Efficient Information Sharing and Coordination in Cooperative Multi-Robot Systems

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***Abstract*— Multi-robot systems involve the distribution of robotic resources and information. Being an opportunity, they require cooperation among robots so that potential advantages of distribution become effective. Cooperation requires in turn efficiently sharing information and proper coordination. This article extends previous work, regarding efficient information sharing in the context of volumetric mapping [1], with a coordinated exploration method based on mutual information minimization. Experimental data obtained with multi-robot systems varying in size demonstrate the performance gain due to the proposed coordination method.**

***Index Terms*— Multi-robot systems, cooperation, coordination, information utility, 3-D mapping, exploration.**

I. Introduction

Multi-robot systems (MRS) are sets of autonomous mobile robots that are assumed to cooperate in order to carry out collective missions [2], [3]. MRS may either substitute humans in risky scenarios [4]–[7] due to the expendability of individual robots, or relieve people from collective tasks that are monotonous and repetitive. Moreover, they allow to automate missions that are inherently distributed in time, space or functionality.

The distribution of robotic resources and information endows MRS with interesting features, such as space and time distribution, managing complexity through distribution, distribution of risk and increased robustness [8]. But these potential advantages require robots' cooperation in order to become effective [9]. Cooperation requires in turn efficient information sharing and proper coordination. Previous work was conducted with the aim of restricting communication in MRS to useful information, in the context of building volumetric maps [1]. This framework is extended herein with coordinated multi-robot exploration, so as to improve collective performance.

1) Sharing information within multi-robot systems: Most of the work about MRS has been devoted to the definition of different distributed architectures [4], [6], [10] that rule the interaction between the behaviors of individual robots. Although communication is a central issue of MRS, because it determines the possible modes of interaction among robots, it has been often neglected in these architectures. Furthermore, most of the work about communication in MRS [10]–[13] has addressed the communication structure, neglecting another important dimension: the communication content.

A distributed group architecture for 3-D mapping was proposed in [1], which endows robots with an altruistic information sharing behavior, wherein communication efficiency is ensured by restricting communication contents to useful information. This framework is extended herein with coordination.

2) Robotic mapping: Robotic mapping addresses the problem of acquiring spatial models of physical environments with mobile robots equipped with range sensors. It is a relevant application domain whether robots are used to build detailed maps of environments, especially hazardous environments for human beings [5], [7], or they require a map to safely navigate within the environment and perform other useful tasks.

As sensors have always limited range, are subject to occlusions and yield noisy data, mobile robots have to navigate through the environment and build the map iteratively. Key challenges include the sensor modeling problem, the representation problem, the registration problem and the exploration problem [14]. This article focuses on coordinated exploration.

3) Exploration and active sensing: When a robot or a team of robots explore an unknown environment to build a map, the main goal is to acquire as much new information as possible with every sensing cycle, so as to minimize the mission time.

Yamauchi *et al.* proposed frontier-based exploration [15] whereby a robot is driven to the closest frontier cell in its neighborhood, located between open space and unexplored regions. Burgard *et al.* used this concept to address coordination in multi-robot exploration, by considering a balance between travel cost and utility of unexplored regions, so that robots explore non-overlapping regions [16]. Bourgault *et al.* [17] addressed the single robot exploration problem as a balance of alternative motion actions, from the point of view of information gain (in terms of entropy), localization quality (using SLAM) and navigation cost. In [18], robots that can communicate with each other are arranged in exploration clusters and the robots within each cluster share a common map and coordinate their exploration actions as in [16].

This article proposes a multi-robot exploration method closely related with [16], but with important improvements: it uses a distributed architecture model with efficient information sharing [1], wherein entropy is used to define a formal information-theoretic background to reason about the mapping and exploration process; and the utility of an exploration viewpoint is formally defined using entropy-related concepts.

