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Semantically-Informed Coordinated Multirobot Exploration of Relevant Areas in Search and Rescue Settings

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***Abstract*— Coordinated multirobot exploration involves autonomous discovering of unknown features in environments by using multiple robots. Autonomously exploring mobile robots are driven by knowledge of the already explored portions of the environment, usually represented in a metric map. In the literature, some works addressed the use of *semantic knowledge* in exploration, which, embedded in a semantic map, associates spatial concepts (like 'rooms' and 'corridors') with metric entities, showing its effectiveness to improve *total* explored area. In this paper, we build on these results and propose a system that exploits semantic information to push robots to explore areas that are *relevant*, according to *a priori* information provided by human users. We tested our semantic-based multirobot exploration system in a reliable robot simulator and evaluated its performance in realistic search and rescue settings with respect to state-of-the-art approaches.**

I. Introduction

Coordinated multirobot exploration [1] autonomously discovers features of initially unknown environments by using mobile robots equipped with sensors. Exploration is fundamental in tasks like map building and search and rescue. Decisions about where to go next and about which robot goes where are crucial in coordinated multirobot exploration and are usually made according to information extracted from the known portion of the environment, represented in a *metric map* that robots incrementally build. A metric map represents the geometrical and spatial features of the environment, like the position of obstacles. In the last years, several methods have been proposed to build *semantic maps* of environments [2], [3], which label some spatial elements with high-level human concepts. For example, an area of the metric map can be labeled as 'corridor' or 'room', thus providing knowledge about the structure of the environment. Despite the great effort in constructing semantic maps, the study of their use for exploration is still limited.

In this paper, we contribute to this study by presenting an exploration system for search and rescue settings that exploits semantic labels to explore *relevant* areas of initially unknown environments. Our system is composed of multiple robots equipped with laser range scanners that operate according to the following steps: they (a) perceive the surrounding environment, (b) integrate the perceived data within a metric and a semantic map representing the environment known so far, (c) decide where to go next and who goes where, and (d) go to their destination locations and start again from (a). In the following, we focus on the decision making (step (c)).

Some works (e.g., [4], [5]) have already addressed this problem, finding out that use of semantic information can reduce the time required to cover a given amount of area and can increase the *total* amount of area mapped in a given time interval. In this paper, we extend these results by showing that semantic knowledge can also be used to significantly improve the exploration of *relevant* areas of indoor environments. We assume that *a priori* reliable information about the relevant areas of the environment is available. For example, in a search and rescue setting, this information could be the possible location of victims or the preferred areas to search first, given by human rescuers. If a disaster happens during office hours, victims are most likely located in the offices, and, thus, robots should focus on searching small rooms. If it happens during lunch time, robots should head to big rooms, like a canteen. We assume that this information is correct. Hence, our system originally addresses the following problem: Is it possible to exploit semantic information to efficiently explore areas that are considered relevant?

II. Related work

The mainstream approach to robotic exploration identifies some candidate locations on the *frontiers* between known and unknown portions of the environment [6], evaluates them, and assigns them to robots, iteratively. For the purposes of this paper, the decision-making process is considered composed of two aspects. We call *exploration strategy* the evaluation of candidate locations and *coordination method* their allocation to robots. These activities are usually based only on metric information, namely on information that can be derived from metric maps that robots build. For example, the robotic exploration system of [7] combines, in an exponential function, the distance between a robot r and a candidate location p and the expected amount of information that r can acquire at p (measured as the maximum amount of unknown area visible from p). A system using the same two criteria, but combining them in a linear function, is that of [1]. The system proposed in [8] adds a criterion that measures the probability that r, once in p, can communicate with a fixed base station (like [9]), and combines all the criteria using a theoretically grounded approach.

Several works have addressed the *construction* of semantic maps of environments. Two significant examples are [2], which labels portions of outdoor environments as 'navigable' or 'non-navigable' and as 'street' or 'sidewalk', and the approach of [3], which classifies laser range scans as belonging to 'rooms', 'corridors', and 'doorways' using AdaBoost.

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Only few exploration systems *use* semantic information to evaluate candidate locations and assign them to the robots. An early attempt in this direction is that of [10], in which candidate locations with a large distinctiveness (e.g., located at the intersections of corridors) are privileged.

The work in [5] exploits the knowledge on the structure of an indoor environment (represented as a hidden Markov model) to "force" robots to select, first, candidate locations that are in corridors.

