A Multi-Objective Exploration Strategy for Mobile Robots under Operational Constraints

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***Abstract*—Multi-objective robot exploration, constitutes one of the most challenging tasks for autonomous robots performing in various operations and different environments. However, the optimal exploration path depends heavily on the objectives and constraints that both these operations and environments introduce. Typical environment constraints include partially known or completely unknown workspaces, limited-bandwidth communications and sparse or dense clattered spaces. In such environments, the exploration robots must satisfy additional operational constraints including time-critical goals, kinematic modeling and resource limitations. Finding the optimal exploration path under these multiple constraints and objectives constitutes a challenging non-convex optimization problem. In our approach, we model the environment constraints in cost functions and utilize the Cognitive-based Adaptive Optimization (CAO) algorithm in order to meet time-critical objectives. The exploration path produced is optimal in the sense of globally minimizing the required time as well as maximizing the explored area of a partially unknown workspace. Since obstacles are sensed during operation, initial paths are possible to be blocked leading to a robot entrapment. A supervisor is triggered to signal a blocked passage and subsequently escape from the basin of cost function local minimum. Extensive simulations and comparisons in typical scenarios are presented in order to show the efficiency of the proposed approach.**

I. Introduction

AUTONOMOUS exploration by a single mobile robot has attracted much research interest in the previous decades giving rise to many robust and efficient solutions. This led to an increasing usage transition of mobile robots from laboratory testbed environments to real world ones. However, this transition has not yet been fully exploited and, therefore, it still remains an active area of research. Compared to the limited constraints found in laboratory testbed robot exploration, the transition to real world operations might pose several new constraints and operational objectives, including: a) limited operational time; b) multi-objective temporal goals; and c) environmental constraints, such as limited communications and sparse or dense clattered workspaces.

In typical robot exploration, the single goal of the robot is to maximize the overall explored area. The solution to this problem is to find optimal target points that the robot should follow, so as to explore as much of the unexplored workspace minimizing, if possible, the potential to explore the same region. During the on-line exploration procedure, the observation positions, and therefore the trajectories along which the robot moves, are computed during the exploration task.

In real world scenarios, the robot exploration goal might be accompanied with operational time limitations, extending the problem to a more complex one, since the robot must explore as much of the workspace as possible in a minimum time. An adequate exploration strategy should be: effective, to build an accurate, precise and reliable map, efficient, to cover the environment as fast as possible, and adaptable, to work in different kinds of environments [1]. Robot exploration problem is equivalent with the one of dynamically deploying a mobile sensor to learn about an unknown environment [2]. In other words, such a task is of immediate relevance to the fields of sensor networks, calibration and terrain-aided navigation [3], [4]. It is worth noting that on-line path planing is essential for Simultaneous Planning Localization and Mapping (SPLAM) [5], [6].

In the proposed work, we address a twofold challenge of realistic robotic exploration operations, that is the ability to efficiently handle multiple temporal goals while satisfying the mission constraints. More precisely, the temporal goals, such as multiple region exploration and target finding, are modeled by different cost functions and are constantly monitored. Each cost function is then triggered depending on the occurrence of the required preconditions of each goal. Highly computational burden optimization algorithms were not selected, but a cognitive-based adaptive optimization algorithm was used instead [7]. The used methodology possesses the capability of efficiently handling optimization problems for which an analytical form of the function to be optimized is unknown, but the function is available for measurement at each iteration of the algorithm employed to optimize it. Thus, the overall method is characterized by low computational cost rendering it appropriate for real life robot exploration applications.

The rest of the paper is organized as follows. In section II we briefly revisit approaches related to the proposed single robot on-line expiration strategy, before we select and model a search and rescue problem as our case study in section III. In section IV, we analyze the proposed method, and more particular, we define the mathematical constraints and objectives that are subsequently introduced to the cognitive-based adaptive optimization algorithm. In section V, we report the simulation results and compare the performance of the

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proposed algorithm with other widely used exploration algorithms through quantitative measurements. Finally, we provide concluding remarks in section VI.

II. Related Work

Applications of effective and efficient exploration include planetary exploration [8], search and rescue [9] and military uses [10]. A promising robot exploration approach has been presented in [11], where the time-optimal path tracking problem is transformed into a convex optimal control problem, yet ignoring the high-level geometric constraints of the workspace. Similarly, authors in [12] face the path optimization problem as equivalent to finding the best decision sequence maximizing an auxiliary convex cost function. In this approach, state and decision spaces are assumed to be discrete and finite. The minimization of the search execution time has also been addressed in [13], where time is modeled by a cost function in which a back-projection algorithm propagates constraints from the goal towards the start state. This approach is efficient while it models the uncertainty evolution in time, however, it is applicable only if the final goal remains the same. In [2], Martinez et al. model the path planning problem with a partially observed Markov decision process, with continuous states and actions. The problem of path optimizing for a single robot was also studied by Chekuri and Pal [14], who developed a recursive greedy algorithm with strong theoretical approximation guarantees. Unfortunately, the running time of this algorithm makes the approach impractical. In [15], the authors proposed an expansion of this approach so as to overcome these limitations, making it practical for real world sensing and robot exploration problems. This approach is however restricted to off-line path planning and thus, does not easily adapt to dynamic environments.