II. Probabilistic Volumetric Maps

This section briefly presents the grid-based probabilistic framework proposed in [1] for representing and updating volumetric maps. The 3-D workspace is divided into equal sized voxels with edge $\epsilon \in \mathbb{R}$ and volume ϵ^3. The set of all voxels yielded by such division is a 3-D discrete grid $\mathcal{Y}$. Given a 3-D point $\mathbf{x} \in \mathbb{R}^3$, $v(\mathbf{x})$ denotes the voxel $l \in \mathcal{Y}$ containing the point $\mathbf{x}$. Given a voxel $l \in \mathcal{Y}$, $\mathbf{w}(l) \in \mathbb{R}^3$ denotes the voxel's center coordinates $[x_l, y_l, z_l]^T$. The *coverage* of a voxel $l \in \mathcal{Y}$ is the portion of the the cell which is covered (occupied) by obstacles. It is modeled through the continuous random variable C_l, taking values c_l in the interval $0 \leq c_l \leq 1$. The tuple $M_k = (\mathbf{x}_k, \mathcal{V}_k)$ denotes the k-th batch of measurements, being $\mathbf{x}_k$ the sensor's position from where measurements are obtained and $\mathcal{V}_k$ the set of measurements belonging to the batch, provided by the robot's sensor at $t = t_k,\ t_k \in \mathbb{R},\ k \in \mathbb{N}$. The set $\mathcal{M}_k = \{M_i : i \in \mathbb{N},\ i \leq k\}$ is a sequence of k batches of measurements, corresponding to the period of time $t_0 \leq t \leq t_k$, being t_0 the initial time before any batch of measurements. The knowledge about the voxel's coverage C_l, after k batches of measurements, is modeled through the pdf $p(c_l \mid \mathcal{M}_k),\ 0 \leq c_l \leq 1$. The *probabilistic volumetric map* after k batches of measurements is the set of random variables $\mathcal{C} = \{C_l : l \in \mathcal{Y}\}$, described statistically through the set of coverage probability density functions $\mathcal{P}(\mathcal{C} \mid \mathcal{M}_k) = \{p(c_l \mid \mathcal{M}_k) : \ l \in \mathcal{Y}\}$. The coverage of each individual voxel is assumed to be independent from the other voxels' coverage and thus $\mathcal{C}$ is a set of independent random variables.

The voxel's discrete entropy is denoted as $H(C_l)$ and the map's entropy is

$$H(\mathcal{C}) \equiv \sum_{l \in \mathcal{Y}} H(C_l), \tag{1}$$

which is an absolute measure of how much uncertainty the map contains. Hereafter, the quantity $H(C_l \mid \mathcal{M}_k) = H(t_k)$ denotes the map's joint entropy $H(\mathcal{C} \mid \mathcal{M}_k)$ conditioned to the previous k batches of measurements.

See Fig. 3 for examples of volumetric maps.

III. Distributed Architecture Model

This section briefly describes the distributed architecture model proposed in [1] for building volumetric maps, which is extended herein with a coordinated exploration mechanism. Consider a team $\mathcal{F} = \{1, \ldots, n\}$ of n mobile robots and the architecture's diagram depicted in Fig. 1. Although this diagram refers to an individual robot $i \in \mathcal{F}$, the interaction with the rest of the team (the set of robots $\mathcal{F} \backslash i$) is represented through the communication block and its associated data flow.

The robot's sensor provides new sets of vectors $\mathcal{V}_{k+1}$ where obstacles are detected from the current sensor's pose $Y(t)$. The localization module gives the sensor's pose $Y(t)$, including position and attitude. The actuator changes the sensor's pose accordingly with new selected viewpoints Y^s. Whenever the robot's sensor yields a new batch of measurements $M_{k+1} = (\mathbf{x}_{k+1}, \mathcal{V}_{k+1})$, the map is updated accordingly.

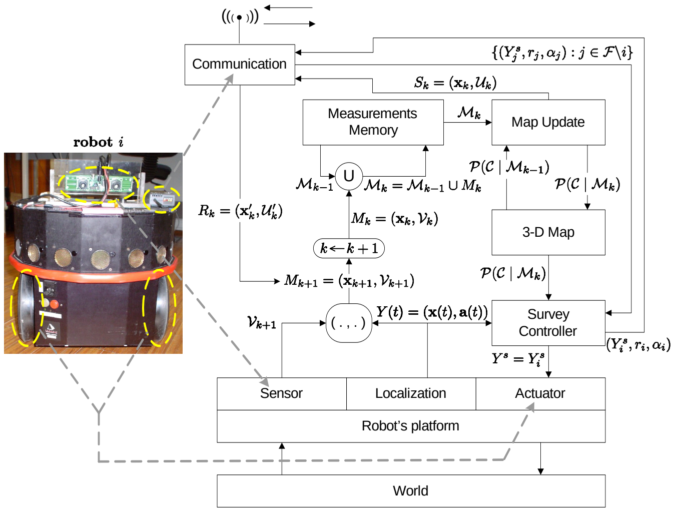


Fig. 1. Block diagram showing the relation between different parts of the process and the resources of a given robot i of the fleet $\mathcal{F}$.

