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Efficiently Approaching Groups of People in a Socially Acceptable Manner in Environments with Obstacles

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***Abstract*— Advancements in mobile robotics have allowed humans and robots to interact in different environments and ways. A problem of great interest in Human-Robot Interaction is how to approach individuals, *e.g.*, to gather information, in a socially acceptable manner. We present a new method for planning sequential visits to various groups of people in cluttered environments. The problem is formulated as a Set Orienteering Problem, where each group denotes a cluster with a set of possible approaching points considering different F-formations. We use the concept of a social probabilistic roadmap to determine safe paths between groups. Simulations considering different cases show that methodology produces efficient tours that maximize the number of approached individuals while respecting social norms of distance and a limited budget.**

I. Introduction

Recently, it is becoming more common to find robots in different environments where human interaction is required. Therefore, an important research topic in Human-Robot Interaction (HRI) is the problem of autonomously approaching groups of people in a socially acceptable manner [1], [2], [3]. Example applications for this problem are a robot providing information in a mall [4], drink-serving service robots [5], and robotic teaching assistants for training activities [6].

Proper approaching behavior is a fundamental capability a social robot must have. It possibly is one of the most important steps to successfully initiate/maintain a human-robot interaction. However, reaching out to people is a challenging task that involves several questions, for example: What individuals/groups should I visit? How do I get to a group? Where should I join the group?

In this context, consider a scenario in which a certain social event where people are displaced in groups (one or more individuals) is taking place in a static and fully-known cluttered environment. A robot needs to approach the groups to provide or retrieve information. The robot is unable to visit all groups due to time constraints or battery life. A group has a set of possible *approachable locations* established according to Proxemics and F-formation rules [7]. Therefore, our objective is to determine a safe and efficient route that maximizes the number of individuals approached. Nonetheless, each group must be visited exactly once, *i.e.*, we must also select the best position to join the group.

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Figure 1 presents an example result of this scenario. The robot leaves and returns to a base position represented as the red point, and its time or length budget is known. The empty circles represent the individuals, and their orientation is the thick line inside them. The groups are formed by a different number of individuals, ranging from one to five. The green points near a group are a discrete representation of the approachable region and are determined by its specific F-formation, for example, face-to-face, side-by-side, V-shaped, circular [8], [9], [7], [10]. The blue dots and green line defines the route, and as can be seen, it avoids obstacles and chooses to visit larger groups (*i.e.*, with more individuals).

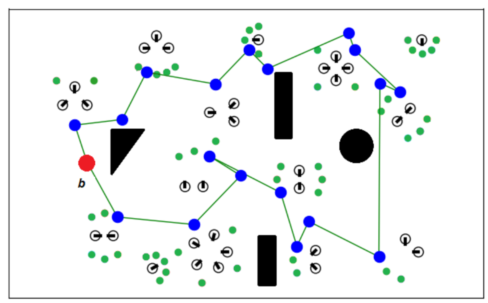


Fig. 1. Example of a viable solution. Scene description: robot base position (*b*) is red point, some individuals alone and others organized in groups of two to five, green approach points, and presence of obstacles (black polygons and circle). Blue dots and green line show the socially acceptable path for the robot to visit as many groups as possible and return to the base point.

To tackle this problem, we propose a routing-based strategy and formulate it as a Set Orienteering Problem (SOP) [11], where each group represents a cluster containing a collection of adequate approaching points. Each cluster has an associated reward, which in our case, is related to its number of members. The objective is to determine a route that maximizes the accumulated reward collected by visiting one point at the cluster. The route must avoid environmental obstacles and not exceed the robot's budget.

This work differs from others in the literature when it considers the visit of multiple groups sequentially, these groups being different from each other (*e.g.*, form, orientation, number of members). Furthermore, to the best of our knowledge, it is the first paper to solve this problem regarding a limited budget and environments with obstacles. Therefore, the main contribution of this article is a way of modeling the approach problem as a SOP. For this, it was also necessary to develop F-formation models for groups of up to 5 individuals and propose how to determine the positions of their possible approach points.