When multiple goals confine the overall robot exploration operation, including for example, the minimization of traveling cost together with the maximization of the estimated information gain, the problem expands to finding an optimal joint policy. These multiple goals are often conflicting and might not be feasible to be reached simultaneously. Most of the existing approaches tend to employ evaluation functions for each goal. In the sequel, they combine the results of the functions in an ad hoc global utility function that is maximized in order to find the next best candidate position [16], [17], [18]. A typical multi-objective scenario was presented in [19], where high-level representation of petri net plans formalism was used to address this problem. The authors attempted to represent effectively concurrent robotic processes in order to specify complex strategies for addressing and resolving the respective multiple goals. However, this approach does not encode such multiple goals in weighted functions to be optimized, but a rather strategic level solution is adopted. A different approach has been adopted in [1], where the values of the evaluation function of each goal are kept separated without combining them in a particular utility function.

Multi-objective optimization solutions have also been widely proposed in the literature, yet their computational complexity remains high, rendering them inappropriate for time critical real world operations. A strive to handle moderately complex robotic tasks in real world robotic applications has been recently proposed in [20]. The efficiency of the system was enhanced by incorporating point-based partially observable Markov decision processes, which sample a limited set of points from robot's state space and by constructing a simplified representation of the state space. The resulted policies for target finding and navigation were reported to be less time consuming and with high success rates. However, in cases where the robot should take multiple actions so as to reach a certain goal, a long time horizon is required. The increased time steps result in an exponential complexity growth, thus hindering the adoption of the aforementioned method in long time robot operations.

Cost functions have been also considered for evaluating candidate observation locations by combining distance, expected information gain and probability of successful communication. Global evaluation of the exploration strategy performance was investigated in [21] according to time and multiple visit metric. This metric is estimated at each step, and the next robot position is chosen by maximizing the expected increase of global performance. Global cost functions were also presented in [22] by combining criteria in an aggregated way and by utilizing a theoretic approach based on multi-criteria decision making. However, this theoretic approach cannot guarantee always a good exploration strategy.

III. Problem Formulation

In a typical search and rescue operation the first responder team must safely and quickly reach an incident inside a building without any robotic agent assistance [23]. Howsoever, the team must be able to retract itself to the nearest exit, when the conditions in the building become dangerous. This simple task of reaching a target and being able to retract from the building becomes a challenge when several constraints are imposed in the operational environment. One typical example is the operation of firefighters when they try to locate a victim inside a certain area of a damaged building. In such scenarios, the firefighters might not afford more than a few minutes or even seconds to reach the victim, before the conditions become threatening against their own lives. Once they locate the victim, they must find their way to the exit as quickly as possible. This may appear to be a particularly troublous occasion in the case that the rescuer workers fail to retreat along the same path they followed to enter the building, e.g. owing to a collapse. Even when the operation conditions are not directly life-threatening, precious time may be wasted by searching the same room twice or failing to search another.

A substantially harder situation is when emergency services have to respond to terrorist attacks in urban environments, where possible explosions may cause loss of life or damage in real estate [24]. In such scenarios, bomb squads are required to search and explore an urban area for locating the threat by deploying remote robotics under demanding time constraints [25]. Conditions such as poor lighting or limited communication range may occur in such fields [26], [27].

In our proposed framework, we will study and model the operation of a first responder robot holding the common goals and constraints of the aforementioned emergency scenarios. More precisely, the robot will share the same initial knowledge as the first responder units and will operate in multi-objective and multi-constraint scenarios. In natural language, the desired robot multi-objective scenario is described as follows: *Given an initial unexplored map, your initial position and a certain time window, try to find the subject around a target position. If you find the subject, explore as much of the target region as you can and then return to the exit. If you did not find the subject, resume the search. When returning to exit, provided that the time constraints allow, explore as much of the unexplored region map. In any case, keep your communication link and do not exceed the given time window.*

More precisely, our work focuses on mobile robot path planning in high dimensional and partially known environment, with timing and multi-objective considerations. The kinematic problem is not considered throughout the methodology, assuming accurate and deterministic models. Additionally, we assume that the robots are perfectly localized. The same assumption has been adopted in [28], [29], [18]. The goal-directed mobile robot path planing, entails a robot moving from some initial state to a target state while satisfying constraints and updating map information through an onboard sensor. The state space is continuous and bounded. In each time step, the robot moves from the current location to a new one, located on the circumference of a circle whose center is considered the current position of the robot.

IV. Proposed Methodology

A. Mathematical Problem Formulation

In order to achieve all the aforementioned first responder goals we must firstly model all the operational conditions and constraints in a unified structure. This section aims to define both the parameters and the constraints and subsequently introduce them as cost functions to the cognitive-based adaptive optimization algorithm.

Vectors $\mathbf{R}, \mathbf{G}, \mathbf{S}, \mathbf{H} \in \mathbb{R}^2$ define the robot, target point, entry point and wireless node transmitter coordinates, respectively. C_r is the maximum safe range that allows communication between the deployed wireless node transmitter and the first responder robot on-board receiver. The two vector input operator $D(\mathbf{x}_1, \mathbf{x}_2) : \mathbb{R}^2 \to \mathbb{R}$, computes the respective Euclidean norm between $\mathbf{x}_1$ and $\mathbf{x}_2$.

The universe set V contains all possible states of a point in a map. The complementary subsets $V_1, V_2, V_3, V_4 \subset V$, where $V_i \cap V_j = \varnothing, i \neq j$, represents a possible state as follows:
V_1 : {Traversable and explored by the robot}
V_2 : {Traversable and not explored by the robot}
V_3 : {Known Obstacle}
V_4 : {Obstacle explored by the robot}

The matrix $\mathbf{P}$ represents the initial belief of the state space as provided by blueprint CAD models of the emergency scenes. Apart from the known obstacles defined by the blueprints, the rest points are initially defined as traversable. Thus, in matrix $\mathbf{P}$ all elements may belong to any of the subsets V_1, V_2, or V_3. The matrix $\mathbf{M}$ initially contains the known obstacles, as in matrix $\mathbf{P}$, whereas the rest of the points are considered to be unexplored. While the robot scans the emergency scene, the points that stand within the field of view, transit to subsets V_1 or V_4. In other words, the corresponding matrix $\mathbf{M}$ is iteratively updated and enriched with information from the first responder robot exploration.

