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Multi-Robot 3D Coverage of Unknown Terrains

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Abstract— **In this paper we study the problem of deploying a team of flying robots to perform surveillance coverage missions over an unknown terrain of arbitrary morphology. In such a mission, the robots should simultaneously accomplish two objectives: firstly, to make sure that the overall terrain is visible by the team and, secondly, that the distance between each point in the terrain and one of the robots is as small as possible. These two objectives should be efficiently fulfilled given the physical constraints and limitations imposed at the particular coverage application (i.e., obstacle avoidance, limited sensor capabilities, etc). As the terrain's morphology is unknown and it can be quite complex and non-convex, standard multi-robot coordination and control algorithms are not applicable to the particular problem treated in this paper. In order to overcome such a problem, a new approach that is based on the Cognitive-based Adaptive Optimization (CAO) algorithm is proposed and evaluated in this paper. Both rigorous mathematical arguments and extensive simulations on unknown terrains establish that the proposed approach provides an efficient methodology that can easily incorporate any particular constraints and quickly and safely navigate the robots to an arrangement that optimizes surveillance coverage.**

I. Introduction

The use of multi-robot teams has gained a lot of attention in recent years. This is due to the extended capabilities that the teams have to offer comparing to the use of a single robot for the same task. Robot teams can be used in a variety of missions including: surveillance in hostile environments (i.e. areas contaminated with biological, chemical or even nuclear wastes), environmental monitoring (i.e. air quality monitoring, forest monitoring) and law enforcement missions (i.e. border patrol), etc. In all the aforementioned tasks the positioning of limited resources to maximize the area monitored is the key issue. This can be achieved deploying the robots so that two objectives are simultaneously optimized:

(O1) the part of the terrain that is "visible", i.e. that is monitored by the robots is maximized;

(O2) the team members are arranged so that for every point in the terrain, the closest robot is as close as possible to that point.

The majority of existing approaches for multi-robot surveillance coverage, which concentrate mostly on the 2D case of ground robots, deal only with one of the objectives (O1) or (O2); see e.g. see [1], [2], [3], [4], [5], [6] and the references therein. Furthermore, in most of the existing approaches the terrain morphology is considered convex and/or known. In such cases the problem of multi-robot surveillance coverage can be seen to be equivalent to a standard optimization problem where the robots' trajectories are generated according to a gradient-descent or gradient-descent-like methodology. However, in the case where it is required that both of the objectives (O1) and (O2) are simultaneously addressed and the terrain's morphology is non-convex and unknown, standard optimization tools are not applicable anymore as these tools require full knowledge of an objective function that depends on the unknown terrain's morphology.

To approach this problem we propose a new solution based on the recently introduced Cognitive-based Adaptive Optimization (CAO) algorithm [8], [9]. The main advantage of CAO as compared to standard optimization tools is that it does not require that the objective function to be optimized is explicitly known; CAO instead requires that at each-time instant a value (measurement) of this objective function is available. By introducing an appropriate objective function, that is defined so that both objectives (O1) and (O2) are simultaneously taken into account, we achieve to render the CAO algorithm applicable to the particular problem of 3D multi-robot surveillance coverage treated in this paper. This objective function depends on the unknown terrain's characteristics and thus its explicit form is not known. However, for any given team configuration the value of this objective function can be directly computed from the robots' sensor measurements, and thus the CAO algorithm can be applied to the problem by using such an objective function. It has to be emphasized that apart from rendering the optimization problem solvable, the CAO-based approach preserves additional attributes that make it particularly tractable: it can handle a variety of physical constraints and limitations and it is fast and scalable.

The rest of the paper is organized as follows. In section II we describe in detail the cognitive based adaptive optimization approach, while in section III we formulate the problem for the 3D multi-robot coverage over unknown terrains. Finally, in section IV extensive simulation results are presented to validate the proposed approach.