Robot i selects a new viewpoint $Y^s = Y_i^s$ given the current map, its current pose $Y_k = Y_{k,i}$, its current visibility parameters r_i and α_i, and visibility information $\{(Y_j^s, r_j, \alpha_j) : j \in \mathcal{F} \backslash i\}$ about all the other robots in the team $\mathcal{F} \backslash i$. The new selected viewpoint Y^s is the reference input to the robot's actuator. Whenever the robot selects a viewpoint for its sensor, the communication module is used to communicate the tuple (Y_i^s, r_i, α_i) to other robots, *i.e.* the new selected viewpoint and its current visibility parameters. This minimal communication increase the robot's awareness about its teammates and enables to coordinate the multi-robot exploration.

As part of the map updating process, it is built a batch of measurements $S_k = (\mathbf{x}_k, \mathcal{U}_k)$ containing the most useful data from sensor $\mathcal{U}_k \subseteq \mathcal{V}_k$. Those selected measurements are shared between robot i and the other robots in the fleet $\mathcal{F} \backslash i$ through the communication module. This module can also provide robot with batches of measurements $R_k = (\mathbf{x}'_k, \mathcal{U}'_k)$ given by other robots and the map is updated accordingly. Cooperation among robots arises because of this altruistic commitment to share useful information [1].

A. Results

An uncoordinated version [1] of the distributed architecture model was implemented in the mobile robots depicted in Fig. 2, which use stereo-vision as range sensor. Fig 3 shows three different versions of the map obtained in a mapping mission performed by these robots. The robots started the experiment with a maximum entropy map and followed the entropy gradient-based exploration method proposed in [1], in order to explore the environment until $H(\mathcal{C}) < 500$. The same mapping mission was also carried out with a single robot; the time $t_k(1)$ that it needed to obtain maps with entropy equal to the ones depicted in Fig 3 is shown therein in red, so as to better understand the reduction of the mission execution time yielded by the team of two robots.

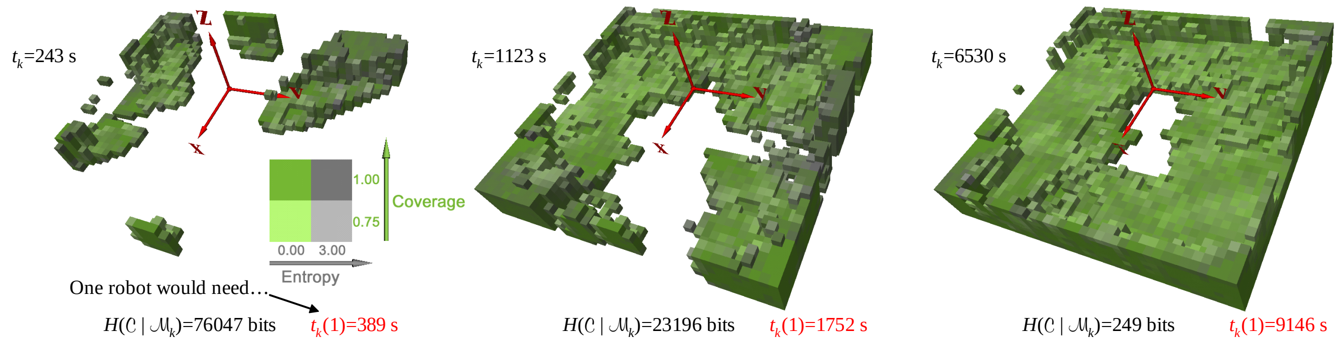
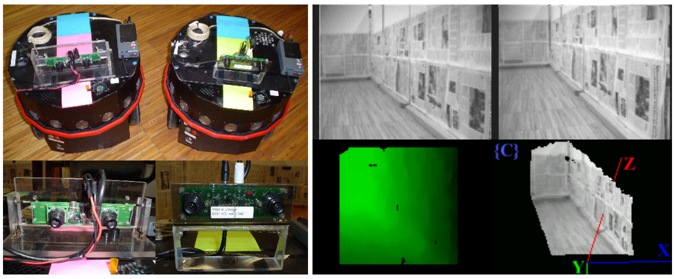


Fig. 3. Map's evolution along a volumetric mapping mission with two robots. Each column is a snapshot of the map at a different instant time t_k and entropy level $H(\mathcal{C} \mid \mathcal{M}_k)$. The time $t_k(1)$ that a single robot needs to obtain a map with the same entropy is shown in red. The maps' resolution is $\epsilon = 0.1\ m$.