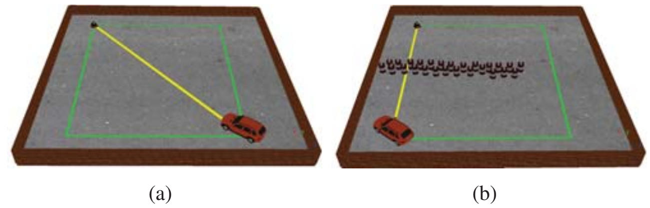


Fig. 1. Two different world maps and the potential path trajectories for $w_1 >> w_3$ (green path) and $w_1 << w_3$ (yellow path), respectively.

Given a radius r_c and the coordinates of the goal $\mathbf{G}$, the circular goal area C_g is defined as the matrix points that lie within that circle. The following equations summarize the regions of an emergency scene as follows:

$$A_e = \sum_{i,j \in V_1} M_{ij} \tag{1}$$

$$A_b = \sum_{i,j \in V_1, V_2} P_{ij} \tag{2}$$

$$G_e = \sum_{i,j \in V_1} M_{ij}, \quad \forall M_{ij} \in C_g \tag{3}$$

$$G_b = \sum_{i,j \in V_1, V_2} P_{ij}, \quad \forall P_{ij} \in C_g \tag{4}$$

Exploiting the above regions of interest, we define the following terms:

$$F_1 = \frac{A_e}{A_b} \tag{5}$$

$$F_2 = \frac{G_e}{G_b} \tag{6}$$

$$F_3 = e^{-\frac{D(\mathbf{R},\mathbf{G})}{\max |D(\mathbf{R},\mathbf{G})|}} \tag{7}$$

$$F_4 = e^{-\frac{D(\mathbf{R},\mathbf{S})}{\max |D(\mathbf{R},\mathbf{S})|}} \tag{8}$$

where F_1 is a regularized term that indicates the exploration percentage of the emergency scene. The F_1 term will be equal to one only in the case that there are no explored obstacles in the area apart from the known ones. The F_2 regularized term indicates the percentage of the target area that has been explored. The F_3 term defines a function that encourages the emergency situation robot to reach a position near the target, since the exponential term acts as a strong attractor to $\mathbf{G}$ due to its rapidly decreasing nature. Similarly, the F_4 term promotes positions nearby the initial point $\mathbf{S}$. With all the above definitions we can now define the following two cost functions:

$$CF_1 = \frac{(w_1 F_1 + w_2 F_2 + w_3 F_3)}{1 + e^{(|D(\mathbf{R},\mathbf{H})| - C_r)}} \tag{9}$$

$$CF_2 = \frac{(w_1 F_1 + w_3 F_4)}{1 + e^{(|D(\mathbf{R},\mathbf{H})| - C_r)}} \tag{10}$$

where w_1, w_2 and w_3 are user defined weight factors reflecting the respective importance in each different emergency scenario. When the ratio $\frac{w_1}{w_3}$ increases, the robot is highly motivated to explore the area and, as a result, it lags behind with reaching the C_g. At the same time, a high $\frac{w_1}{w_3}$ value ensures that even if the target is not within the robot's field of view, it will be able to find the target $\mathbf{G}$ by partially contributing in the local minimum avoidance, as shown in Fig. 1. The reader can find more detailed information about the selected local minimum avoidance strategy in the next two subsections. When the ratio $\frac{w_1}{w_3}$ decreases, the robot will reach the target position $\mathbf{G}$ faster, tending, however, to get trapped in a local minimum.

Figure 1 illustrates two potential path trajectories for two different maps, depending on the parameter selection. The first path is calculated when $w_1 >> w_3$ and the second one when $w_1 << w_3$. In Fig. 1(a) the resulting path for $w_1 >> w_3$ aids the robot to explore the unknown area while it approaches the target position. On the other hand, the second resulting path, i.e. for $w_1 << w_3$, is a straight line heading the robot straight towards the target position. In a more confined world, such as the one depicted in Fig. 1(b), the estimated path when $w_1 >> w_3$ tends to explore the unknown area, helping ultimately the robot to overcome the obstacle and reach the target area. However, the estimated path when $w_1 << w_3$ follows a straight line approach and, thus, fails to approximate the goal area beyond the obstacle.

By setting the value of parameter w_2 greater than w_1 and w_3, the robot is motivated to explore the area nearby C_g. The numerator of Eq.(9) guides the robot to explore as much of the emergency area along with the target area and also helps the robot to find a position, such that the goal will be in its line of sight. The denominator acts as an attractor to the wireless node transmitter position $\mathbf{H}$, according to its maximum signal range.

When the robot has eventually explored adequate target area, it should act as the human first responders do, i.e. it must retreat to the initial exit point as soon as possible. Within the same time interval, the second cost function of Eq. (10) is enabled, the numerator of which boosts the robot to reach its starting point and sets out to explore the rest of the region to the maximum extent possible. This trade off between the two objectives is highly correlated with the available time remaining. As stated earlier in this section, the initial ratio $\frac{w_1}{w_3}$ motivates the task of exploration, but as the time horizon decreases, this ratio progressively drops driving the robot to the exit.