II. The Cognitive-based Adaptive Optimization Approach

The Cognitive-based Adaptive Optimization (CAO) approach [7]-[9] was originally developed and analyzed for

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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. In this section, we will describe how the CAO approach can be appropriately adapted and extended so that it is applicable to the problem of multi-robot coverage. More explicitly, let us consider the problem where M robots are involved in a coverage task, attempting to optimize a given coverage criterion. Apparently, the coverage criterion is a function of the robots' positions or poses (positions and orientations), i.e.

$$J_k = \mathcal{J}\left(x_k^{(1)}, \ldots, x_k^{(M)}\right) \tag{1}$$

where $k = 0, 1, 2, \ldots$ denotes the time-index; J_k denotes the value of the coverage criterion at the k-th time-step; $x_k^{(1)}, \ldots, x_k^{(M)}$ denote the position vectors of robots $1, \ldots, M$, respectively; $\mathcal{J}$ is a nonlinear function which depends, apart from the robots' positions, on the particular environment where the robots live. For instance, in the 2D case the function $\mathcal{J}$ depends on the location of the various obstacles that are present, while in the 3D case with flying robots monitoring a terrain, the function $\mathcal{J}$ depends on the particular terrain morphology.

Due to the dependence of the function $\mathcal{J}$ on the particular environment characteristics, the explicit form of the function $\mathcal{J}$ is not known in most practical situations. However, in most practical cases like the one treated in this paper, the current value of the coverage criterion can be estimated from the robots' sensor measurements. In other words, at each time-step k, an estimate of J_k is available through robots' sensor measurements,

$$J_k^n = \mathcal{J}\left(x_k^{(1)}, \ldots, x_k^{(M)}\right) + \xi_k \tag{2}$$

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 robots' sensors.

Apart from the problem of dealing with a criterion for which an explicit form is not known but only its noisy measurements are available at each time, efficient robot coverage algorithms have additionally to deal with the problem of restricting the robots' positions so that obstacle avoidance as well as robot formation constraints are met. In other words, at each time-instant k, the vectors $x_k^{(i)}, i = 1, \ldots, M$ should satisfy a set of constraints which, in general, can be represented as follows:

$$\mathcal{C}\left(x_k^{(1)}, \ldots, x_k^{(M)}\right) \leq 0 \tag{3}$$

where $\mathcal{C}$ is a set of nonlinear functions of the robots' positions. As in the case of $\mathcal{J}$, the function $\mathcal{C}$ depends on the particular environment characteristics (e.g. location of obstacles, terrain morphology) and an explicit form of this function may be not known in many practical situations; however, it is natural to assume that the coverage algorithm is provided with information whether a particular selection of robots' positions satisfies or violates the set of constraints (3).

Given the mathematical description presented above, the multi-robot coverage problem can be mathematically described as the problem of moving $x_k^{(1)}, \ldots, x_k^{(M)}$ to a set of positions that solves the constrained optimization problem: minimize (1) subject to (3). As already noticed, the difficulty in solving in real-time and in real-life situations this constrained optimization problem lies in the fact that explicit forms for the functions $\mathcal{J}$ and $\mathcal{C}$ are not available. To circumvent this difficulty, the CAO approach, appropriately modified to be applicable to the problem in hand, is adopted. This method is capable of efficiently dealing with optimization problems for which the explicit forms of the objective function and constraints are not known, but noisy measurements/estimates of these functions are available at each time-step. Next we describe the CAO approach as applied to the multi-robot coverage problem described above.

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

$$\hat{J}_k\left(x_k^{(1)}, \ldots, x_k^{(M)}\right) = \vartheta_k^\tau \phi\left(x_k^{(1)}, \ldots, x_k^{(M)}\right). \tag{4}$$

Here $\hat{J}_k\left(x_k^{(1)}, \ldots, x_k^{(M)}\right)$ denotes the approximation 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 (4). The parameter estimation vector ϑ_k is calculated according to

$$\vartheta_k = \underset{\vartheta}{\operatorname{argmin}} \frac{1}{2} \sum_{\ell=\ell_k}^{k-1} \left(J_\ell^n - \vartheta^\tau \phi\left(x_\ell^{(1)}, \ldots, x_\ell^{(M)}\right)\right)^2 \tag{5}$$

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 (5).