II. Related Work

Studies on socially acceptable ways a robot approaches people are relatively new in the literature, since [12], which models an approaching behavior so a robot can initiate a conversation with people walking. The authors classified human interactions based on the concept of public and social distance. The robot starts approaching the individual's path considering a public distance and notify its presence, and when it reaches the social distance, it nonverbally shows its intention to interact. Still exploring the theory of personal space, in [13], a strategy that models the intimate space to enable a mobile robot to come to a person from the front is presented. A fast-marching planner determines an optimal path to approach the person. Satake *et al.* [14] presents a planner that first searches for a target person in public distance zones anticipating their future position and behavior. Next, it chooses a person who does not seem busy and is achievable from a frontal direction. Finally, once the robot successfully approaches the person within the social distance zone, it identifies the person's reaction and provides a timely response by its body orientation. All these works just consider the approach of a single individual.

More recently, the focus of research has been on approaching groups of individuals. This new challenge requires the robot to trace trajectories that avoid collisions and without causing discomfort to group members, for example, by getting too close or approaching them from behind [15], [16], [17].

Yang *et al.* [18] proposes a trajectory prediction model capable of generating trajectories in autonomous conversational groups trained on a dataset of safe and socially acceptable ways, based on a Generative Adversarial Network (GAN). In a subsequent work [9], the authors examined the impact of three trajectory generation methods to approach groups from various directions, considering group types, camera viewpoints, and approach directions.

An important feature to be observed during social interactions is the spatial arrangement of the individuals towards the group, usually represented by the so-called F-formations [19]. It is a socio-spatial configuration in which individuals establish and maintain a convergent zone (called *O-space*) to which everyone in the set has direct, easy, and equal access [20]. In addition to the O-space, F-formations usually consist of two more areas or larger spaces, which define the level of intimacy and the social norms of the interaction; the *P-space* is the area where people are in a pattern, *i.e.*, the intersection between the personal spaces of each group member. The *R-space* is the surrounding region outside the group and generally used by external entities to perform the approximation and initiate an interaction with the group [8], [21]. Most works generally deal with F-formations applied to detecting a group of interaction [8], [20], [22], [21], [23] and do not address the approach planning itself. Others like [10], [24] suggest a navigation planner based on standard F-formations so that a robot can move close to humans without interfering. In [25], the F-formation concepts are used to propose a socialization model for the robot while participating in an interaction with a human peer group to achieve their socially ideal position.

In addition, we could not find any work that tackles the task of approaching people as a routing problem, *i.e.*, considering the order of visits and the robot's budget. On a previous work [26] we focused on approaching individuals and modeled it as a Generalized Travelling Salesman Problem, *i.e.*, we should visit all persons. Another closer work is [27], which considers a people search problem, defined as an Orienteering Problem (OP), which goal is to find a group of dynamic users before a deadline.

Our proposed method is developed from the idea of how F-Formation detection works, considering the common positions and orientations of individuals in the arrangements. We present a new modeling of the problem of approach to groups of individuals as a SOP, producing efficient paths while maintaining a socially acceptable approaching behavior.

III. Problem Formulation

Given $\mathcal{E} \in \mathbb{R}^2$ a fully defined static cluttered environment. Let $\mathcal{N} = \{\mathbf{n}_1, \ldots, \mathbf{n}_h\}$ be a set of spatially distributed individuals that need to be visited by a robot. An individual i is represented by a configuration $\mathbf{n}_i = \langle x_i, y_i, \theta_i \rangle$. We consider that individuals are organized into disjoint groups $c_1, \ldots, c_g$, each group composed of one or more members.

When navigating through the environment, the robot must not collide with a set of obstacles $\mathcal{O} = \{o_1, \ldots, o_m\}$ or disrespect simple social conventions, *e.g.*, get too close to an individual or invade a group's P-space. Furthermore, the robot is subjected to a predefined travel budget T_{max}.

We model our problem as a Set Orienteering Problem, which considers a set of clustered locations, and the goal is to determine a tour considering a restricted budget that maximizes the *profit* collected by visiting the clusters. The tour starts and ends on a predefined *base cluster* $\mathbf{b} \in \mathbb{R}^2$, and in our case, the profit p_i associated with a group c_i is directly related to its number of members.

In summary, our problem can be defined as:

Problem 1 (Efficient Sequential Group Approaching in Cluttered Environments)**.** *Given a 2D static cluttered environment $\mathcal{E}$ and a set of groups $\mathcal{C} = \{c_1, \ldots, c_g\}$. The goal is to find a collision-free tour $\mathcal{L}$ with the maximal collected reward, i.e., maximizes the number of individuals visited, while respecting the robot's travel budget and social rules.*

This problem involves the selection of an optimized subset of clusters to be visited and their permutation. Furthermore, we must choose an appropriate approaching location to join the group. Finally, the path must be designed in such a way that it allows for a safe and socially acceptable navigation.