In both Eq. (9) and Eq. (10) the individual terms in which the numerator is more persistent depends on the operator's discretion and the current emergency scenario needs. The critical transition between the two cost functions is achieved if the conditions in Eq. 11 and Eq. 12 hold. More precisely, a vector of length T_n stores the most recent values of F_2. Given a threshold T_{f2}, where $0 < T_{f2} < 100$, a transition is allowed when the mean value of T_n is greater than zero (Eq. 11) and the absolute difference between the mean value and the value of F_2 is smaller than a percentage of the mean value. That threshold percentage is defined via the T_{f2}, as expressed by Eq. 12. By defining the mean value greater than zero, it is ensured that the goal area will be at least partially explored by the first responder robot. A second threshold T_m for the mean value can be also applied, forcing the robot to explore the goal area in a defined desired level.

$$\frac{\sum_{i=0}^{T_n} F_2[i]}{T_n} > 0 \tag{11}$$

$$\left| \frac{\sum_{i=0}^{T_n} F_2[i]}{T_n} - F_2[i+1] \right| < \frac{\sum_{i=0}^{T_n} F_2[i]}{T_n} \frac{T_{f2}}{100} \tag{12}$$

In each time-step the robot moves a distance α from its current position towards a given direction. Considering the robot current position $\mathbf{R}$ in time-step T_c as the center of a circle with radius α, the possible next positions in time-step T_c+1 would lie on the circumference of that circle. However, when the condition in Eq. 13 holds, a local minimum situation is detected. The adaptive optimization algorithm will then try to avoid such minima by increasing the value of α iteratively, seeking for new possible robot positions that would lie in the circumference of the updated circle. For any time step in which the condition in Eq. 13 holds α is increased by one until the condition is no longer valid; then the value α returns to one. The consecutive number of time-steps in which the robot is trapped in a local minimum equals to the expansion rate of the parameter α. Equation 13 affects the robot performance in the same fashion as the one in 12. The criteria to select the most suitable future position of the robot are described in subsection IV-C.

$$\left| \frac{\sum_{i=0}^{T_g} F_1[i]}{T_g} - F_1[i+1] \right| < \frac{\sum_{i=0}^{T_g} F_1[i]}{T_g} \frac{T_{f1}}{100} \tag{13}$$

B. *Cognitive-Based Adaptive Optimization Approach*

The Cognitive-based Adaptive Optimization (CAO) approach [7], [30], [31] was originally developed and analyzed for the optimization of functions for which an explicit form is unknown but their measurements are available as well as for the adaptive fine-tuning of large-scale nonlinear control systems. Recently, CAO based methodologies have been applied in a wide range of robotics related applications. In [32] CAO was used to position a team of mobile robots for a surveillance task in a non-convex 2D environment with obstacles. The robots were equipped with global positioning capabilities and visual sensors able to monitor the surrounding environment. In [33] CAO was used to align a team of flying robots to perform surveillance coverage missions over an unknown 3D terrain of complex and non-convex morphology. The performance of the proposed approach was analyzed in terms of convergence, scalability and applicability. CAO was combined in [34], with a state-of-the-art visual-SLAM algorithm [35] in a two-step procedure which allowed the alignment of a team of aerial robots to perform terrain surveillance coverage over a terrain of arbitrary morphology by using only onboard vision. CAO was also implemented in the case of teams Autonomous Underwater Vehicles (AUVs), to fully-autonomously navigate them when deployed in exploration of unknown static and dynamic environments towards providing accurate static/dynamic maps of the environment [18]. Another application in the case of mobile robots is presented in [36], where CAO was utilized to facilitate navigation in an unknown complex environment, while interacting with humans considering their comfort.

In this section, we will describe how the CAO approach can be appropriately adapted and extended, so as to be applicable to the problem of a first-responder robot, where it must generate a sufficiently accurate map of the environment for reporting target location and possible traversable paths, in a strictly defined time window. More explicitly, let us consider the problem as formulated in section IV-A. The optimization criterion can be expressed as a function of the robot's positions:

$$J_k = \mathcal{J}(x_k) \tag{14}$$

where $k = 0, 1, 2, \ldots$ denotes the time-index, J_k denotes the value of the optimization criterion at the k-th time-step, x_k denote the position of the robot and $\mathcal{J}$ is a nonlinear function which depends – apart from the robot's positions – on the particular environment where the robots live; for instance, it depends on the location of the various obstacles that are present. At each time-step k, an estimate of J_k is available through robot's sensor measurements,

$$J_k^n = \mathcal{J}(x_k) + \xi_k \tag{15}$$

where J_k^n denotes the estimate of J_k and ξ_k denotes the noise introduced in the estimation of J_k due to the presence of noise in the robot's sensors.

Apart from the problem of dealing with the optimization criterion, we have to consider the constraints deriving from the operation of the robot, i.e obstacle avoidance. In other words, at each time-instant k, the vector x_k should satisfy a set of constraints which, in general, can be represented as follows:

$$\mathcal{C}(x_k) \leq 0 \tag{16}$$

where $\mathcal{C}$ is a set of nonlinear functions of the robot's positions. As in the case of $\mathcal{J}$, the function $\mathcal{C}$ depends on the particular environment characteristics (e.g. location of obstacles).