As soon as the estimator $\hat{J}_k$ is constructed according to (4), (5), the set of new robots' positions is selected as follows: firstly, a set of N candidate robots' positions is constructed according to

$$x_k^{i,j} = x_k^{(i)} + \alpha_k \zeta_k^{i,j}, i \in \{1, \ldots, M\}, j \in \{1, \ldots, N\}, \tag{6}$$

where $\zeta_k^{i,j}$ is a zero-mean, unity-variance random vector with dimension equal to the dimension of $x_k^{(i)}$ and α_k is a positive real sequence which satisfies the conditions:

$$\lim_{k\to\infty} \alpha_k = 0, \quad \sum_{k=1}^{\infty} \alpha_k = \infty, \quad \sum_{k=1}^{\infty} \alpha_k^2 < \infty. \tag{7}$$

Among all N candidate new positions $x_k^{1,j}, \ldots, x_k^{M,j}$, the ones that correspond to non-feasible positions, i.e. the ones that violate the constraints (3), are neglected and then the new robots' positions are calculated as follows:

$$\left[x_{k+1}^{(1)}, \ldots, x_{k+1}^{(M)}\right] = \underset{\substack{j \in \{1, \ldots, N\} \\ x_k^{i,j} \text{not neglected}}}{\operatorname{argmin}} \hat{J}_k\left(x_k^{1,j}, \ldots, x_k^{M,j}\right)$$

The idea behind the above logic is simple: at each time-instant a set of many candidate new robots' positions is generated. The candidate, among the ones that provide with a feasible solution, that provides the "best" estimated value $\hat{J}_k$ of the coverage criterion is selected as the new set of robots' positions. The random choice for the candidates is essential and crucial for the efficiency of the algorithm, as such a choice guarantees that $\hat{J}_k$ is a reliable and accurate estimate for the unknown function $\mathcal{J}$; see [8], [9] for more details. On the other hand, the choice of a slowly decaying sequence α_k, a typical choice of adaptive gains in stochastic optimization algorithms (see e.g. [14]), is essential for filtering out the effects of the noise term ξ_k [cf. (2)]. The next theorem summarizes the properties of the CAO algorithm described above:

Theorem 1: Let $x^{(1^*)}, \ldots, x^{(M^*)}$ denote any local minimum of the constrained optimization problem. Assume also that the functions $\mathcal{J}, \mathcal{C}$ are either continuous or discontinuous with a finite number of discontinuities. Then, the CAO-based multi-robot coverage algorithm as described above guarantees that the robots' positions $x_k^{(1)}, \ldots, x_k^{(M)}$ will converge to one of the local minima $x^{(1^*)}, \ldots, x^{(M^*)}$ with probability 1, provided that the size L of the regressor vector ϕ is larger than a lower bound $\bar{L}$.

The proof of this theorem, not presented here for brevity purposes, is among the same lines as the main results of [8], [9]; the main difference between the proof of the theorem presented below and that of [8], [9] is that while in the case of [8], [9] it is established that the CAO algorithm used there is approximately a gradient-descent algorithm, the CAO algorithm used in this paper is proven to be approximately a projected gradient-descent algorithm.

