# Comparison of Classical and Interactive Multi-Robot Exploration Strategies in Populated Environments

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***Abstract*—Multi-robot exploration consists in efficiently observing all the reachable space of the environment. This task raises several issues concerning task allocation, robot coordination, path planning and communication. We are interested in exploring human-populated environments. Human movement and actions render these environments dynamic, and thus difficult to explore. In this paper, we propose to evaluate to which extent exploiting human presence can help rather than hinder exploration. We present a model for exploration in populated environments and define a human-robot interaction cost. We also formalise an interaction-based exploration framework inspired by classical frontier exploration. Finally, we evaluate the impact of considering human-robot interactions in frontier-based exploration.**

## I. Introduction

Mobile robots interfere in our daily life and provide services (*e.g.* guidance, assistance [1], [2]) or also leisure (*e.g.* company, dance [3], [4]). This intrusion of mobile robots into citizens' day-to-day lives must be done with respect to the people, whilst seeking social compliance. Human motion patterns and activities are already studied [5], [6]. Therefore, robots can acquire a 'consciousness' of the people by observing them, and then mimicking their behaviour for example.

Introducing 'human awareness' into a robotic exploration system for populated environments can constitute an interesting route for study. Indeed, it paves the way for human-robot interaction (HRI) based exploration approaches. Multi-Robot Exploration (MRE) consists in reconstructing all the reachable space of an unknown environment by controlling mobile robots. In populated environments, this task raises new concerns regarding clean reconstruction and efficient robot coordination.

Concerning reconstruction quality, separating static aspects (background) from dynamic aspects (people, robots) of the scene is particularly difficult [7]. Obviously, mobile robot perceptions can be biased due to the environment dynamics, thus hindering localisation and mapping. Regarding the selection of targets to explore, people motion and actions create spatio-temporal reachability of unknown areas making exploration tricky. In fact, the reachable space evolves dynamically according to the density of human presence.

Nevertheless, humans can understand their environment, sense, decide and act adequately. In this sense, we can assume that every person has an 'adaptive heuristic' depending on the local environment that allows him or her to slip in dense areas (*e.g.* crowds) readily. Therefore, we are interested in exploiting 'human heuristics' as possible 'robotic heuristics' for the exploration task. We propose a 'parametric heuristic' that incorporates human presence for areas selection or human-robot interactions initiation.

This is followed by a brief state of the art of MRE, and also we situate our approach among HRI applications in mobile robotics. In the third section, we formalise the multi-agent system for exploration in populated environments and present our study framework. The fourth section defines the mixed exploration approach (robot-frontier/interaction) and a proposition of human-aware exploration heuristic for establishing human following interactions. Next, we perform several experiments of our mixed approach in simulation, to underline the performance variability depending on the environment. In the end, we discuss our results and perspectives regarding machine learning for adaptive heuristic parameterisation.

## II. Related Work

First, this section presents some previous works in the field of MRE. Then, we situate our study among mobile robotic applications of HRI.

### A. Multi-Robot Exploration

The MRE problem consists in acquiring an accurate representation of an environment by efficiently coordinating robots' actions within it. Representation accuracy is the degree of closeness to the ground truth. The coordination of robots arises from the teamwork involved in solving the task. Its efficiency can be evaluated at several levels such as time to completion, distance travelled, energy consumed, reduced overlapping, etc.

Thus, MRE solutions design efficient robots' control for accurately completing a chosen representation of the environment (*e.g.* graph, grid). The proposed solutions can be roughly classified into non directed (random walk, Q-learning), directed [8]–[15], or bio-inspired approaches [16]–[18].

Within directed approaches, we distinguish reactive solutions using navigation rules [8], [9] from deliberative resolutions [10]–[15]. Deliberative resolutions of the task allocation formulated MRE are achieved by informed or uninformed search algorithms.

Uninformed search algorithms optimise immediate costs such as distance or energy to access an unexplored/frontier area [10], [11]. These algorithms struggle to coordinate close robots having substantially similar costs to optimise. Informed algorithms incorporate heuristics and exhibit better coordination (utility, position rank, motivation [12]–[15]). Their main drawback is that the heuristic weight is often tuned arbitrarily or experimentally.

Thus far in our present study, we are looking for parametric robotic exploration heuristics that can exploit human adaptive navigation heuristics.