Given the mathematical description presented above, the problem can be mathematically described as the problem of moving x_k to a position that solves the following constrained optimization problem:

$$\begin{array}{ll} \text{maximize} & (14) \\ \text{subject to} & (16)\,. \end{array} \tag{17}$$

As a first step, the CAO approach makes use of function approximators for the estimation of the unknown objective function $\mathcal{J}$ at each time-instant k according to

$$\hat{J}_k(x_k) = \vartheta_k^\tau \phi(x_k). \tag{18}$$

Here $\hat{J}_k(x_k)$ denotes the approximation/estimation of $\mathcal{J}$ generated at the k-th time-step, ϕ denotes the nonlinear vector of L *regressor terms*, ϑ_k denotes the vector of *parameter estimates* calculated at the k-th time-instant and L is a positive user-defined integer denoting the *size* of the function approximator (18). The vector ϕ of regressor terms must be chosen so that it satisfies the so-called *Universal Approximation Property* [37], i.e. the approximation accuracy of the approximator (18) should be an increasing function of the approximator's size L. Polynomial approximators, radial basis functions, kernel-based approximators, etc, are known to satisfy such a property (see [37] and the references therein). The parameter estimation vector ϑ_k is calculated according to:

$$\vartheta_k = \underset{\vartheta}{\text{argmin}} \frac{1}{2} \sum_{\ell=\ell_k}^{k-1} (J_\ell^n - \vartheta^\tau \phi(x_\ell))^2 \tag{19}$$

where $\ell_k = \max\{0, k - L - T_h\}$ with T_h being a user-defined nonnegative integer. Standard least-squares optimization algorithms can be used for the solution of (19).

As soon as the estimator $\hat{J}_k$ is constructed according to (18), (19), the set of new robot's positions is selected as follows:

Firstly, a set of N candidate robot's positions is constructed according to:

$$x_k^i = x_k + \alpha \zeta_k^i, i \in \{1, \ldots, N\}\,, \tag{20}$$

where ζ_k^i is a zero-mean, unity-variance random vector with dimension equal to the dimension of x_k. As mentioned in section IV-A, α is the distance the robot moves in each time-step. This value remains constant and equal to 1, while the condition in Eq. 13 does not hold. In order to avoid the entrapment of CAO algorithm in a local minimum, for any time step in which the condition in Eq. 13 holds, α increases by one, until the condition is no longer valid.

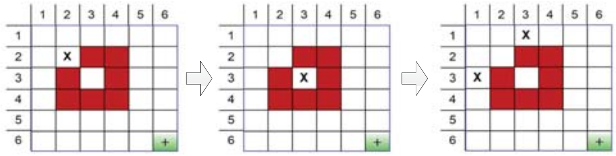
Among all N candidate new positions $x_k^i, \ldots, x_k^i$, the ones that correspond to non-feasible positions/poses – i.e. the ones that violate the constraints (16) – *are neglected* and then the new robot's positions are calculated as follows:

$$x_{k+1} = \underset{\substack{i \in \{1, \ldots, N\} \\ x_k^i \text{not neglected}}}{\text{argmax}} \hat{J}_k(x_k^i)$$

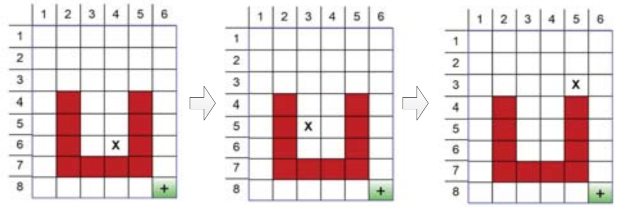
In this work we apply the CAO methodology using the cost functions described in details in section IV-A. The optimization criterion used corresponds to Eq. 9 and Eq. 10, depending on the value of the threshold T_{f2}. We have also considered the physical constraints which apply in the aforementioned case, which include the following:

- the robot remains within the terrains limits, i.e. within $[x_{min}, x_{max}]$ and $[y_{min}, y_{max}]$ in the x- and y-axes, respectively;
- the robot do not approach the obstacles closer than a minimum allowable safety distance dr.
- the robot can move only towards to a fully estimated and within the line of sight position

It is not difficult for someone to realize that all the above constraints can be easily cast in the form of Eq. 16 and thus can be handled by the CAO algorithm.



(a)



(b)

Fig. 2. Two local minimum states and the respective solutions provided by the supervisor.

Fig. 3. The Open Dynamics Engine mobile robot simulation environment.

C. Local Minimum Avoidance

This section presents the selected local minimum avoidance strategy that is followed by the first responder robot. Using the definitions described in subsection IV-A, the proposed method defines the entrapment in a local minimum by exploiting the F_1 term. Since F_1 is a regularized term that indicates the percentage of the map that has been explored, it can be treated also as a strictly accumulative term. Thus, Eq. 13 can be considered as an inequality where the left part stands for the absolute difference between the current value of F_1 and the mean of previous T_g values, while the right part of the inequality acts as a threshold value.

A hypothetical supervisor monitors Eq. 13 in every T_l steps and, in case that the inequality is valid, it indicates the entrapment of CAO in a local minimum. The value of α is then increased by one, initiating a phase where the CAO algorithm attempts to step away from the current local minimum. Since CAO tries to leave the basin of attraction of the current local minimum, a small increase of α by one guarantees that it will not step away too far and possibly miss the optimum which is expected to be somewhere nearby the current local minimum. After T_l steps, the supervisor recomputes the left term of Eq. 13, increasing iteratively the α value only if the inequality is satisfied. In any other case the α value is reset to its initial value of one, identifying a successful completion of local minimum avoidance.