Remark 1: We close this section by mentioning that similarly to the proposed approach, global optimization methods such as simulated annealing and genetic algorithms do not require that the explicit form of the function $\mathcal{J}$ is known. Moreover, these methods can guarantee global convergence as opposed to the proposed approach which guarantees only a local one. However, simulated annealing, genetic algorithms and other similar global optimization methods require that a large amount of different combinations of robots' positions is being evaluated all over the robots' application area. Such a requirement renders these methods practically infeasible as a huge amount of time and energy would have to be spent in order for the robots to visit many different locations all over their application area. ◇

III. CAO FOR 3D MULTI-ROBOT COVERAGE OVER UNKNOWN TERRAINS

In our previous works [10], [11] we have extensively described the case of using the CAO approach for maximizing the monitored area in a given region by using a team of mobile robots in the 2D plane, without any assumption on the topology of the environment. In this section, where the main contribution of this paper is presented, we will extend our approach to the 3D case.

Consider a team of M flying robots that is deployed to monitor an unknown terrain $\mathcal{T}$. Let $z = \Phi(x, y)$ denote the unknown height of the terrain at the point (x, y) and assume for simplicity that the terrain $\mathcal{T}$ is rectangular along the (x, y)-axes, i.e. $x_{min} \leq x \leq x_{max}, y_{min} \leq y \leq y_{max}$. Let $\mathcal{P} = \{x^{(i)}\}_{i=1}^{M}$ denote the configuration of the robot team, where $x^{(i)}$ denotes the position of the i-th robot.

Given a particular team configuration $\mathcal{P}$, let $\mathcal{V}$ denote the *visible area* of the terrain, i.e. $\mathcal{V}$ consists of all points $(x, y, \Phi(x, y)) \in \mathcal{T}$ that are visible from the robots. Given the robots' sensor capabilities, a point $(x, y, \Phi(x, y))$ of the terrain is said to be visible if there exists at least one robot so that

- the robot and the point $(x, y, \Phi(x, y))$ are connected by a line-of-sight;
- the robot and the point $(x, y, \Phi(x, y))$ are at a distance smaller than a given threshold value.

Apparently, the main objective for the robot team is to maximize the visible area $\mathcal{V}$. However, this cannot be the only objective for the robot team in a coverage task: trying to maximize the visible area will simply force the robots to "climb" as high as[1] possible.

In parallel to maximizing the visible area, the robot team should try to minimize the average distance between each of the robots and the terrain subarea the particular robot is responsible for, where the subarea of the terrain the i-th robot is responsible for is defined as the part of the terrain that (a) is visible by the i-th robot and (b) each point in this subarea is closer to the i-th robot than any other robot of the team. This second objective for the robot team is necessary for two practical reasons: firstly, the closer is the robot to a point in the terrain the better is, in general, its sensing ability to monitor this point and, secondly, in many multi-robot coverage applications there is the necessity of being able to intervene as fast as possible in any of the points of the terrain with at least one robot.

Having in mind that the robot team has to meet the two above-described objectives, we define the following combined objective function the robot team has to minimize:

$$J(\mathcal{P}) = \int_{q \in \mathcal{V}} \min_{i \in \{1, \ldots, M\}} \left| x^{(i)} - q \right|^2 dq + K \int_{q \in \mathcal{T} - \mathcal{V}} dq \quad (8)$$

where K is a large user-defined positive constant and $|\cdot|$ denote the Euclidean norm. The first of the terms in above equation is the usual cost function considered in many coverage problem for 2D environment related to the second objective (minimize the average distance between the robots and their subarea, see [1]). The second term is related to the invisible area in the terrain ($\int_{q \in \mathcal{T} - \mathcal{V}} dq$ is the total part of the terrain that is not visible by any of the robots). The positive constant K is used to make sure that both objectives are taken into account. To see this, consider the case where $K = 0$, in which case we will have that the robots, in their attempt to

[1]Note also that in the ideal case where there are no limits for the robot's maximum height and the robot has unlimited sensing capabilities, it suffices to have a single robot at a very high position to monitor the whole terrain.

minimize their average distance to their subarea, may also seek to minimize the total visible area. On the other hand, in case where the first of the terms in (8) is negligible, we will have the situation mentioned above where the robots in their attempt to maximize the visible area will have to "climb" as high as they are allowed to.