Another work that uses semantic information to improve exploration is presented in [4]. In this case, contextual information related to the mission (e.g., the relative importance of a goal with respect to another goal), to the environment (e.g., the presence of rooms and corridors and the difficulty for traversing a given area and for detecting victims in that area), and to the agents (e.g., the presence of loop closures for improving localization of robots) is represented by a PROLOG rule-based system and exploited to enhance the performance of a robotic system operating in a search and rescue scenario.

Another system that exploits the structure of the environment for determining the candidate locations and assigning them to the robots is presented in [11]. The known portion of the map of the environment is segmented and a single robot is assigned to (one of the frontiers of) each segment.

All these works show that the *total* explored area in a given time interval can be improved by using semantic information, but do not exploit semantic information to push robots to explore areas that are considered *relevant*, according to *a priori* information available.

In the above systems, the coordination between multiple exploring robots is achieved in different ways, but all of them attempt to spread the robots around the environment. More precisely, the implicit assumption is that the exploration problem is considered to involve, according to the classification in [12], single-task robots (ST) and single-robot tasks (SR), where the task is to reach a candidate location. ST means that each robot executes one task at a time and SR means that each task requires one robot. The approach of [5] discounts the utility of candidate locations within the range of other robots in order to discourage the assignment of more robots to the same candidate location. The system of [11] allocates a single robot to each segment, unless there are more available robots than unexplored frontiers. Also widely-used coordination methods for exploration, like the market-based approach of [13], acts basically as ST-SR.

In this paper, we aim at showing that, when *a priori* knowledge on victims' locations is available or preferred areas to search are specified, the use of semantic information about the type of places could improve the performance of exploration of relevant areas of the environment. Moreover, we attempt to overcome the implicit ST-SR assumption by allocating more robots to the same candidate locations according to a multi-robot tasks (MR) paradigm. In addressing these issues, we tear apart the aspects of evaluating the candidate locations (exploration strategy) and of allocating robots to candidate locations (coordination method), to assess their relative impacts on exploration.

III. SEMANTIC-BASED EXPLORATION SYSTEM

A. System overview

The robotic platform used is a Pioneer P3AT equipped with two laser range scanners, mounted at the same height and back-to-back for covering a $360°$ area around the robot with radius $R = 20$ m and angular resolution at $1°$, and with a sonar ring.

Each robot builds a two-dimensional occupancy grid map of the explored environment. Each cell is either known, if the robot perceived the corresponding area, or unknown. Known cells can be free or occupied (by obstacles). The map of the environment is maintained by a base station, whose position is fixed in the environment, and to which robots send their maps every 2.5 s. We assume that communication is error-free and unlimited in range and bandwidth (effects of more realistic communication models on exploration are discussed in [14]). Our exploration system is largely independent of the mapping system employed to incrementally build the grid map. In our experiments, we used a simple scan matching method, inspired to that in [15], in which a new acquired scan is aligned with the current map (using odometry as initial guess) and the occupancy grid is updated correspondingly. Since we are not interested in analyzing the quality of the resulting map, we assume that the mapping module is error-free. Given the grid map, clusters of (adjacent) free cells that are on the frontier between known and unknown parts of the map are extracted. The central point of such a cluster of boundary cells is considered as a *candidate location* to reach. Paths are planned using A* on the grid map. Sonars are used for obstacle detection during navigation.

We assume that the system has a semantic map that labels each free cell of the grid map with its room type (i.e., 'corridor', 'small room', 'medium room', 'big room') and with the number of doorways present in the room in which the cell is located. This semantic map can be built at the same time the metric map is built by exploiting any available method (e.g., [3]). However, in this paper we assume the semantic map as available, because we are only interested in its use.

B. MCDM-based exploration strategy

Our exploration strategy is used to estimate the utility $u(p, r)$ of every candidate location p for all robots r. It combines the following criteria:

- $A(p)$ is the expected amount of free area beyond the frontier of p computed according to the length (in cells) of the frontier. The larger its value, the more information is expected to be acquired from p.
- $d(p, r)$ is the Euclidean distance between p and current position of r. Using Euclidean distance instead of actual distance calculated by path planner drastically reduces the computational effort without affecting too much the estimated utility $u(p, r)$, as some preliminary experiments have shown.
- $b(r)$ is the battery level of r; the larger its value, the smaller the amount of residual energy in the battery.