(a) (b)

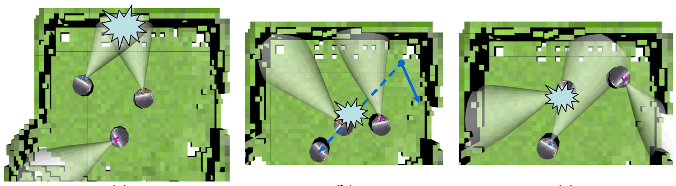
Fig. 2. Mobile robots used in the mapping experiments: (a) Scout mobile robots (top) equipped with stereo-vision sensors (bottom); (b) a stereo image pair (top) and its disparity (bottom-left) and depth map (bottom-right).

Although the two mobile robots accomplished the mapping mission in less time than a single robot — 72% of the time needed by a single robot — this performance gain is far away from a linear performance gain with team size, wherein two robots would spend just half of the time of a single robot. The main reason for this result is the lack of coordination in the robots' exploration actions.

IV. Coordinated Exploration

In an exploration mission, the objective is to acquire as much new information about the environment as possible with every sensing cycle. An entropy gradient-based exploration method was proposed in [1], which directs the robot's sensor to frontier voxels [15] between more explored and less explored regions. This method was proved to be successful with a single robot [1], but coordinating the robots' exploration actions with multiple robots is crucial to ensure a good collective performance.

Fig. 4 illustrates the three types of undesirable situations yielded by the lack of coordination. Firstly, a robot may choose the same exploration viewpoint selected by other robots or, at least, the map's region that a robot can sense may overlap the sensed regions by other robots (Fig. 4-a). Secondly, a robot may select an exploration viewpoint for which its chosen trajectory is blocked by other robots (Fig. 4-b). Thirdly, the robot's sensor may me occluded by other robots located within its sensory field of view (Fig. 4-c).



(a) (b) (c)

Fig. 4. Typical undesirable situations due to uncoordinated exploration.

A. Robot's visibility

Consider a robot and its pose $Y = (\mathbf{x}, \mathbf{a})$, which includes its position $\mathbf{x} \in \mathbb{R}^3$ and orientation $\mathbf{a} = \{\theta, \phi, \psi\}$. The angles θ, ϕ and ψ are the yaw angle, the pitch angle and the roll angle, respectively, and are assumed to be positive in the counterclockwise direction. The *robot's visibility* is the maximum volume the robot can sense upon its current pose. Given the maximum range distance r and the maximum angle α with the heading $\hat{\mathbf{p}}$ of the robot's sensor, it is the volume defined as the continuous set of points:

$$\begin{aligned} \mathbf{V}(\mathbf{x}, \mathbf{a}, r, \alpha) = \{\mathbf{y} \in \mathbb{R}^3 :& \|\mathbf{y} - \mathbf{x}\| \leq r, \\ & 0 \leq \arccos\left(\frac{(\mathbf{y} - \mathbf{x}) \cdot \hat{\mathbf{p}}}{\|\mathbf{y} - \mathbf{x}\|}\right) \leq \alpha\}, \end{aligned} \quad (2)$$

with

$$\hat{\mathbf{p}} = [\cos\theta.\cos\phi, \sin\theta.\cos\phi, -\sin\phi]^T. \quad (3)$$

Whether the robot is currently exploring a wide open area or a narrower space, the robot's visibility is dynamically conditioned by the presence of obstacles in front of the sensor, which hide the space behind them and reduce the sensor's intrinsic range. In order to dynamically adapt the robot's visibility, the latest sensor data is used to estimate r and α. Given the latest batch of m_k measurements $M_k = (\mathbf{x}, \mathcal{V}_k)$, the robot's visibility parameters are estimated as:

$$(\hat{r}, \hat{\alpha}) = \left(\frac{1}{m_k}\sum_{i=1}^{m_k} \|\overrightarrow{\mathbf{v}}_{k,i}\|,\ \max_i \left[\arccos\left(\frac{\overrightarrow{\mathbf{v}}_{k,i} \cdot \hat{\mathbf{p}}}{\|\overrightarrow{\mathbf{v}}_{k,i}\|}\right)\right]\right). \quad (4)$$