IV. Methodology

The proposed methodology is structured in the following steps (Figure 2): (i) group F-formation representation; (ii) generation of possible approaching positions; (iii) generation of a social probabilistic roadmap; and (iv) formalization of the problem as a SOP instance and determination of the tour.

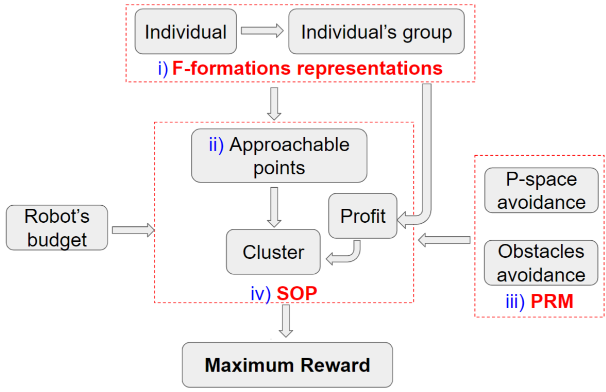


Fig. 2. Solution diagram for obtaining an efficient sequential group approaching in cluttered environments.

There are individuals the robot needs to visit, which are organized into groups. First, we model the arrangement of each group considering an F-formation. We define a discrete set with suitable approaching positions for each formation and gather them to form clusters. To avoid collisions and execute a socially acceptable navigation, we create a randomized social roadmap. Finally, we combine the approaching points clusters and the social roadmap vertices to model the problem as a SOP instance. Each vertex initially on the social roadmap will be considered a null-gain cluster. As for the groups, each cluster will receive a profit value proportional to its number of members. In addition, the robot's budget limits the maximum distance it can travel and, consequently, the number of clusters that can be visited. Therefore, the goal is to find a tour that maximizes the total profit collected, in our cases, the number of individuals approached.

A. F-formation representation

Initially, we model each group according to its number of members and their arrangements and make use of the F-formation system designed by [19]. The most important part of an F-formation is the O-space, a convex empty space to which everybody in the gathering has direct, easy, and equal access. For simplicity, we consider the O-space to be a circle, similar to [25]. So, for each specific formation, we determine the coordinates of the center of the O-space (x_c, y_c) and its radius r_c, and from these parameters, we define the radius of the P-space, r_p, as:

$$r_p = r_c + r_b + d, \tag{1}$$

where r_b corresponds to the average body radius of an adult person, and d is equals the distance of the personal space, and the R-space, r_R, given by:

$$r_R = r_p + s, \tag{2}$$

where $s = 1.2$m, is the average value attributed to a social distance [28]. Table I shows the formulation adopted for the calculations of each coordinates of the F-formations shown in Figure 3. For the face-to-face formation we use the formulation described in [25], and we propose a generalization for others types. Variables x_i, y_i, $i \in \{1, 2, ..., 5\}$, refer to the Cartesian coordinates of the center of each person considering groups of one to a maximum of five individuals. Angles θ_1, θ_2 refer to the orientation of persons one and two in each respective formation and, θ_c is the orientation of the center of the O-space. At last, x_c, y_c and r_c are equivalent to the coordinates and the radius of the center of the O-space, respectively. Hence, the first column of Table I informs on the F-formation, and the other columns on the values or mathematical equations assigned to x_c, y_c, θ_c, and r_c, for each specific formation.

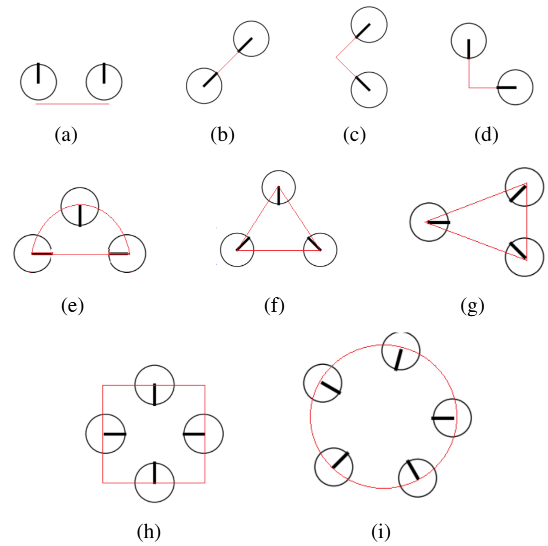


Fig. 3. Example F-formation configurations adopted in this paper. a) side-by-side; b) face-to-face; c) V-shaped; d) L-shaped; e) semicircle; f) equilateral triangle; g) isosceles triangle; h) rectangular; i) circular.