### B. Human-Robot Interaction

HRI is defined as the study of humans, robots and their mutual influences [19]. To our knowledge, the only HRI application of mobile robotic exploration, is the office-conversant robot Jijo-2. This robot exhibits socially embedded learning mechanisms [20] by gathering information while conversing with other people. Thus, it realises semi-supervised learning by incorporating local oracle heuristics while exploring.

We present an application in mobile robotics considering close interactions established by proximity or direct perception between humans and robots. This type of interactions is from the 'Intimate Interaction' class defined by Takeda into his HRI classification [21].

Our study bridges together intimate HRI applications and MRE informed algorithms.

## III. Multi-Agent System Formalisation

### A. Environment and Agents Model

We propose a model for representing the multi-agent system for populated environment (FIG.1).

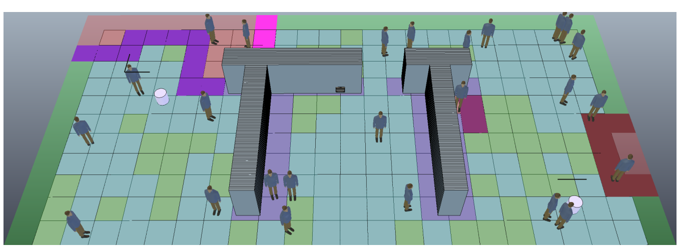


Fig. 1: Multi-Agent System simulated in V-REP [22]

In (1), the environment to explore is described by a set $\mathcal{E}$, which evolves over time. This evolution results from the actions of the agents (humans $\mathcal{H}$ and robots $\mathcal{R}$) within it. At each time $t$, a robot $\mathcal{R}_i$ from $\mathcal{R}$ has a configuration from which it observes the environment. $\mathcal{O}_i^t$ is an observed subset of $\mathcal{E}$, it corresponds to the robot's observation at time $t$.

Formally, let:

$$\begin{aligned} &\mathcal{E} \text{ be an environment} \\ &\mathcal{R} = \{R_1, .., R_n\} \text{ be a set of robots} \\ &\mathcal{H} = \{H_1, .., H_m\} \text{ be a set of humans} \\ &\mathcal{O}_i \subset \mathcal{E} \text{ be the observation of } \mathcal{R}_i \end{aligned} \tag{1}$$

### B. Exploration and Completion

For the exploration task, we must represent the environment explored by the robots over time (2). Let $\theta_i^{0:t}$ be the set of observations, namely local t-time history, the agent $R_i$ ever experienced up to time $t$. Similarly, $\Theta^{0:t}$ is the global t-time history, which aggregates local t-time histories from $R$.

Thus, we have:

$$\begin{aligned} \theta_i^{0:t} &= \theta_i^{0:t-1} \cup \mathcal{O}_i^t \\ \Theta^{0:t} &= \bigcup_{i=1}^{n} \theta_i^{0:t} \end{aligned} \tag{2}$$

It is paramount for the robots to know when the exploration is finished. The completion criterion determines this moment and can be defined locally on each robot. Robots determine exploration completion based upon already explored space $\Theta$. Mission is over as soon as there is no configuration in the already explored space that allows for new observations.

### C. Instantiating the Multi-Agent System

We represent $\mathcal{E}$ as a discrete grid of $l \times w$ square cells. Each cell has 4 possible states: the unknown (not observed), occupied (walls, objects), animated (humans, robots) and free (empty) states. States transitions are illustrated in FIG.2. In this grid representation, $\mathcal{R}$ becomes the set of cells animated by the robots and $\mathcal{R}_i$ describes the positon of one robot on the grid. The observation area of each robot is within a limited circle.

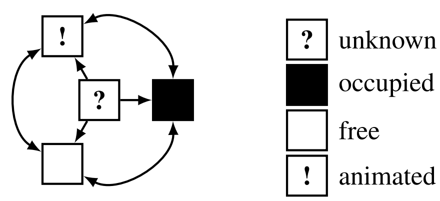
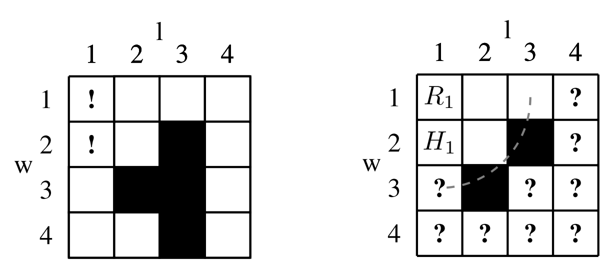