B. Visible maps and mutual information

Consider the fleet $\mathcal{F} = \{1, \ldots, n\}$ of n robots performing a 3-D mapping mission and one of the robots, $i \in \mathcal{F}$, belonging to the team. Its visibility $\mathbf{V}_i = \mathbf{V}(\mathbf{x}_i, \mathbf{a}_i, r_i, \alpha_i) \subset \mathbb{R}^3$ represents a sub region of the environment being mapped that robot i is able to sense and, thus, measurements gathered from its current pose $Y_i = (\mathbf{x}_i, \mathbf{a}_i)$ will only influence its knowledge about that sub region. That sub region refers to the subset of voxels

$$\mathcal{Z}^i = \{l \in \mathcal{Y} : \mathbf{w}(l) \in \mathbf{V}(\mathbf{x}_i, \mathbf{a}_i, r_i, \alpha_i)\} \subset \mathcal{Y}. \tag{5}$$

The subset of coverage random variables

$$\mathcal{C}^i = \{C_l, \ l \in \mathcal{Z}^i\} \subset \mathcal{C} \tag{6}$$

denotes the *robot's visible map*, which models the robot's knowledge about the visible sub region defined by the voxels $l \in \mathcal{Z}^i$, with entropy

$$H(\mathcal{C}^i) = \sum_{l \in \mathcal{Z}^i} H(C_l) < H(\mathcal{C}). \tag{7}$$

The inequality in equation (7) means that the robot's visible map covers less uncertainty than the map's uncertainty.

The other robots in the fleet, $\mathcal{F} \backslash i$, cover the set of voxels

$$\mathcal{W}^i = \bigcup_{j \in \mathcal{F} \backslash i} \mathcal{Z}^j \subseteq \mathcal{Y} \tag{8}$$

and have a joint visible map $\mathcal{T}^i$ with entropy

$$H(\mathcal{T}^i) = \sum_{l \in \mathcal{W}^i} H(C_l) \leq H(\mathcal{C}). \tag{9}$$

The fleet covers the set of voxels $\mathcal{W} = \mathcal{Z}^i \cup \mathcal{W}^i$ and has a joint visible map $\mathcal{T} = \mathcal{C}^i \cup \mathcal{T}^i$, with entropy

$$H(\mathcal{T}) = H(\mathcal{C}^i) + H(\mathcal{T}^i) - I(\mathcal{C}^i; \mathcal{T}^i). \tag{10}$$

Equation (10) measures the uncertainty being covered by the team. The mutual information $I(\mathcal{C}^i; \mathcal{T}^i)$ between the robot's visible map and the joint visible map of the other robots is null if the robot's visible map does not overlap with the other robots' visible maps; otherwise, it is equal to the sum of the entropy of the voxels belonging to the overlapping [9].

C. Coordinated exploration strategy

In an exploration mission, the objective is to acquire as much new information about the environment as possible with every sensing cycle. Intuitively, this is equivalent to select new regions to explore so that the robot's visible map entropy $H(\mathcal{C}^i)$ is maximized. This is indeed the aim of the entropy-gradient based exploration proposed in [1] for a single robot. With multiple robots, the robot's goal should be the maximization of the fraction of the map's uncertainty covered by the team, $H(\mathcal{T})$. As equation (10) shows, this is a twofold goal: to maximize the joint entropy of its own visible map $H(\mathcal{C}^i)$, likewise in the single robot case; *and* to avoid the overlapping with the other robots' visible maps, so that the mutual information $I(\mathcal{C}^i; \mathcal{T}^i)$ is minimized (see Fig. 5).

Considering a given robot $i \in \mathcal{F}$, the coordinated exploration method proposed herein selects the best voxel from a subset of $\mathcal{Y}$ in its neighborhood, by computing entropy gradient, visible map's mutual information, reachability and

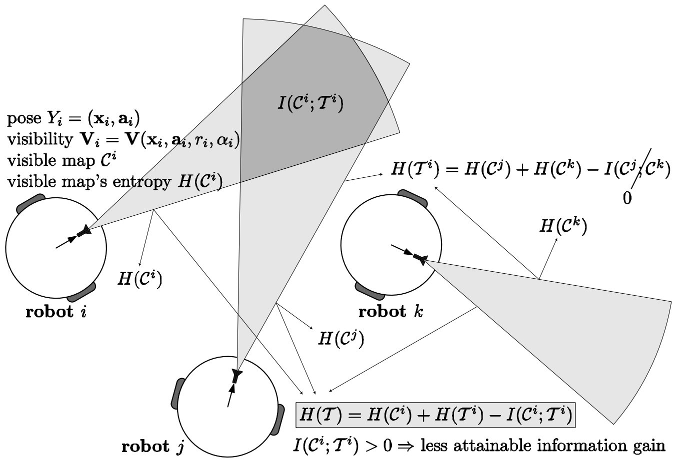


Fig. 5. Example showing visible maps with 3 robots i, j and k. The mutual information $I(\mathcal{C}^i; \mathcal{T}^i) > 0$ decreases the team's visible map joint entropy, *i.e.* the team covers a smaller part of the map's uncertainty $H(\mathcal{C})$.