B. Approaching points

Different psychological studies discuss about implicit nonverbal social rules that need to be respected in human-human interaction, *e.g.*, proxemics [28], and which can also be considered in human-robot interaction scenarios.

It is known that the most acceptable way to approach an individual is preferably from the front, keeping a minimum distance that respects the personal space. When considering a group, its members' disposition also constraints the space where a new individual could join it and start interacting.

Therefore, given a certain group, we define a set of possible approaching positions according to its F-formation. This modeling is one of the main contributions of this work. For example, groups with two face-to-face individuals can be visited in the two directions lateral to the center of the O-space. In contrast, groups with side-by-side F-formation can only receive visits in the frontal direction of the angle of the center of their O-space.

Figure 4 shows this discretization for the L-shaped formation and a single person. Depending on the F-formation and number of individuals in the group, each set may have a different number of approaching points. The points are always positioned in relation to θ_c, thus preventing any individual from being approached from behind.

The points will be placed in a circular region of radius

$$r_{app} = r_p + (r_R - r_p)/2, \tag{3}$$

TABLE I

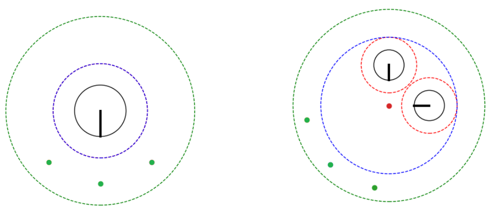
VALUES AND EQUATIONS USED TO CALCULATE THE O-SPACE CENTER COORDINATES AND RADIUS FOR THE F-FORMATIONS IN FIGURE 3.

F-formation	$\mathbf{x_c}$	$\mathbf{y_c}$	θ_c	$\mathbf{r_c}$
Side-by-side	$(x_2 - x_1)/2 + x_1$	$y_1 + (x_c - x_1) * \tan(\theta_c)$	$\pi - (\theta_1 + \theta_2)$	$(y_c - y_1)/\cos(\theta_c)$
Face-to-face	$x_1 + (x_2 - x_1)/2$	$y_1 + (y_2 - y_1)/2$	$(\theta_1 + \theta_2) - \pi$	$(y_2 - y_1)/(\sin(\theta_1) - \sin(\theta_2))$
V-shaped	$x_1 + (x_2 - x_1)/2$	$y + (y_2 - y_1)/2$	$\pi - (\theta_1 + \theta_2)$	$(y_c - y_1)$
L-shaped	x_1	y_2	$\pi - (\theta_1 + \theta_2)$	$(y_1 - y_2)$
Semicircle	$x_1 + r_c * \cos(\theta_1)$	$y_1 + r_c * \sin(\theta_1)$	$2\pi - (\theta_1 + \theta_2 + \theta_3)$	$(x_2 - x_3)/(2 * \tan(2\pi/10))$
Equilateral triangle	x_3	$(y_3 - y_1)/3 + y_1$	$\pi + \theta$ for each θ	$2 * (y_3 - y_1)/3$
Isosceles triangle	$(x_1 + x_2 + x_3)/3$	$(y_1 + y_2 + y_3)/3$	$\theta_2 - 5\pi/36,\ \theta_3 + 5\pi/36$	$\sqrt{(x_c - x_1)^2 + (y_c - y_1)^2}$
Rectangular	$x_2 = x_4$	$y_1 = y_3$	$\pi/4,\ 3\pi/4,\ 5\pi/4,\ 7\pi/4$	$x_c - x_1$
Circular	$x_1 + r_c * \cos(\theta_1)$	$y_1 + r_c * \sin(\theta_1)$	$\pi + \theta$ for each θ	$(x_2 - x_3)/(2 * \tan(2\pi/10))$

and the coordinates of an approaching point $\mathbf{p}_i^a$ is given by

$$\mathbf{p}_i^a = r_{app} \cdot \begin{bmatrix} \cos(\theta_c + \alpha) \\ \sin(\theta_c + \alpha) \end{bmatrix} + \mathbf{n}_i{}^{x,y}, \quad (4)$$