In Fig. 2, for the shake of comprehension, we simplify the state model. In this case, we assume that in each time step the robot moves from its current position to one of the 8 discrete neighbour cells. This simplified approach illustrates two different cases of local minimum, where the supervisor initiated a local minimum avoidance loop. More explicitly, in Fig. 2(a) the CAO falls into a local minimum and entraps the robot between the two only possible positions of $P_1 = (2, 2)$ and $P_2 = (3, 3)$. In that example the constant alternation between these two positions prevents the robot from exploring the area. One of the great advantages of CAO approach relies in the fact that in each time step (iteration) the algorithm selects the most appropriate position for the robot, among a set of randomly selected neighboring positions and not among the total available positions. In this example, an exhaustive search algorithm would select as the most appropriate position, the one resulting in a local minimum ($P(3, 3)$). In this example, at the specific time interval, CAO is evaluating the two randomly selected position $P_1(3, 1)$ and $P_2(1, 3)$. As it can be seen, both new possible positions can help the robot to escape from its local minimum.

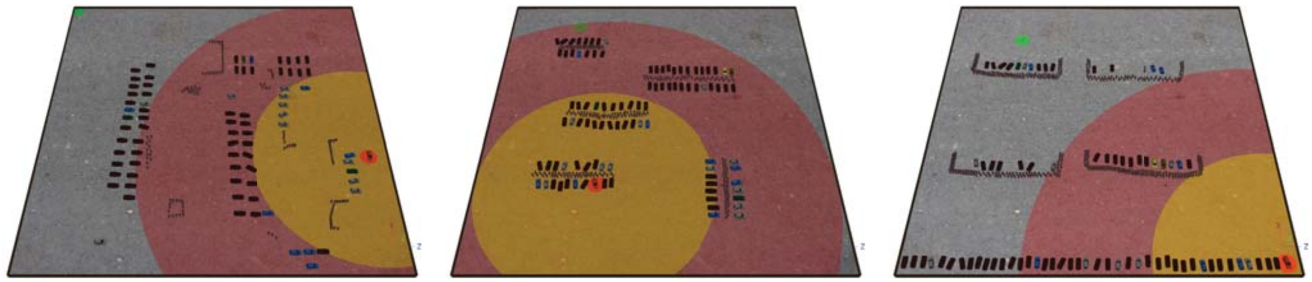
In Fig. 2(b) the robot is trapped between the two positions of $P_1 = (6, 4)$ and $P_2 = (5, 3)$, thus, the left part of the Eq. 13 constantly decreases, until it becomes lower than the threshold value. In that case, in order to avoid the depicted local minimum, the α value is equivalently increasing to 3.

V. Simulation Results

This section presents simulation results based on the Webots real-time dynamic simulation platform. In our simulation experiments, each scenario is represented as a 150m by 150m 3D virtual world of an outdoor parking lot where the Pioneer 3-AT mobile robot is equipped with a SICK 291 laser measurement system fixed to a pan servo actuator as shown in Fig. 3.

The Open Dynamics Engine library was utilized for all the necessary physics features such as mass, friction, communication range and laser accuracy. More precisely, the utilized laser sensor range was 8 meters with an angular resolution of $0.5°$, performing a full $360°$ rotation per second. A bidirectional communication between the robot node and the supervisor node was also modeled. The cruising speed as well as the rotation speed of the robot were kept uniform. The simulation environment was particularly useful because it allowed us to perform fast, automatic sensor data collection and analysis over various parameter sets in extensively large operational fields such as the $22500m^2$ parking lots.

The experimental evaluation was performed by comparing the final explored map produced by the search algorithms under evaluation along with the ground truth map which is considered to be the fully explored map. Furthermore, an equal and predefined time window was set for all the map scenarios and the search algorithms as well. Figures 4(a), 4(b) and 4(c) depict the ground truth maps of Scenario #1, Scenario #2 and Scenario #3, respectively. The known obstacles where modeled



(a) (b) (c)

Fig. 4. a) Scenario #1 ground truth map for $r_c = 50$ and $r_c = 100$, b) Scenario #2 ground truth map for $r_c = 50$ and $r_c = 100$, c) Scenario #3 ground truth map for $r_c = 50$ and $r_c = 100$.

as red barrels, while the unknown ones are considered to be the parked cars. The orange circle is used to point out the position of the goal and the green one the starting position of the robot along with the stationary communication node. Finally, the two overlaid red and yellow circles indicate the circumference of r_c for 50 and 100 meters, respectively.

Comparison results using different parameters for both scenarios are shown in Tables I, II and III respectively. The proposed algorithm was compared with both the random [38] and the Simultaneous Perturbation Stochastic Approximation (SPSA) [39], [40] search techniques. The random one was selected as the baseline method while the SPSA due to the fact that it emulates gradient descent optimization in similar terms, as CAO does. The SPSA differs from the CAO approach since the first one employs an approximation of the gradient of the appropriate cost function utilizing only the latest samples, while the CAO approach employs linear parameter approximators that incorporate information of past experiments in certain time intervals together with the concept of candidate perturbations for efficiently optimizing the unknown function.

For each set of parameters the experimental procedure was repeated ten times, due to the stochasticity of all the compared methods, thus, the presented results are the mean values of those iterations. Different values for r_c radius were examined during the simulations. The r_c radius is used for defining the circular area C_g around the target and the r_v radius defines the laser sensor range. In our experiments we defined $r_v = 8m$, a typical range used in such applications. The comparison tables illustrate for all the three aforementioned search algorithms the influence of r_c parameter into the maximum values of cost functions CF_1 and CF_2, along with the explored percentage of the goal area and the overall explored percentage of the map. It must be noticed that the standard deviation of the exploration percentage derived from the proposed method is very small in all the simulations conducted, indicating the proposed algorithm's stability.