Fig. 2: Cell states transition diagram

An environment, a robot and a human are represented in FIG.3a. The robot is located on cell $\mathcal{R}_1$ at $(1,1)$ and the human on cell $\mathcal{H}_1$ at $(1,2)$. The maximum field of view is within the dashed arc in FIG.3b. $\mathcal{O}_1^1$ consists of 6 cells: 3 are free, 2 occupied and 1 animated. The explored environment $\theta_1^{0:1}$ is limited to this first observation.




(a) $\mathcal{E}$, $\mathcal{R}_1$,$\mathcal{H}_1$ (b) $\theta_1^{0:1} = \mathcal{O}_1^1$

Fig. 3: Full grid and robot observation at $t = 1$

We have instantiated an environment with a discrete grid, agents with localised cells and observations are done casting rays within a circle. Our study is based on this multi-agent system representation. In the next section, we present the frontier/interaction exploration approach.

## IV. Mixed Exploration Approach by Frontiers and Interactions

First, let us consider the MRE problem defined as a target allocation problem of robots in an unknown environment [11]–[13]. A solution to the MRE problem defines a way to explore an unknown space, *i.e.* how to allocate robots from $\mathcal{R}$ to tasks/targets from $\mathcal{T}$. For achieving this, we can look for an assignment matrix $\mathcal{A}_{\mathcal{R}\mathcal{T}}$ that optimises a cost matrix $\mathcal{C}_{\mathcal{R}\mathcal{T}}$ (*cf.* Fig.4).

| $c_{\mathcal{R}_i\mathcal{T}_j}$ | $\mathcal{T}$ |
|---|---|
| $\mathcal{R}$ | $\mathcal{C}_{\mathcal{R}\mathcal{T}}$ |

$\xrightarrow{\text{opt.}}$

| $a_{\mathcal{R}_i\mathcal{T}_j}$ | $\mathcal{T}$ |
|---|---|
| $\mathcal{R}$ | $\mathcal{A}_{\mathcal{R}\mathcal{T}}$ |

Fig. 4: Multi-Robot Exploration as a Task Allocation Problem

### A. *Different Approaches for Multi-Robot Exploration*

We show how different sets of targets define the classical frontier based exploration, our new interactive approach and the mixed one (frontier/interaction)

*1) Frontier Based Exploration:* A frontier is the observed boundary between explored and unexplored space [10]. Classical frontier based exploration is defined by choosing the targets from the set of frontiers $\mathcal{F}$ (3).

Let:

$$c_{\mathcal{R}_i\mathcal{F}_j} \text{ be the cost for } \mathcal{R}_i \text{ to reach } \mathcal{F}_j \tag{3}$$
$$a_{\mathcal{R}_i\mathcal{F}_j} = \begin{cases} 1 \text{ if } \mathcal{R}_i \text{ must go to } \mathcal{F}_j \\ 0 \text{ otherwise} \end{cases}$$

In populated environments this approach can fail when the path to a chosen frontier is congested by humans.

*2) Interactive Exploration:* Human-robot interaction is defined as the reciprocal influence between a human and a robot, followed by one or more effects. We introduce an interactive approach that takes into account human presence for establishing human-robot interactions (opening a door, guiding though a crowd, etc.). Targets are chosen from the set of humans $\mathcal{H}$ (4).

Let:

$$c_{\mathcal{R}_i\mathcal{H}_j} \text{ be the cost for } \mathcal{R}_i \text{ to interact with } \mathcal{H}_j \tag{4}$$
$$a_{\mathcal{R}_i\mathcal{H}_j} = \begin{cases} 1 \text{ if } \mathcal{R}_i \text{ must interact with } \mathcal{H}_j \\ 0 \text{ otherwise} \end{cases}$$

A purely interactive approach can be inefficient in sparsely populated environments. Indeed without any perception of human presence, the robots adopt a wait-and-see policy and pause the exploration.

*3) Mixed Exploration:* Mixed exploration enables to initiate interactions and also to reach frontiers. Thus, we combine the two target sets (frontiers and humans) to define a new set $\mathcal{G}$ (5).