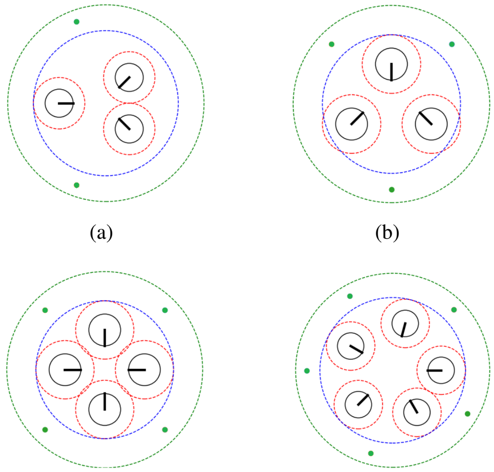
where $\alpha = [-\pi/4, \pi/4]$. The sample resolution of α defines the number of targets positions that will be obtained.



(a) (b)

Fig. 4. Representation of the approaching points discretization (green points). a) Single individual who is not interacting in any group. The blue circle is the personal space that matches the P-space in this case. The green circle is the R-space. b) Group with two members in L-formation. The red dot shows the center of the O-space. Red circles delimit each individual's personal space. A blue circle delimits the P-space.

Therefore, for rectangular, circular, and triangular formations, the approach points are positioned so that they are frontally visible to at least one of the group members (Fig. 5).



(a) (b) (c) (d)

Fig. 5. Special cases of the approaching points discretization (green points). a) Isosceles triangle - two approach points; and, b) Equilateral triangle - three approach points. c) Rectangular formation - four approach points; d) Circular formation - five approach points.

C. Social Probabilistic Roadmap

Next, based on the classic Probabilistic Roadmap (PRM) [29] method, we create a social probabilistic roadmap to obtain obstacle-free paths between groups that will also meet the social constraints.

For that, we generate a set of valid samples randomly distributed in the environment, where a valid sample is one that does not lie inside an obstacle or a group's P-space. The social roadmap has as nodes all the approaching points in each group and the valid random samples. We create edges connecting all valid samples with each other and the approaching points as long as they do not intersect an obstacle or a P-space. There are only edges between approaching points that belong to different groups.

Figure 6 shows an example of a social roadmap generated using the aforementioned strategy.

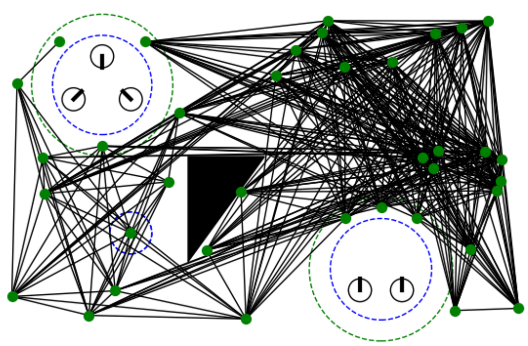


Fig. 6. Example of the social roadmap created by the PRM for a scene with one obstacle and two groups, one with three people and equilateral triangle formation, other with two people in side-by-side formation. Each group with three approach points. We consider 40 random samples and the robot's base position is show as the single point in blue circle.

D. Set Orienteering Problem

Finally, as mentioned earlier, we formulate and solve the problem as a SOP [11]. In our SOP instance, all nodes in the social roadmap are grouped into a set of clusters S_g. These clusters are obtained by the previously defined groups in $\mathcal{C}$ and by the random samples, where each sample is considered a cluster with a single element.

A profit p_g is associated with each cluster as follows: clusters with approaching points (belong to $\mathcal{C}$) have a profit value proportional to the number of members in the respective group; on the other hand, profits from the other vertices of the graph, *i.e.*, random samples, will be equal to zero. Moreover, these profits are collected only if at least one node in the cluster is visited and can be collected at most once.

The objective is to find a tour that maximizes the total profit collected and that the associated cost does not exceed $T_{\max}$ (robot budget). We assume that the costs satisfy the triangular inequality, and an optimal solution always exists where at most one vertex per cluster is visited.

V. Experiments

In order to solve the SOP instance, we apply the VNS-SOP algorithm [30], based on the Variable Neighborhood Search (VNS) metaheuristic. This heuristic uses a greedy initial solution that minimizes the distance per additional profit gained by visiting a new, not previously visited cluster. Afterward, the VNS tries to improve the currently best incumbent solution by a set of predefined neighborhood operators. However, for the VNS-SOP algorithm, the problem can be partially separated into selecting the clusters to visit, determining the order of visits to the selected clusters, and selecting the vertices to visit in the chosen clusters. For a given permutation of clusters, the solution is the subproblem of selecting individual vertices within clusters can be addressed as finding the shortest path in a graph of the visited clusters.