All these criteria can be calculated from the robots' status and from the metric grid map.

In addition to the above criteria, the following criteria employing information from semantic map are considered:

- $S(p)$ is the relevance of p (from 0, not relevant, to 1, relevant), calculated according to the semantic label of p and the *a priori* knowledge on victims' locations. The values for $S(p)$ have been manually set to obtain good performance after experiments with different combinations of values. For example, if it is known that victims are most likely in big rooms, and p is in a big room, $S(p) = 1$, while if p is in a small room, $S(p) = 0$. If p is in a corridor, regardless the hypothesis on victims' locations, $S(p) = 0.15$, as corridors are usually important to reach relevant rooms. Different value combinations (e.g., range $[0.10, 0.50]$ for $S(p)$ with p in corridors) have been experimentally demonstrated to have similar performance.
- $ND(p)$ is the number of doors in the room where p is located. This criterion evaluates the connectivity of a room with other rooms: a highly-connected room should be visited to ease finding relevant rooms.

We assume that semantic information is perfect (this assumption will be relaxed later to experimentally verify the robustness of the approach).

All the criteria $N = \{A, d, b, S, ND\}$ are combined using the Multi-Criteria Decision Making (MCDM) approach introduced in [8], to which we refer for a complete description; here we just summarize the approach. We selected the MCDM approach because it is theoretically grounded and allows to easily integrate several criteria in a utility function. $u_j(p, r)$, with $j \in N$, is the utility value for candidate location p and robot r according to criterion j. The larger $u_j(p, r)$, the better the pair p and r. To apply MCDM, utilities need to be normalized to a common scale $I = [0, 1]$. We use a linear relative normalization for each u_j. With a slight abuse of notation, we call $u_{(j)}$, with $(j) \in N$, the j-th criterion according to an increasing ordering with respect to utilities: for candidate location p and robot r, $u_{(1)}(p, r) \leq \ldots \leq u_{(n)}(p, r) \leq 1$ ($u_{(0)}(p, r) = 0$ and $n = |N|$, $n = 5$ in our case). The MCDM strategy integrates the criteria in N with the following function:

$$u(p, r) = \sum_{j=1}^{5} (u_{(j)}(p, r) - u_{(j-1)}(p, r))\mu(\mathscr{A}_{(j)}), \quad (1)$$

where $\mu : \mathcal{P}(N) \rightarrow [0, 1]$ ($\mathcal{P}(N)$ is the power set of set N) are weights, and the set $\mathscr{A}_{(j)}$ is defined as $\mathscr{A}_{(j)} = \{i \in N | u_{(j)}(p, r) \leq u_i(p, r) \leq u_{(n)}(p, r)\}$. Equation (1) provides a sort of "distorted" weighted average that accounts for synergies and redundancies between criteria.

After the selection of set of criteria N, we need to define weights μ for each subset of criteria. For our semantically-informed exploration strategy (*S-MCDM*), we use weights reported in the following table (left). The combinations not reported in the table are calculated by summing the weights of the individual criteria. Weights have been set to obtain good performance, according to criteria importance and relations [8]. Varying the selected weights values ($\pm 10\%$), we experimentally obtained similar performance.

S-MCDM

criteria	$\mu()$	criteria	$\mu()$	criteria	$\mu()$
A	0.09	d, b	0.09	A, b	0.15
d	0.09	d, S	0.8	d, b, S	0.8
b	0.02	b, S	0.6	A, S	0.65
S	0.5	A, d, b	0.3	A, d, b, S	0.8
ND	0.3	A, d, S	0.8		
A, d	0.3	A, b, S	0.65		

D-MCDM

criteria	$\mu()$
A	0.4
d	0.4
b	0.2
A, d	0.95
A, b	0.7
d, b	0.4

For comparing the performance of S-MCDM with a state-of-the-art exploration strategy, we defined another MCDM-based exploration strategy (*D-MCDM*), whose criteria set is $N = \{A, d, b\}$, similarly to [8], and the weights are reported in the above table (right). The D-MCDM exploration strategy has been shown in [8] to be very effective in exploring environments (in particular, it outperformed the exploration strategies of [9] and [16]).