occlusions due to other robots. Accordingly with Fig. 1, page 2, it is assumed that whenever a robot $j \in \mathcal{F}$ selects a new pose $Y_j^s = (\mathbf{x}_j^s, \mathbf{a}_j^s)$, the other robots in the team, $\mathcal{F} \backslash j$, are informed through explicit communication about its new selected pose and its current range parameters r_j and α_j, *i.e.* they receive the tuple (Y_j^s, r_j, α_j). This minimal communication enables each robot $i \in \mathcal{F}$ to compute the mutual information $I(\mathcal{C}^i; \mathcal{T}^i)$ between its visible map $\mathcal{C}^i$ and the joint visible map of the rest of the team $\mathcal{F} \backslash i$.

Assuming that robots' motion is restricted to a plane Γ (ground mobile robots), the new robot's position is selected as the center of a voxel from a set of voxels $\mathcal{N}_\Gamma(\mathbf{x}, r)$ traversed by Γ, in the neighborhood defined by its current position $\mathbf{x}$ and range r.

Consider a given candidate voxel $l \in \mathcal{N}_\Gamma(\mathbf{x}, r)$. Being $\overrightarrow{\nabla} H_\Gamma(l)$ the projection on Γ of the entropy gradient computed at the voxel's center $\mathbf{w}(l)$, the normalized gradient magnitude to the interval $[0, 1]$ is denoted as $\left\| \overrightarrow{\nabla} H_\Gamma(l) \right\|_N$. If the center of the voxel is selected to be the next robot's selected position $\mathbf{x}^s$, the method proposed herein claims that the robot should select the gaze direction $\mathbf{a}(l)$ defined by the unitary vector

$$\hat{\mathbf{p}}(l) = \frac{\overrightarrow{\nabla} H_\Gamma(l)}{\left\| \overrightarrow{\nabla} H_\Gamma(l) \right\|}, \ \overrightarrow{\nabla} H_\Gamma(l) \neq \overrightarrow{0}. \tag{11}$$

Given any candidate voxel $l \in \mathcal{N}_\Gamma(\mathbf{x}, r)$, and denoting its associated candidate pose as Y^l, the non-redundancy coefficient is the function $\lambda : \mathcal{Y} \rightarrow]0, 1]$, defined as

$$\lambda(l) = \exp\left[-\frac{1}{\xi} I(\mathcal{C}^i(Y^l); \mathcal{T}^i)\right], \tag{12}$$

wherein ξ is a scale factor and $\lambda(l) = 1$ means that candidate voxel l is associated with a visible map which does not overlap with the other robots' visible maps.

The reachability of a given voxel is a function of how much covered are the voxels traversed by the robot when it moves its sensor along its path from its current pose $Y = (\mathbf{x}, \mathbf{a})$ to the pose Y^l. These voxels may be either occupied with obstacles in the environment or other robots. The reachability of a candidate voxel $l \in \mathcal{N}_\Gamma(\mathbf{x}, r)$ is denoted as $\rho(\mathbf{x}, l)$, taking values between 0 (invalid path) and 1 (path completely clear of obstacles).

The presence of other robots within the robot's visibility region yields undesirable occlusions and interference. Using equation (5), the robot computes the visible voxels $\mathcal{Z}^i(Y^l)$ when its sensor's pose is Y^l and checks if there are other robots occupying those voxels. The non-interference coefficient of a candidate voxel $l \in \mathcal{N}_\Gamma(\mathbf{x}, r)$ is computed through a function $\eta : \mathcal{Y} \to]0, 1]$, where in $\eta(l) = 1$ means that the robot's visible map associated with l is not interfered by the presence of other robots.