A. Illustrative example

Initially, we present a simple test case to better understand and visualize the solutions. In this experiment, we consider an environment with three obstacles, four groups with a different number of members, 100 samples in the social roadmap, and $T_{\max} = 80$. Each cluster has a profit equal to the number of members multiplied by 100.

We aim to show that the VNS-SOP method can find a socially acceptable path that satisfies the problem. Figure 7 illustrate the route found, with a total reward of 900, length of 75m, and 2 groups visited. As can be seen, the final path respects social and geometric constraints and the given budget. Furthermore, it prioritizes visiting bigger groups, which benefits our objective (approach more individuals).

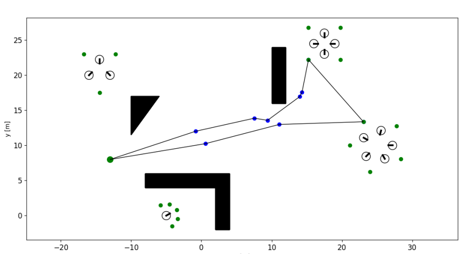
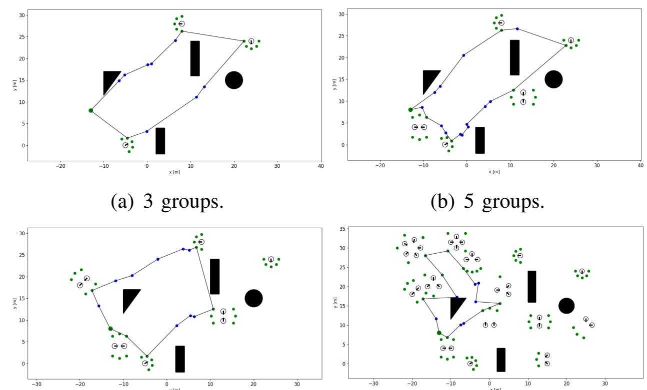


Fig. 7. Final tour obtained for the illustrative case for four heterogeneous groups. Green points are possible approaching points in the clusters (groups), and blue points are clusters (samples) from the social roadmap.

B. Varying number/types of groups

For this test, we will set the budget (T_{max}) to 80. We will start with an environment containing only three small groups. Then, at each test, we will add groups of different f-formations and quantities to the environment, always adding groups more significant in the number of individuals, thus verifying which groups were visited and the reward earned. Figure 8 exemplifies the routes found for settings with three, five, six, and fourteen groups, respectively.



(a) 3 groups. (b) 5 groups.

(c) 6 groups. (d) 14 groups.

Fig. 8. Results for the varying number/types of groups. Tour obtainable for: a) Three groups; b) five groups; c) six groups and; d) fourteen groups.

We further detail the results in Figure 9. It shows two relationships; in blue, we can see the ratio between the total reward possible in the scene and the total number of groups, and in red, the correlation between the reward earned and the total number of visited groups. Therefore, as we introduce new groups, we observe that the solver correctly chooses to visit the ones with the highest profit, which allows for higher gains while still respecting the budget.

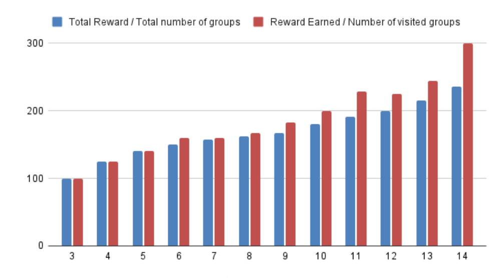


Fig. 9. Results considering the variation of number/types of groups. Blue columns show the ratio of the total possible reward in the scene to the total number of groups; red columns show the correlation between the reward collected and the total number of groups visited.

C. Varying robot budget

In this experiment, our objective was to understand the behavior of the solutions as the budget ($T_{\max}$) decreases. It is expected that the method seeks to find ways to obtain greater rewards, preferentially choosing the clusters with the most significant number of people.