C. ST-MR coordination method

Coordination methods are used to assign candidate locations p to robots r. The mechanism we use is market-based [13]. Base station regularly sets up auctions in which candidate locations (generated as discussed before) are auctioned to robots, which bid on them. This process allocates candidate locations p to robots r attempting to maximize sum of utilities $u(p, r)$. In our system, coordination method can allocate multiple robots (MR) to the same candidate locations. For example, allocating two robots to the same candidate location in a big room could speed up the exploration of the room, overcoming potential negative effects due to the initially overlapping views of the two robots.

We employ a fuzzy-based function $i(p)$ that computes the ideal number of robots (1, 2, or 3) that should be assigned to a candidate location p, according to the semantic label given to p and to some other features. In particular, if p is located in a room ('small room', 'medium room', or 'big room'), the features considered are the room area, the free area percentage of the total area in the room (visibility), the number of doors, and the already perceived area of the room. When the room is only partially known, these features can be estimated using models of buildings, like those in [17]. Fig. 1 illustrates membership functions for the input features and for the output. A sample of the rules for determining the ideal number of robots $i(p)$ to allocate to p (in a room) follows.

1 **if** *RoomSize* is *SMALL* **and** *#Doors* is *HIGH* **and** *Visibility* is *LOW* **and** *AlreadyPercArea* is *MEDIUM* **then** *#Robots* is *MEDIUM*;
2 **if** *RoomSize* is *BIG* **and** *#Doors* is *LOW* **and** *Visibility* is *LOW* **and** *AlreadyPercArea* is *HIGH* **then** *#Robots* is *LOW*;
3 **if** *RoomSize* is *BIG* **and** *#Doors* is *MEDIUM* **and** *Visibility* is *MEDIUM* **and** *AlreadyPercArea* is *LOW* **then** *#Robots* is *HIGH*;

Similarly, if p is located in a corridor (label 'corridor'), the features considered are the length of the corridor, the number of doors, the number of intersecting corridors, and the already perceived area of the corridor. The membership functions and the rules are similar to those for the room case and are not shown here due to space constraints.

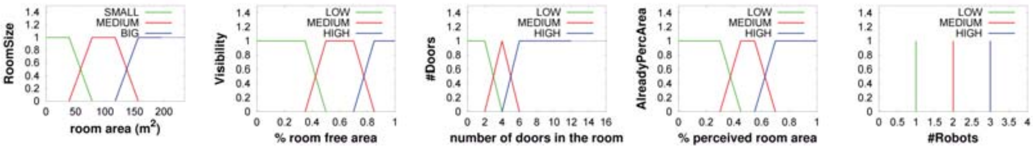


Fig. 1: Membership functions for input features (four leftmost graphs) and output (rightmost graph), when p is in a room.

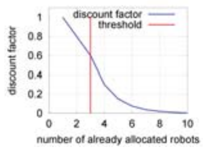


Fig. 2: Discount factor vs. the number of robots already allocated to p, when $i(p) = 3$.

Each robot r evaluates all candidate locations p, auctioned by the base station every 5 s or when requested by a robot that has reached its assigned location, according to the exploration strategy, and submits bids $u(p, r)$ accordingly. We propose two coordination methods (executed by the base station) to allocate candidate locations to robots. The first coordination method (*MRv1*) is reported in Algorithm 1.

1 collect bids $u(p, r)$, which are calculated using (1);
2 **while** $\exists$ *robot* r *not allocated* ***and*** *candidate location* p **do**
3   find the pair (p^*, r^*): $(p^*, r^*) = \arg\max_{p,r} u(p, r)$;
4   allocate p^* to r^*;
5   **if** $i(p^*)$ *is equal to the number of robots already assigned to* p^* **then**
6   eliminate p^*;
    end
7   eliminate robot r^*;
end

Algorithm 1: MRv1.

The second coordination method, called *MRv2*, is similar to MRv1, but, after each allocation of a robot to a p^* (step 4), it discounts the utility of p^* for other robots, according to the number of robots already allocated to p^* (similarly to [5]). Fig. 2 shows the discount factor that decreases linearly until the number of allocated robots is less or equal to $i(p^*)$, and then decays exponentially. The rationale is that assigning to p^* less robots than $i(p^*)$ could be a necessity (e.g., there are not enough robots) and that assigning to p^* more robots than $i(p^*)$ is not useful to speed up exploration.

The two proposed ST-MR coordination methods are experimentally compared to a state-of-the-art coordination method (ST-SR) [13], which allocates just one robot to a candidate location in a greedy fashion. Namely, $i(p) = 1$ for every p.