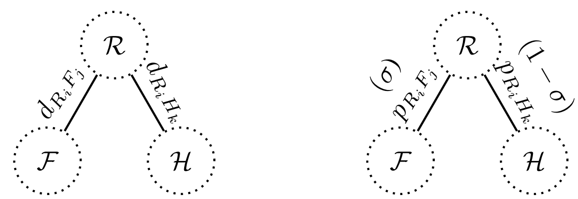
Let:

$$c_{\mathcal{R}_i\mathcal{G}_j} \text{ be the mixed cost for } \mathcal{R}_i \text{ to } \mathcal{G}_j \tag{5}$$
$$a_{\mathcal{R}_i\mathcal{G}_j} = \begin{cases} 1 \text{ if } \mathcal{R}_i \text{ is assigned to } \mathcal{G}_j \\ 0 \text{ otherwise} \end{cases}$$

This seems to be an interesting approach, but it requires to smartly equilibrate interactions and frontiers assignments.

### B. *Mixed Cost Model*

In this study, robots can interact only by following humans. The optimisation criterion is to explore a possibly populated environment with minimum distance and time. Thus, we define mixed costs using distances and a weighted penalty heuristic. The weight modulates interaction and frontier assignments (see Fig.5).




(a) Distances (b) Penalties

Fig. 5: Distances and penalties considered in the system

*1) Distance:* First, we incorporate distances between robots and targets as immediate costs (Fig.5a). Thus, we initialise $\mathcal{C}_{\mathcal{R}\mathcal{G}}$ with normalised robot-frontier and robot-human distances ($\mathcal{D}_{\mathcal{R}\mathcal{F}}$, $\mathcal{D}_{\mathcal{R}\mathcal{H}}$) in (6).

$$\mathcal{D}_{\mathcal{R}\mathcal{G}} = (\mathcal{D}_{\mathcal{R}\mathcal{F}} | \mathcal{D}_{\mathcal{R}\mathcal{H}}) \tag{6}$$
$$\mathcal{D}_{\mathcal{R}\mathcal{X}} = \begin{bmatrix} d_{R_1X_1} & \cdot\cdot & d_{R_1X_{|\mathcal{X}|}} \\ \vdots & \ddots & \vdots \\ d_{R_nX_1} & \cdot\cdot & d_{R_nX_{|\mathcal{X}|}} \end{bmatrix}$$

Distance costs have multiple drawbacks, here are two examples:

If a robot travels towards a frontier but a crowd hinders its navigation: the robot cannot adapt the exploration depending on navigation feasibility. Remote but reachable frontiers are not reevaluated as good options. The distance is prohibitive and the next target is always chosen between the last frontier and close humans. A solution is to use a planned distance, set to infinity when a target is momentarily unreachable.

If a robot follows a human walking nearby but the human stops to discuss with other people: the robot cannot decide whether to maintain or stop the current interaction depending on human activity. Due to distances, the robot will resume exploration only if a person moves again, which also causes a growing unease for the people. A solution consists in *a priori* evaluating an interaction and *a posteriori* updating its evaluation while it is taking place.

*2) Penalty:* We tackle these two drawbacks with a heuristic that associates penalties to each pair robot-frontier/human (FIG.5b).

A penalty $p_{R_iX_j}$ is defined as the sum of a time penalty and an orientation penalty. The time penalty $t_{R_iX_j}$ is the time elapsed since a frontier discovery or a human remains stationary. The orientation penalty $o_{R_iX_j}$ is the smallest unsigned angle between a robot orientation and a frontier/human orientation (a frontier is oriented towards the unknown). Thus, we define $\mathcal{P}_{\mathcal{RG}}$ with normalised robot-frontier and robot-human penalties ($\mathcal{P}_{\mathcal{RF}}$, $\mathcal{P}_{\mathcal{RH}}$) in (7).

$$\mathcal{P}_{\mathcal{RG}} = (\sigma\mathcal{P}_{\mathcal{RF}}|(1-\sigma)\mathcal{P}_{\mathcal{RH}}),\ \sigma \in [0,1] \tag{7}$$

$$\mathcal{P}_{\mathcal{RX}} = \begin{bmatrix} p_{R_1X_1} & \cdots & p_{R_1X_{|\mathcal{X}|}} \\ \vdots & \ddots & \vdots \\ p_{R_nX_1} & \cdots & p_{R_nX_{|\mathcal{X}|}} \end{bmatrix}$$

$$p_{R_iX_j} = t_{R_iX_j} + o_{R_iX_j}$$

The parameter $\sigma$ sets more or less weight on frontier or human penalties. When this parameter is high, it increases frontier costs and decreases interaction costs. This results in favouring interactions over frontiers.