If it is also worth to reduce the traveled distance during exploration, the cost associated with each candidate voxel $l \in \mathcal{N}_\Gamma(\mathbf{x}, r)$ has to be considered, being the distance between current robot's position $\mathbf{x}$ and the center of the candidate voxel l. The cost factor is defined as the function $\vartheta : \mathbb{R}^3 \times \mathcal{Y} \to [0, 1]$, wherein $\vartheta(\mathbf{x}, l) = 1$ means that the distance is equal to r.

Given the set of candidate voxels $\mathcal{N}_\Gamma(\mathbf{x}, r)$ in the robot's neighborhood, the robot is directed to the voxel

$$l^s = \underset{l \in \mathcal{N}_\Gamma(\mathbf{x},r)}{\operatorname{argmax}} \left(\left\| \overrightarrow{\nabla} H_\Gamma(l) \right\|_N . \lambda(l) . \rho(\mathbf{x}, l) . \eta(l) - \kappa . \vartheta(\mathbf{x}, l) \right), \tag{13}$$

with a gaze on arrival defined by the unitary vector $\hat{\mathbf{p}}(l^s)$, computed through equation (11). In the argument of equation (13), the left term measures utility and the right term measures cost, being κ a cost sensitivity coefficient. Further details about this formulation can be found in [9].

D. Results

The multi-robot coordinated exploration method represented by equation (13) was implemented in the mobile robots depicted in Fig. 2, which were used to carry out mapping experiments. Besides implementing the method on physical robots, a simulator was also built in Matlab with enough detail, so as to be able to predict the physical robots' behavior through computer simulations. Moreover, the simulator made possible to simulate teams with arbitrary team sizes.

Extensive experiments were carried out in the same environment with varying number of robots in the range $n \in \{1 \ldots 10\}$, using both the uncoordinated and the coordinated exploration methods. With up to two robots, the experiments were carried out both with the physical robots and the simulator, so as to fine tune the simulator. At the end of this tuning process, the results obtained through simulations were statistically quite similar to the ones obtained with physical robots. The simulator was used afterwards to extrapolate the team's performance with more than two robots.

1) Uncoordinated exploration versus coordinated exploration: The graph represented in Fig. 6 compares the average mission execution time $t_{k_{max}}$ as a function of the team size n, using either the the coordinated and the uncoordinated exploration methods. In these experiments, the cost sensitivity coefficient κ was equal to 0.

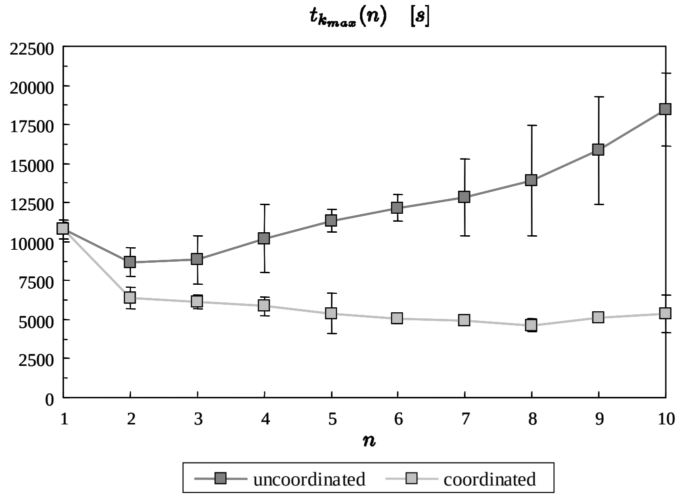


Fig. 6. Mission execution time $t_{k_{max}}$ as a function of team size n using both the uncoordinated and the coordinated exploration methods.

Using the uncoordinated method, two robots took on average 81% of the time needed by a single robot, though the team's performance became significantly worse for $n > 2$. For $n > 2$, adding more robots to the system always led to an increase of $t_{k_{max}}$. For $n > 5$, the average mission execution time was even greater than the time of a single robot, which is a disastrous performance. These results reveal that coordination is crucial to attain effective cooperation, especially for larger teams.

On the other hand, using the coordinated method, two robots took on average only 59% of the time needed by a single robot, yielding therefore a slightly sub-linear speedup with the team size increase. Moreover, the mission execution could be further decreased for $3 \leq n \leq 8$. For $n > 8$, the average mission execution time tended to increase with the team size, which indicates that using more than eight robots was completely worthless for the workspace considered in the experiments. This reveals that, although the coordinated method minimized the interference among robots, the benefit of having teams with more than two robots was not particularly noticeable, due to the relatively confined workspace where the experiments took place: an area with just 23 m^2.