IV. Simulation Activity

In order to perform replicable tests under controlled conditions, we use a robot simulator. We selected USARSim [18], because it is a realistic and reliable 3D robot simulator.

We report simulations conducted in two indoor environments, called *office* and *mall* (Fig. 3), where robots start from fixed starting locations. The first environment is part of the "vasche_library_floor1", taken by Radish repository [19], and is characterized mainly by the presence of small rooms. The second one is a floor of a (real) mall, and is characterized by the presence of some very big rooms. Some obstacles (shown as short line segments in Fig. 3) have been added to the rooms to make the exploration task more difficult. We consider structured indoor environments because many semantic maps have been built for indoor environments and search and rescue scenarios are often indoor (like those of the Virtual Robot Competition of RoboCup Rescue Simulation League). We consider teams of 4, 6, and 8 robots. We consider two *a priori* hypotheses (assumed to be correct) on victims' location, namely victims in big rooms and in small rooms. We define a configuration as an environment (office or mall), a number of robots (4, 6, or 8), an exploration strategy (D-MCDM or S-MCDM), a coordination method (SR, MRv1, or MRv2), and an hypothesis on the victims' location (big or small rooms). For each configuration, we execute 10 runs of 20 minutes each.

In a search and rescue setting, the goal is to explore an initially unknown environment for finding the largest number of human victims within a short time. Assuming *a priori* knowledge about the relevant area in which victims are supposed to be, and assuming that victims are uniformly distributed in the relevant areas, the problem of maximizing the number of victims found in a given time interval is equivalent to the problem of maximizing the amount of *relevant area* covered by robots' sensors in the same interval. Thus, we assess our system performance by measuring the amount of relevant area (area of small or of big rooms, according to the victims' location hypothesis) explored, every 1 minute of exploration. Due to space limitations, we report only data at the end of runs (after 20 minutes).

Table I (left) reports simulation results for the office environment. The values reported in each entry are the average and the standard deviation (in parentheses) over the 10 runs of the corresponding configuration. With all the three coordination methods (rows), S-MCDM behaves better than D-MCDM, and differences are statistically significant, according to an ANOVA analysis with a threshold for significance p-value < 0.05 [20]. For example, the difference between the relevant area mapped at 20 minutes with S-MCDM and D-MCDM, in the case of victims in big rooms, with SR and 6 robots, is statistically significant (p-value$= 2.42 \cdot 10^{-7}$). This result holds also for the hypothesis about victims in small rooms (p-value$= 1.34 \cdot 10^{-5}$). For both exploration strategies (columns), MRv1 and MRv2 appear to perform relatively better than SR, and differences are statistically significant (e.g., p-value$= 9.24 \cdot 10^{-10}$ with S-MCDM, considering the hypothesis of victims in big rooms and 6 robots, MRv2 vs. SR). Only considering 4 robots, in the case of victims in

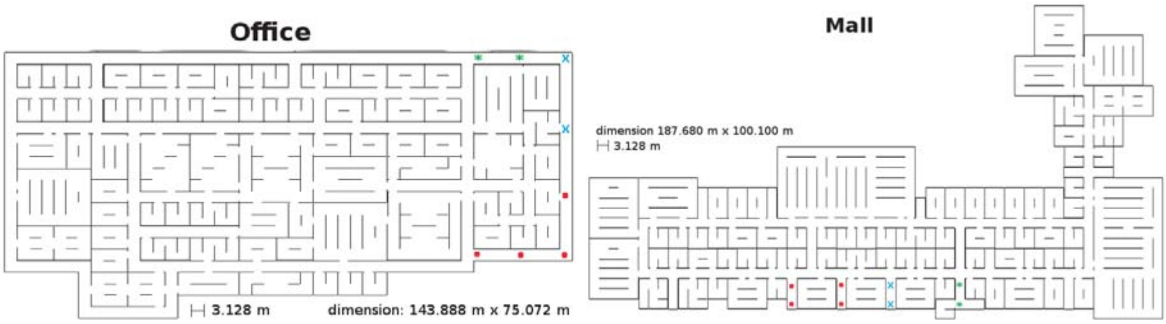


Fig. 3: Test environments. Red points represent initial positions for the robots in the configurations with 4 robots, blue crosses refer to the addition of two robots (6 robots), and green stars to the addition of further two robots (8 robots).