*3) Distance and Penalty:* The mixed cost matrix $\mathcal{C}_{\mathcal{RG}}$ which incorporates distances $\mathcal{D}_{\mathcal{RG}}$ and penalties $\mathcal{P}_{\mathcal{RG}}$ is represented in (8).

$$\mathcal{C}_{\mathcal{RG}} = \alpha\mathcal{D}_{\mathcal{RG}} + (1-\alpha)\mathcal{P}_{\mathcal{RG}},\ \alpha \in [0,1] \tag{8}$$

The parameter $\alpha$ modulates immediate distance cost and information coming from the penalty heuristic. When $\alpha$ is high the heuristic importance is reduced and conversely, low information allows to focus on immediate costs. Counterbalancing distances and penalties is achieved with $\alpha$, while $\sigma$ sets more or less focus on frontiers or interactions.

We present the influence of $\alpha$ and $\sigma$ on the cost formula in (FIG.6). Values range from 0 to 1 for each parameter and the formula written on each side is obtained when one parameter is set to its extreme value.

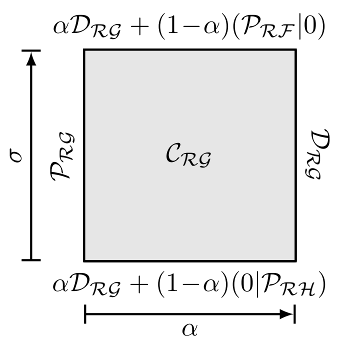



Fig. 6: $\mathcal{C}_{\mathcal{RG}}$ according to $\alpha$ and $\sigma$.

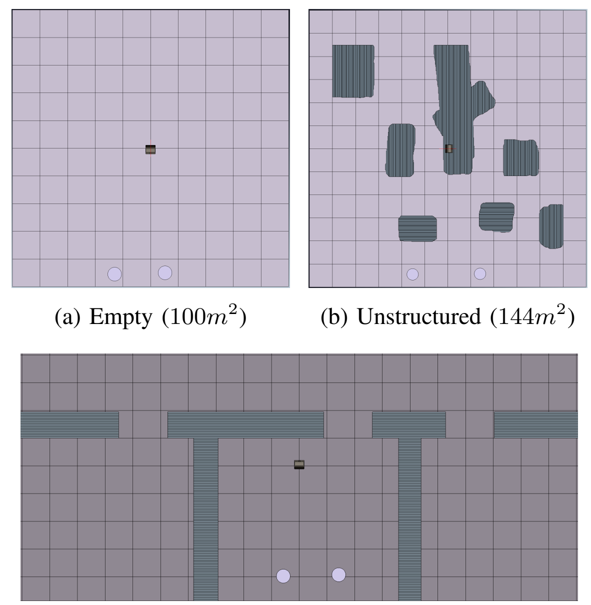
We have adopted a mixed approach and defined a parametric cost matrix based on a penalty heuristic. Now, we evaluate the exploration performance of this heuristic for two optimisation strategies, assuming different values of $\alpha$ and $\sigma$.

## V. EXPERIMENTAL FRAMEWORK

We use V-REP robotic simulator for our experiments [22]. The environment is discretised with $0.5m$ square cells. Robots share their exploration map, thus the frontiers discovered are known by every robot. Contiguous frontier cells are grouped together into a frontier area. Inside a frontier area, the targeted cell minimises the sum of distances to the others.

Assignments are computed locally by each robot. For optimising its assignment, it takes into account the entire set of frontiers known until now but only the robots and humans perceived locally (within a $2m$ radius). Planning is done using a potential field propagated on the grid.

### A. Protocol



(a) Empty ($100m^2$)

(b) Unstructured ($144m^2$)

(c) Structured ($242m^2$)

Fig. 7: Environments

Parameters are as follows:

- Map: Three environments are considered, the first contains no obstacle, the second has unstructured obstacles (cave) and the third one is composed of a corridor and three rooms. Maps are shown in (FIG.7).
- Population density: Environments are human populated with 0 or 30% of occupation. Every human agent moves in a straight line and avoid obstacles by stopping and rotating.
- Number of robots: Two explorers are used for each experiment, they are represented as cylinders.
- Optimisation strategy: We use two different cost optimisation strategies:
  The first one is $minDist$ where each robot chooses the minimum cost target among only its own possible targets [10].