It was concluded with a confidence level equal to 99% that the coordinated method yields a faster mission execution time than the uncoordinated method for any team size.

2) Impact of the cost sensitivity in collective performance: In order to evaluate how the cost sensitivity coefficient κ influences the team's performance, further experiments were carried out with the robots depicted in Fig. 2, using coordinated exploration and other values for that parameter than 0.

The graph on the top of Fig. 7 plots the mission time $t_{k_{max}}$ and the traveled distance by one of the robots, d_T, as a function of κ. It shows that being more sensible to the traveled distance, *i.e.* increasing κ, leads to a monotonous increase of the mission

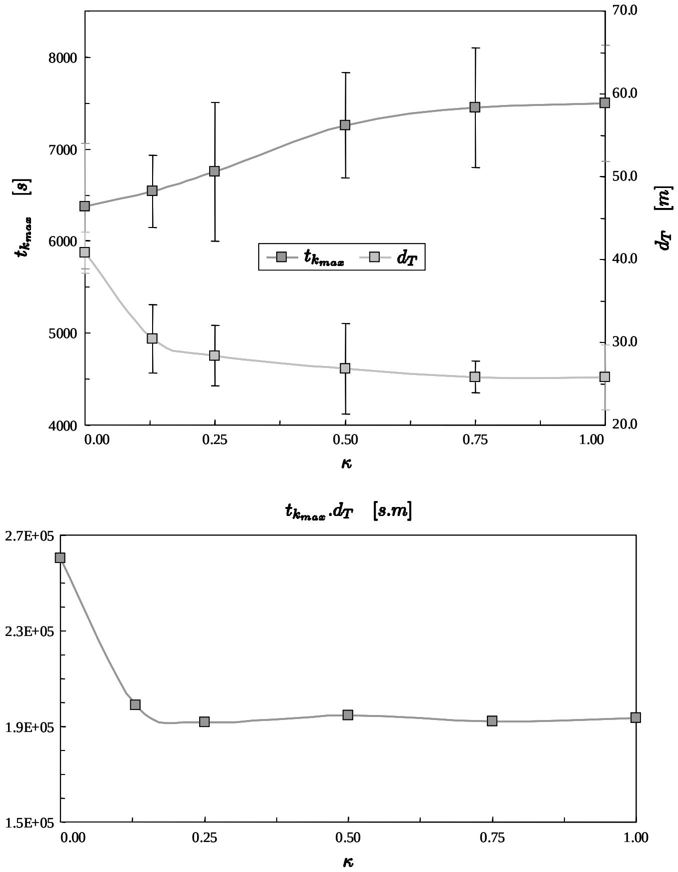


Fig. 7. Performance of a team of two robots using the coordinated exploration method with different values of the cost sensitivity coefficient κ: graph of the mission execution time $t_{k_{max}}$ and of the traveled distance d_T (top) and graph of the product $t_{k_{max}}.d_T$ (bottom), as a function of κ.

execution time $t_{k_{max}}$ and to a monotonous decrease of the traveled distance d_T. Furthermore, these variations are not linear: the reduction of d_T is more noticeable in the interval $0 \leq \kappa \leq 0.25$; the increase of $t_{k_{max}}$ is more accelerated in the interval $0.125 \leq \kappa \leq 0.5$.

If both variables are required to be optimized, the graph on the bottom of Fig. 7, which plots the variables' product, stabilizes for roughly $\kappa > 0.25$. This means that distance can be significantly reduced without compromising too much the mission time for roughly $\kappa < 0.25$. For greater values of κ, the product remains slightly constant, *i.e.* any reduction of distance is accompanied by an increase of mission time with the same order of magnitude.

V. Conclusion

This article addressed the problem of building volumetric maps with multi-robot systems, efficient information sharing and proper coordination. After briefly presenting a probabilistic framework which allows to represent and update volumetric maps, special emphasis was given to the formulation of multi-robot exploration using entropy-related concepts. Results obtained within experiments with mobile robots equipped with stereo-vision demonstrated the importance of coordinating robots' exploration actions, so as to improve the team's performance. It was statistically demonstrated that coordinated teams always perform faster than their uncoordinated counterparts.

An important future direction is to demonstrate the application of the concepts related with efficient information sharing and coordination herein presented to other robotics application domains than robotic mapping and, as well, to domains outside robotics. For instance, human organizations involve complex cooperative interactions supported on some flow of information. Redundancy, consistency, information utility and coordination are certainly important issues in the context of these complex social systems.

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