To achieve this objective and test our hypothesis, we consider the environment shown in Table III, in which we set the maximum number of groups that could be visited at nine, set the number of random nodes generated by PRM at

200, and start with a budget of 1000, for which the robot can visit all groups. Then we decrease the value of the budget to 100 and continue decreasing by 10 and observe the results found for *Reward Earned* and *Length*.

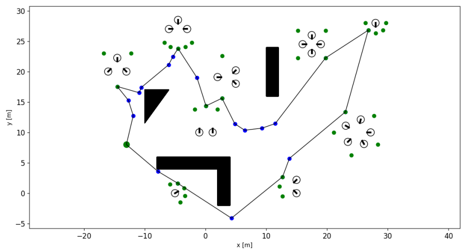


Fig. 10. Experiment Varying robot budget result, with T_{max} = 1000. Nine groups of people, three obstacles, green points are targets in clusters formed by groups of persons, and blue points are clusters from the social roadmap.

According to the initial hypothesis, it is noticeable that the solver prioritizes larger clusters as the budget decreases. Furthermore, the relationship between $T_{\max}$ and the total reward is proportional. We highlight that the heuristic does not work towards finding the shortest path among them all.

TABLE II

RESULTS FOR EXPERIMENT VARYING ROBOT BUDGET.

T_{max}	Reward Earned	Length
1000	2400	109
100	2300	95
90	2000	90
80	1500	69
70	1500	62
60	1200	57
50	1100	41
40	900	37
30	600	30

D. Varying number of random samples

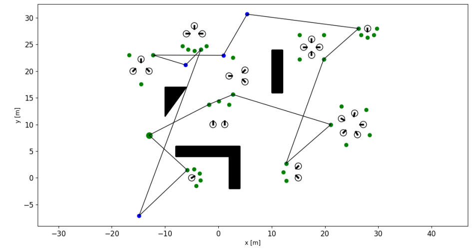
Finally, this experiment aims to analyze the behavior of the tour when the number of samples in the social roadmap increases. Given the same set of groups and obstacles as in the previous experiment, we set $T_{\max}$ at a sufficiently high value (1000). We varied the samples from 10 to 500 with initially small intervals (increased by 20) and then slightly larger (increased by 100). Table III shows the results. As expected, there is a relationship between the increase in the number of samples and the decrease in the path length. This happens because it is possible to find more optimized paths connecting different groups. Furthermore, it is important to notice that not optimal paths can be found (Fig. 11(a)) as long as they respect the budget.

VI. CONCLUSION AND FUTURE WORK

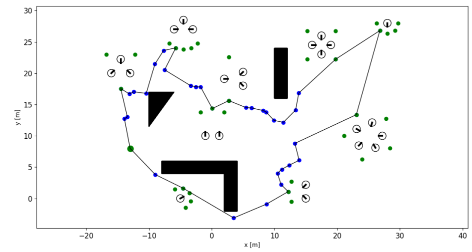
We proposed a strategy for sequentially approaching groups in environments with obstacles. We formulate the problem as an SOP, which goal is to maximize a reward by visiting the maximal number of clusters allowed by a limited budget. In our case, the vertices are the possible approaching points in each group, respecting their F-formations. In addition, we use a randomized social roadmap to obtain a path that respects social constraints and avoids collisions.

Experiments confirmed our hypotheses that the methodology produces safe and efficient tours with socially acceptable behavior for the simulated scenarios. Furthermore, the main contribution of this work is that it considers the planning problem of approaching groups of people in a socially acceptable manner as a routing problem, defined as a Set Orienteering Problem. Since socially acceptable ways to approach people is a relatively new area of research, this is the first work that solves this problem regarding a travel budget limit and environments with obstacles.

In future work, we plan to evaluate other solutions for our social SOP, for example, genetic algorithms. We also intend to study the impact of dynamic environments, *e.g.*, with moving individuals, and different rewards for each approach point according to its relative position to the O-space center. Furthermore, we consider investigating the use of multiple robots. Finally, we plan to design and execute experiments in a real-world scenario.



(a) 10 samples.



(b) 500 samples.

Fig. 11. Results for the varying number of random samples scenario.

TABLE III

RESULTS FOR THE VARYING NUMBER OF RANDOM SAMPLES SCENARIO.

Number of samples	Length	Path nodes	Reward Earned
10	180	4	2400
30	139	6	2400
50	125	5	2400
70	123	12	2400
90	127	8	2400
110	119	13	2400
130	121	14	2400
200	115	14	2400
300	112	31	2400
400	114	26	2400
500	108	28	2400

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