The second one is *greedy* where at each time step, the minimum cost target among all the known robots possibilities is selected until the local robot is assigned.

- Modulators: $\alpha$ and $\sigma$ are discretised from 0 to 1 with a step of 0.25.

### B. Metrics

Each scenario is evaluated with classical MRE metrics: coverage, distance and time. In addition, we use a common metric in HRI, called the 'Robotic Attention Demand' (RAD), that measures the autonomy of a robot during its task [23], [24]. Here we consider the number of interactions initiated during exploration.

### C. Results

First, let us consider environments without humans. We study the influence of $\alpha$ by fixing $\sigma$ to 1. This allows to only adjust the distance and frontiers penalty. It is legitimate since no human implies no interaction penalty. The performances averaged over 10 runs are plotted in FIG.8 for $minDist$, and FIG.9 for $greedy$.

For $minDist$ in FIG.8, regarding the *empty* and *structured* maps, we distinguish two phases. In the first phase, distance and time increase, and in the second one they both decrease until $\alpha=1$. The *unstructured* map for $minDist$ and all maps for $greedy$ (FIG.9) present only one phase where distance and time are lower when increasing $\alpha$. In these cases, when $\alpha$ is high, penalties fade and robots do less round trips between remote frontiers in the scene. Thus, in not populated environments, our heuristic does not give better performances.

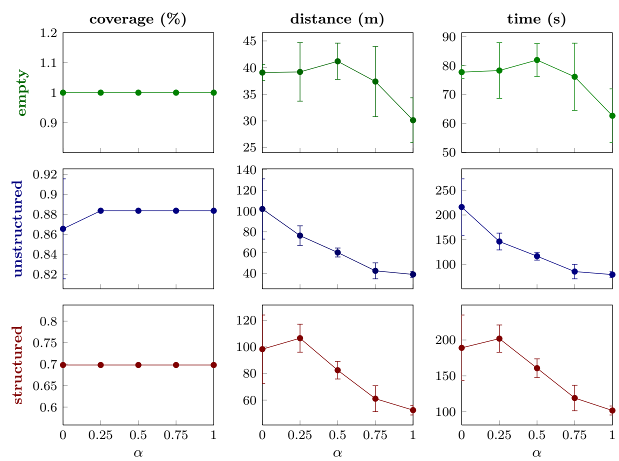



Fig. 8: $MinDist$ not dense: l.1) empty l.2) unstructured l.3) structured

Now we consider human presence. The maps are populated at 30% up to 1 human/$m^2$, thus enabling human-robot interactions. FIG.10 and 11 give the mean performances of $minDist$ and $greedy$ repectively for 10 runs of each ($\alpha$,$\sigma$) combination. When $\sigma$ increases, the penalty of interactions is reduced, favouring interactions to the detriment of frontiers.

For the *empty* case (FIG.10), full coverage with lowest distance and time are at $(\alpha, \sigma) = (0, 0)$. Only penalties are used

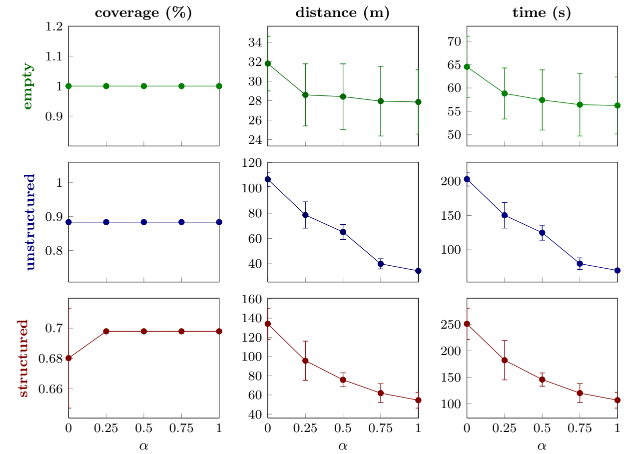



Fig. 9: $Greedy$ not dense: l.1) empty l.2) unstructured l.3) structured

and frontiers are preferred over interactions. No interaction was initiated (RAD), but an average of 28 frontiers were assigned. In the *unstructured* case, the best average performance is at (0.75,0). Distances are overweighted compared to penalties, and interactions are heavily penalised. Nevertheless, an average of 18 interactions (RAD) were initiated against 26 frontiers assignments. In the *structured* environment, best performances and lowest standard deviations are at (0.5,0). Distance and penalty are equally weighted and again interactions are penalised. An average of 31 frontier and 18 interaction assignments took place. Here, interactions are interesting because a robot can discover the corridor by following someone.

