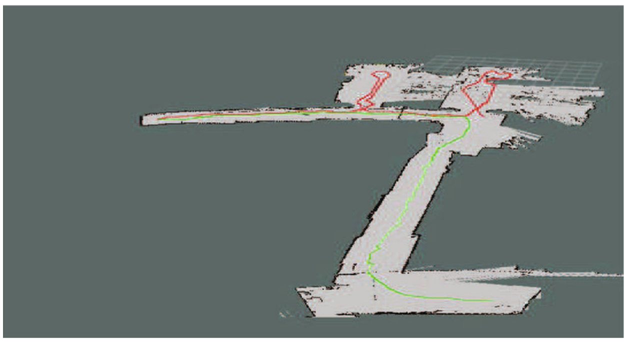
[9] http://wiki.ros.org/gmapping.

[10] http://www.ros.org/wiki/.

[11] The charge state of the batteries was only used by our exploration algorithm.

[12] Wireless routers were used for covering all areas of the environment where the experiments were achieved.

(a) The two mobile robots exploring a long corridor



(b) Resulting map of the real world experiment including the trajectories of the two individual robots

Fig. 6 Coordinated exploration by a team of two mobile robots in a real-world experiment

part of the environment (the corridor, the office rooms, and the hall) is considered as a segment to explore. Figure 6a depicts the two mobile robots during their exploration mission, while Fig. 6b shows their combined map[13] resulting from the exploration of this part of the environment which has a size of approximately 35 m × 51 m. The robots trajectories are also represented on the map.

As can be seen, both robots start to explore their environment from the same position in the corridor. Once they arrive in the first office room, the robots separate. One of them keeps exploring all the corridor[14] until reaching the hall (see the green trajectory in Fig. 6b), while the second robot successively explores the two adjacent office rooms (see the red trajectory in Fig. 6b). This demonstrates the ability of our coordination approach to distribute the robots over an unknown environment in order to explore it.

The second experiment with the two mobile robots was conducted to evaluate the impact of the map segmentation technique on our coordination approach. In this framework, the two mobile robots were redeployed considering the frontiers between the unknown and the explored accessible areas

[13] Note that the inaccuracy of the map is mainly due to the limited field of view and range of the Kinect's depth sensor.

[14] Which is considered as a segment that must be completely explored by the robot.

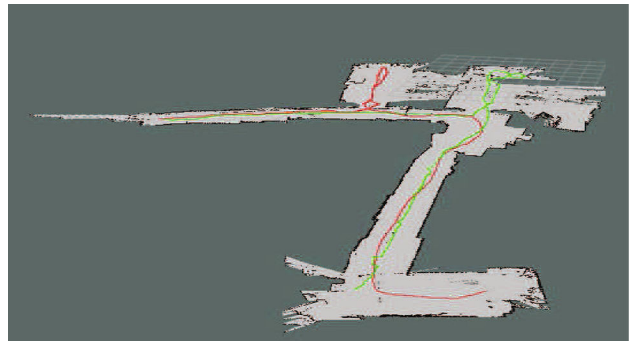


Fig. 7 Resulting maps with the robots trajectories obtained using the proposed coordination approach without the map segmentation technique

Table 1 Overall exploration time and percentage of the total energy consumed by the robot team in the two experiments

Results	First experiment	Second experiment
Exploration time (s)	215	405
Total energy consumed (%)	31	53

as the targets to explore. Figure 7 shows the resulting maps with the robots trajectories generated from the exploration process.

Despite the similarity of the maps between the second and the third experiment, the behavior of the two mobile robots during the exploration process seems completely different (see Figs. 6b and 7). Indeed, using our coordination approach without the map segmentation technique, the robots begin to discover the corridor which they leave for exploring separately the two adjacent office rooms. Once explored, the robots meet to discover the rest of the corridor that leads to the hall (see Fig. 7). It is interesting to note that during the exploration of this last part of the environment, a problem of obstruction between the robots[15] has frequently occurred. This distribution of the robots in the environment is not efficient in reducing the overall exploration time and the total motion energy consumption of the robot team compared to the use of our coordination approach considering the map segmentation technique. This ascertainment is confirmed by the results reported in Table 1 which represent the overall exploration time and the rate of the total motion energy consumed by the robot team during the two experiments.