Office		Exploration			
	Coord.	D-MCDM (B)	S-MCDM (B)	D-MCDM (S)	S-MCDM (S)
#Robots = 4	SR	747.3(112.5)	1473.9(202.7)	80.4(22.4)	276.2(83.9)
	MRv1	953.8(111.4)	1729.9(81.9)	103.1(22.7)	224.6(73.1)
	MRv2	921.6(130.3)	1773.8(65.4)	112.9(24.4)	272.1(52.1)
#Robots = 6	SR	1024.6(220.7)	1603.2(59.1)	127.6(38.5)	235.7(43.1)
	MRv1	1123.6(143.6)	1851.3(7.8)	148.6(21.2)	400.5(100.4)
	MRv2	1164.9(94.2)	1856.7(36.3)	162.5(22.2)	429.0(83.8)
#Robots = 8	SR	1222.6(133.0)	1653.5(129.2)	170.3(43.0)	312.0(28.1)
	MRv1	1379.8(122.8)	1877.6(62.6)	186.2(31.7)	496.3(101.8)
	MRv2	1284.9(144.5)	1854.3(80.3)	185.6(42.7)	454.3(125.2)

Mall		Exploration			
	Coord.	D-MCDM (B)	S-MCDM (B)	D-MCDM (S)	S-MCDM (S)
#Robots = 4	SR	265.4(212.9)	1868.0(160.1)	567.0(66.6)	737.3(61.9)
	MRv1	517.3(164.6)	1785.2(232.5)	615.9(24.2)	836.4(94.4)
	MRv2	380.3(67.7)	1780.7(233.8)	633.4(37.7)	809.3(104.2)
#Robots = 6	SR	634.4(209.3)	1978.6(200.0)	638.1(74.4)	888.0(72.6)
	MRv1	574.2(73.8)	2151.7(228.8)	702.3(52.5)	1018.3(93.3)
	MRv2	545.2(129.4)	2105.3(241.4)	701.7(18.8)	983.9(76.7)
#Robots = 8	SR	768.6(190.1)	2050.0(189.3)	708.8(56.4)	953.3(97.4)
	MRv1	606.5(207.5)	2304.5(161.6)	755.9(44.0)	1149.5(95.9)
	MRv2	540.7(139.5)	2336.9(214.5)	751.8(56.8)	1046.5(80.4)

TABLE I: Results (average and standard deviation) of explored relevant area (m^2) for the office (left) and mall (right) environments, after 20 minutes of exploration. B indicates victims most likely are in big rooms, S in small rooms.

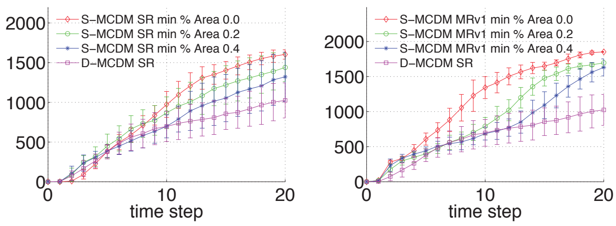
small rooms, SR seems to have better results than MRv1 and MRv2, even if not statistically significant (e.g., for SR vs. MRv2, p-value$=0.80$). This similar performance of SR and MRv1/MRv2 can be explained noting that, when the number of robots is small, the exploration becomes too unbalanced if more robots are assigned to the same candidate location. Another consideration from Table I (left) is that, as expected, increasing the number of robots, the amount of explored relevant area increases (apart from one degenerate case with SR and S-MCDM considering victims in small rooms from 4 to 6 robots), even if the increase is not statistically significant. The total amount of explored area (full data are not shown here due to space constraints) increases from D-MCDM to S-MCDM in the case of victims in big rooms (e.g., with 6 robots and SR, from 3115.6 (367.0) m^2 to 3958.0 (187.9) m^2, p-value$=5.91 \cdot 10^{-6}$), while in the case of victims in small rooms is more or less the same. The total amount of explored area is similar for all coordination methods.

Table I (right) shows simulation results for the mall environment. All the above observations hold also in this setting. The only difference is relative to the case D-MCDM and victims in big rooms, for which the results obtained by MRv1 and MRv2 worsen with respect to SR, and only with 8 robots the difference between SR and MRv2 is statistically significant (p-value$=0.01$). This could imply that using a coordination method that exploits semantic information and an exploration strategy that does not can be inefficient.