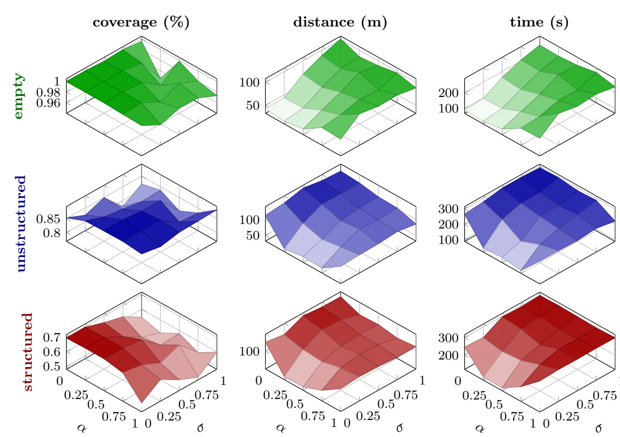



Fig. 10: $MinDist$ dense: l.1) empty l.2) unstructured l.3) structured

For $greedy$ (FIG.11), the best performance is located at $(0.25, 0)$ for the *empty* scene. Penalty has more weight than distance; frontiers are preferred over interactions. An average of 16 frontier and 7 interaction assignments is noticed. The *unstructured* environment has maximum coverage, with minimum travelled distance and time at (0.5,0). The average number of frontiers assigned is 8 times the number of interactions (only 4). For the last map, the best average performance is at (0.25,0) for a frontier/interaction ratio of 29/4. With these

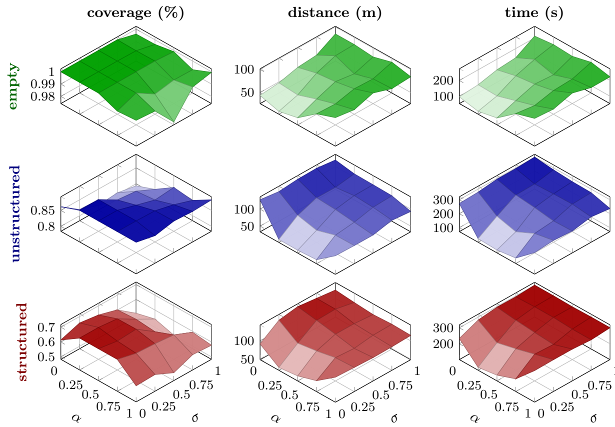



Fig. 11: *Greedy* dense: l.1) empty l.2) unstructured l.3) structured

new results, the distance does not suffice for choosing the best targets with human presence. Instead, a smart equilibrium with our penalty heuristic always gives the best performance ($\alpha \neq 1$). Here with ($\sigma = 0$), the frontiers were chosen considering only distances, but interactions were chosen carefully by adding heavy penalties. Thus our heuristic is already sufficient for selecting interactions (only if necessary) but also it is not yet able to promote them.

## VI. Conclusion

In this article, we have defined the interaction based exploration by targeting the humans perceived by the robots. Interactive exploration paves the way to exploit human natural heuristics, for better understanding of populated environment dynamics. The mixed approach, based upon frontier and interactive exploration, aims at bringing out the best of both approaches. For this purpose, we designed a parametric heuristic to equilibrate frontiers and interactions (human following) assignments. This heuristic considers penalties for the stationary state of the targets (frontier, human) and their orientation.

We have shown in simulation that in some cases, incorporating an interactive aspect into exploration can be beneficial, even with this simplistic heuristic. Discovering these particular cases is thus paramount for enabling efficient dynamic exploration. In this sense, machine learning and dynamic parameters tuning might be of interest for achieving a robotic heuristic adaptation. This work opens up prospects for exploiting human adaptiveness in robotic exploration of populated environments.

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