Figures 5 and 6 illustrate in eight time steps the derived trajectory of the proposed methodology for the Scenario #1 and the Scenario #2, respectively. In both figures, the known obstacles are the barrels in red color, while the unexplored area -colored in black- turns into a visible area along each progressive scan conducted by the laser measurement sensor mounted on the robot. We selected to include known obstacles in our experiments since this represents a typical emergency scenario, where the blueprints of a critical infrastructure are available to the first responder teams. The green dot indicates the robot starting position, while the yellow circle indicates the target area, C_g, to be explored. Starting from an initial position, the robot heads towards the circle C_g, in order to explore this particular area. When the T_n value of F_2 term meets the predefined threshold, a transition between CF_1 and CF_2 is triggered. As a result the robot explores in the remaining available time the rest of the unexplored area and eventually returns in its initial position.

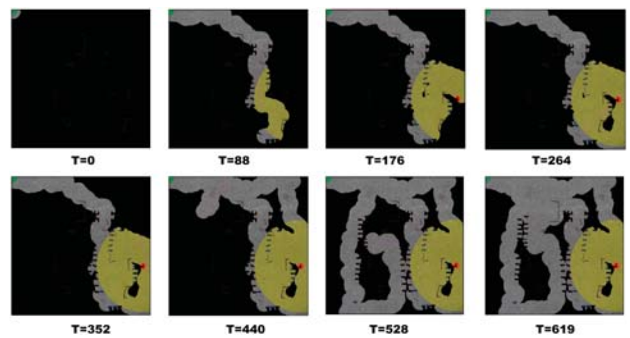


Fig. 5. The explored area in different time steps T for the Scenario #1.

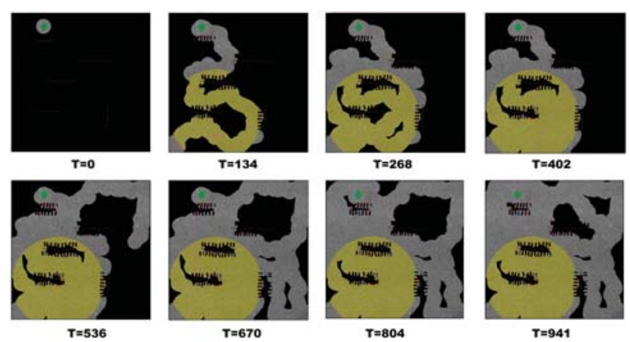


Fig. 6. The explored area in different time steps T for the Scenario #2.

Table I shows the simulations results on Scenario #1. The CF_1 and CF_2 values are derived from the positions of the robot on the map. Since CAO, SPSA and random techniques are responsible for the selection of those positions, higher cost function values demonstrate better fitting and, thus, according to Table I, SPSA selects more appropriate positions than the

TABLE I
SIMULATION RESULTS FOR SCENARIO #1.

	CF_1			CF_2		
r_c	CAO	Random	SPSA	CAO	Random	SPSA
50	16.72	0.03	12.19	0.58	0.32	0.39
100	15.08	2.88	7.03	0.70	0.26	0.38
		Goal Area (%)			Map (%)	
r_c	CAO	Random	SPSA	CAO	Random	SPSA
50	88.88	0.14	65.27	60.23	31.02	39.99
100	81.16	15.69	38.22	72.94	27.85	39.35

TABLE II
SIMULATION RESULTS FOR SCENARIO #2.

	CF_1			CF_2		
r_c	CAO	Random	SPSA	CAO	Random	SPSA
50	16.02	2.64	10.39	0.53	0.21	0.28
100	14.04	3.20	6.13	0.69	0.23	0.28
		Goal Area (%)			Map (%)	
r_c	CAO	Random	SPSA	CAO	Random	SPSA
50	89.09	15.29	59.31	56.24	20.78	28.88
100	76.50	18.11	34.09	72.02	23.79	29.15

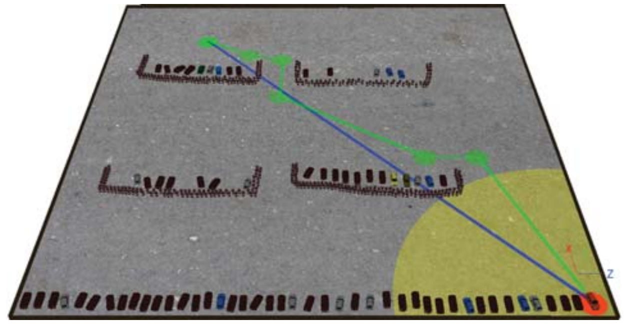
random method. However, for certain parameter values in CF_2 function, some results could be considered comparable. Nevertheless, CAO exceeds in performance both the other two search algorithms in all the sets of parameter values. Regarding the percentages of the goal area exploration, the random method cannot cover more than the 15.69%, while the SPSA manages, under specific parameter values, to cover 65.27%. On the other hand, CAO explores 81% of the goal area in the worst case, while in certain simulations it has accomplished a total of 89% coverage.

Concerning the exploration of the whole map, the random approach performs significantly better than in the previous simulations. The SPSA achieves a very good performance that is superior to the random algorithm performance, nevertheless CAO outperforms both techniques. The simulation results of Scenario #2, as shown in Fig. 6 and Table II, confirm the superior performance of the proposed method since the analogy of the compared results in all the measurable properties remains the same.