In order to validate the simulation results shown in Sect. 4.1 (Simulation experiments), several real-world experiments were conducted with the two mobile robots in the same environment previously used. The aim was to compare the performance of the proposed approach to reduce the overall exploration time and the total energy consumption of the robot team with the three other methods previously

[15] Where one robot's path is blocked by another.

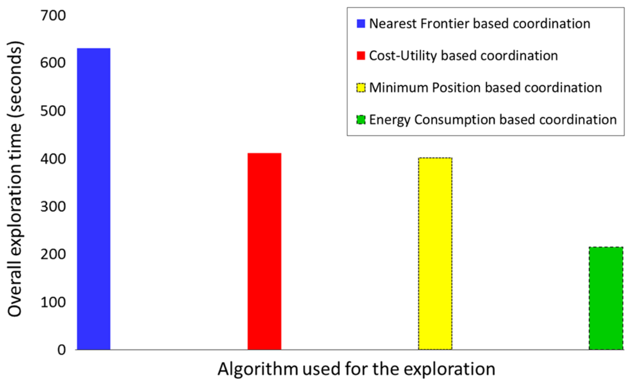


Fig. 8 Overall exploration time of the robot team in the real-world experiment

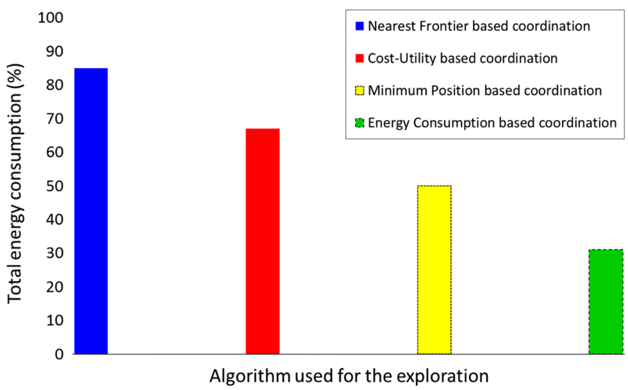


Fig. 9 Percentage of the total energy consumed by the robot team in the real-world experiment

cited which are: the nearest frontier introduced by Yamauchi (1998); the cost-utility-based approach performed by Burgard et al. (2005); and MinPos algorithm proposed by Bautin et al. (2012).

Figures 8 and 9, respectively, show the overall exploration time and the total motion energy consumption of the robot team for all four exploration algorithms. The observation that can be made is the efficiency of our coordination approach to reduce both the exploration time and the motion energy consumption of the two robots compared to the three other methods. These results can be justified by the behavior of the two mobile robots during the exploration process. Indeed, for the cost-utility based approach and the MinPos algorithm, the two robots have approximately the same trajectories as those shown in Fig. 7.

5 Conclusion

The central question addressed in this paper is how to distribute and coordinate a team of mobile robots to ensure an energy-efficient exploration of an unknown environment. For this purpose, a novel approach has been suggested which splits the generated partial map of the environment into different segments, each of which contains one or more frontiers that are the final targets to explore. Based on the motion energy consumption of robots and the remaining energy in their batteries, the coordination is achieved in two phases. Initially, each robot is assigned to the segment for which it has the lowest rank. This rank is defined as the number of robots that can consume less energy to reach the segment than the evaluated one. In a similar way, once the robot has reached the segment, it moves to the next frontier within the segment that minimizes the motion energy consumption. Since the communication between robots is limited to sharing their position and local maps as well as their remaining energy, the decision about which target to visit is independently made, which could make our approach robust despite the loss of communication between robots.

In addition to the simulation runs, the implementation and tests of the proposed coordination strategy on real robots demonstrate its efficiency to reduce the total motion energy consumption of robots and thus to cover more unknown areas of the environment compared to the nearest frontier assignment, the cost-utility-based method and the MinPos algorithm. Regarding the minimization of the overall exploration time, our approach is significantly more efficient in the large and structured environments than the three other methods previously mentioned. This performance is mainly due to the segmentation of the environment and the notion of robot's rank that allow separating the robots in different directions toward the segments. In the crowded configuration of the environment where we cannot benefit from using the map segmentation, the performance of our assignment approach decreases but remains slightly better than the MinPos algorithm and the cost-utility-based method. This last result can be explained by the use of an energy-efficient motion planner that allows finding the energy-efficient paths with a minimum of stops and turns for the robots.

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