In summary, the results for the office and the mall environments show that our semantically-informed exploration strategy largely outperforms a state-of-the-art exploration strategy in discovering areas of interest. This can be explained by the fact that the exploration strategies that do not consider semantic information evaluate candidate locations only according to their metric features, independently of their interest for the possible presence of victims. Another result is that both MRv1 and MRv2 gain better results compared to SR. This behavior is more evident with the hypothesis of victims in big rooms, because MRv1 and MRv2 directly accelerate the exploration of big rooms, as more robots are sent to such rooms. The result is valid in the hypothesis of victims in small rooms as well but, in this case, the reason is because MRv1 and MRv2 send more robots in corridors, to which several rooms are connected and can be easily accessed. However, no statistically significant trend can be observed comparing MRv1 and MRv2. In addition, simulation results suggest that the coordination method has comparatively less impact on the performance than the exploration strategy used. This is in line with the results obtained in [21], for different search and rescue settings. Note also that our semantically-informed approach generally performs better than traditional approaches independently of the percentage of relevant area over total area. However, with few relevant areas (big rooms in office, Fig. 3 (left)), the advantage in using semantic information in coordination is more evident. With many relevant areas (small rooms in mall, Fig. 3 (right)), using semantically-informed coordination is less effective (robots can be simply spread using traditional approaches with good chances of visiting relevant areas).

We also experimentally verified that our results are still valid varying starting locations and the number of the robots (10 or 12). Data are not shown here due to space constraints.

We relax the assumption of perfect semantic information, as our system strongly relies on it. Specifically, we consider a more realistic semantic mapping module which makes errors depending on percentage of area actually discovered. If a candidate location p is located in a room, whose fraction of already explored area is less than a pre-defined threshold (0.2 or 0.4), the semantic mapping module classifies p randomly over the available semantic labels. Otherwise, semantic mapping module correctly classifies p. We tested the system in the office environment, with 6 robots, coordination method SR, victims located in big rooms. Fig. 4 (a) shows the amount of relevant area explored over 20 minutes. The performance does not degrade very much with respect to the performance obtained by our system with perfect semantic information, and, actually, S-MCDM still performs better than D-MCDM. For example, at 20 minutes, with S-MCDM with threshold 0.4, the explored relevant area is 1321.8 (310.2) m^2, while with D-MCDM and perfect semantic information, the explored relevant area is 1024.6 (220.7) m^2 (p-value= 0.02). The same trend is observed considering coordination methods (see Fig. 4 (b)). The configuration of S-MCDM and MRv1 with threshold 0.4 is still better than D-MCDM and SR with perfect semantic information (1629.9 (120.8) m^2 vs. 1024.6 (220.7) m^2, p-value= $5.0 \cdot 10^{-7}$).



(a) Exploration strategies. (b) Coordination methods.

Fig. 4: Explored relevant area (m^2) over 20 minutes by 6 robots with realistic semantic mapping.

Finally, we tested the performance of our system by setting as termination criterion a given percentage of relevant area to be mapped (instead of 20 minutes timeout), as in [11]. In this case, the system performance could be evaluated according to the time spent for accomplishing the mission. This experiment was carried out on a portion of the mall environment, with 8 robots with the goal of mapping 90% of the relevant area (victims located in big rooms). Results (data are not shown here due to space constraints) show that S-MCDM (and MRv1) terminates earlier (around 20 minutes) than the state-of-the-art combination of D-MCDM and SR (around 29 minutes).

V. Conclusions

In this paper, we have presented a semantic-based multirobot exploration approach for search and rescue, which considers *a priori* information about the location of victims. We have shown how to exploit semantic information in both exploration strategy and coordination method. Simulation results show that the proposed semantically-informed approach obtains significantly better performance than state-of-the-art approaches in exploring relevant areas.

Future work will address the further assessment of the proposed system considering different environments, real robots with noisy communication and mapping, existing semantic mapping systems, and a probability distribution on the number of victims for different areas. Similarities with works dealing with sensor-based (e.g., [22]) deserve further investigation. Moreover, a deeper study of the impact of knowledge provided by semantic maps for exploration will be performed. A direction of interest is the investigation of multi-task (MT) coordination methods (i.e., each robot plans how to reach a sequence of candidate locations) or path optimization, starting from results in [23].

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Semantically-informed coordinated multirobot exploration of relevant areas in search and rescue settings

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