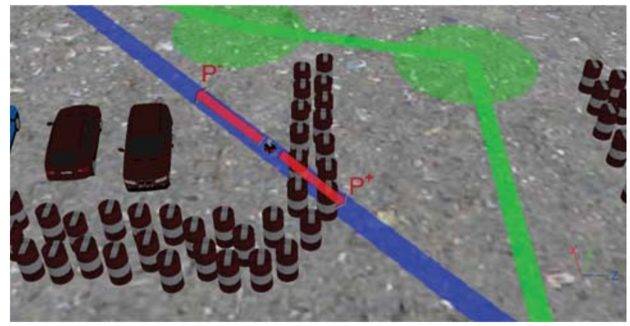
In scenario #3 a rather non typical parking lot was considered, in order to evaluate the presented methodology regarding its local minima avoidance properties. For purposes of comparison, both SPSA and random algorithms were also evaluated. In Fig. 7(a) the thick green dot represents the starting point while the blue line depicts the shortest path in the case where no obstacles where existed, i.e. the euclidean distance. On the contrary, the green line shows the ideal path taking also the obstacles into consideration.

TABLE III
SIMULATION RESULTS FOR SCENARIO #3.

	CF_1		CF_2	
r_c	CAO	Random	CAO	Random
50	16.61	0.84	0.63	0.28
100	15.62	1.54	0.65	0.33
		Goal Area (%)		Map (%)
r_c	CAO	Random	CAO	Random
50	93.76	4.22	64.36	34.41
100	86.32	8.35	67.92	31.56



(a)



(b)

Fig. 7. a) The blue line indicates the shortest path in the absence of obstacles and the green one the ideal path considering the obstacles b) An illustrated example of how the SPSA method "gets stuck" in local minimum.

The first evaluated algorithm was the SPSA, which presented the poorest results. In fact, SPSA did not manage to complete the task for all tested sets of parameter values, since it got trapped in local minima in every trial. In order to minimize the function criterion, SPSA chooses between only two possible values, which are in opposite direction to each other. In a test case, such as the one illustrated in Fig. 7(b), the first value would increase the cost function while the second one would refer to a position on non-traversable obstacle. More precisely, the red arrow denoted with P^- corresponds to the first possible value which increases the cost function and the red arrow denoted with P^+ corresponds to the second possible position which leads to a non-traversable position. In these particular but possible states, SPSA gets trapped in a local minimum, for all tested sets of parameter values.

Figure 8 presents in eight time steps the derived trajectory of the proposed methodology. In time step $T = 13$ the robot is trapped for the first time in a local minima, while in $T = 22$ it manages to get away. The same process is repeated in $T = 57$ and $T = 67$, respectively. The CF_2 is initiated at $T = 356$ and the rest of the area is explored while the robot returns to its initial position. The correspondence between the ideal course in Fig. 7(a) (green line) and the one derived by the proposed method, as illustrated in Fig. 8, demonstrates the ability of the proposed algorithm not to step too far away from the global optimum, while avoiding local minima. The summarization of the simulation results is shown in Table III, where the superiority of the proposed algorithm is confirmed once more. In particular, CAO was shown to exhibit satisfactory (local)

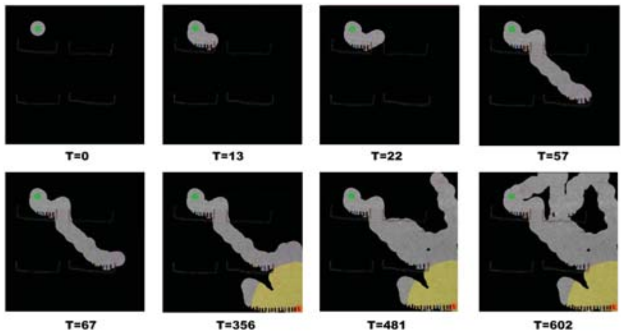
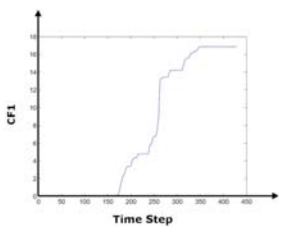
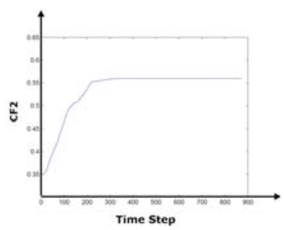


Fig. 8. The explored area in different time steps T for the Scenario #3.



(a)



(b)

Fig. 9. The values of CF_1 and CF_2 with respect to time steps in a single repetition, for $r_c = 100$ and $r_v = 8$.

convergence characteristics where SPSA and random failed to provide convergent solutions for any choice of their design parameters.

Figure 9 presents of cost functions CF_1 and CF_2, with respect to time step T. Although, the criterion for the transition from CF_1 to CF_2 includes only the F_2 term, it is shown that the cost function CF_1 also converges to a certain value as well.

VI. Conclusions

In this paper we have proposed a systematic multi-objective strategy for search and rescue mobile robots based on multi-constraint scenarios. The proposed strategy can effectively address multiple non binary temporal goals utilizing a low computational cost cognitive optimization algorithm. The search and rescue temporal goals were modeled thought different cost functions which can only be triggered when certain operational preconditions are met. The overall method is characterized by low computational cost rendering it appropriate for real-time search and rescue applications. Simulation results demonstrated the effectiveness of our approach when compared with other well known search optimization techniques. For future work, we plan to extend the proposed technique from a single-robot approach to multi-robot one. Systems employing multi-robots have several advantages over single robot systems but pose several new challenges, including: Coordination and cooperation, integration of information collected by different robots into a single map, dealing with limited communication, uncertainty in localization and sensing, Decision making, reasoning, task sharing and navigation [41].

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