It has to be emphasized that the positive constant K should be chosen sufficiently large so that the second term in (8) dominates the first term unless no or a negligible part of the terrain remains invisible. In this way, minimization of (8) is equivalent to firstly making sure that all, or almost all, of the terrain is visible and then to locate the robots so that their average distance to the subarea they are responsible for is minimized.

A large choice for the positive term K plays another crucial role for the practical implementation of the CAO algorithm in multi-robot coverage applications: the problem with the performance index defined in (8) is that its second term $\int_{q \in \mathcal{T}-\mathcal{V}} dq$ cannot be, in general, computed in practice; as this term involves the part of the terrain that is not currently visible, its computation requires that the geometry this part is known or equivalently that the whole terrain is known. To overcome this problem, instead of minimizing (8) the following performance index is actually minimized by the CAO approach:

$$\bar{J}(\mathcal{P}) = \int_{q \in \mathcal{V}} \min_{i \in \{1,\ldots,M\}} \left| x^{(i)} - q \right|^2 dq + K \int_{(x,y,\phi(x,y)) \in \mathcal{T}-\mathcal{V}} \mathcal{I}(x,y) dx dy \qquad (9)$$

where $\mathcal{I}(q)$ denotes the indicator function that is equal to 1 if the point $(x, y, \phi(x, y))$ belongs to the invisible area of the terrain and is zero, otherwise. In other words, in the cost criterion $\bar{J}(\mathcal{P})$ and for the whole invisible area, the unknown terrain points $(x, y, \phi(x, y))$ are replaced by $(x, y, 1)$, i.e. $\bar{J}(\mathcal{P})$ assumes that the whole invisible area is a flat subarea.

The replacement of the cost criterion (8) by the criterion (9) has a negligible implication in the team's performance: as a large choice for K corresponds to firstly making sure that the whole terrain is visible and then to minimizing the average distance between the robots and their responsible subareas, minimizing either of criteria (8) or (9) is essentially the same.

An efficient trajectory generation algorithm for optimal coverage, i.e. for minimization of the cost criteria (8) or (9), must make sure that the physical constraints are also met throughout the whole coverage task. Such physical constraints include, but are not limited to, the following ones:

- The robots remain within the terrain's limits, i.e. they remain within $[x_{min}, x_{max}]$ and $[y_{min}, y_{max}]$ in the $x-$ and y-axes, respectively.
- The robots satisfy a maximum height requirement while they do not "hit" the terrain, i.e. they remain within $[\Phi(x, y) + d, z_{max}]$ along the z-axis, where d denotes the minimum safety distance (along the z-axis) the robots' should be from the terrain and z_{max} denotes the maximum allowable height for the robots.
- The robots do not come closer to the other ones than a minimum allowable safety distance d_r.

It is possible to see that all the above constraints can be easily cast in the form (3) and thus can be handled by the CAO algorithm.

Having defined the optimization problem, a fundamental point for a good behavior of the CAO algorithm is an appropriate choice of the form of the regressor vector ϕ, introduced in equation (4) (for details about its construction see [10]). Once the regressor vector ϕ has been set and once the values of the cost function (9) are available for measurement at each time step, it is possible to find at each time step the vector of parameter estimates θ_k and thus the approximation of the cost function $\hat{J}_k$.

Remark 2: Please note that the CAO algorithm's computational requirements are dominated by the requirement for solving the least-squares problem (5). As the number of free parameters in this optimization problem is L, most popular algorithms for solving least-squares problems have, in the worst case, $\mathcal{O}(L^3)$ complexity (polynomial complexity with respect to L). For a realistic situation where 3-5 robots are employed, our simulation investigations indicate that a "good" value for L is around 20. ◇

IV. Performance Evaluation

To evaluate the efficiency of the proposed approach, several scenarios were considered using a simulated flying robot team. In all cases studied, the team was homogeneous consisted of 4 robots with the same monitoring capabilities. This assumption has been made only for simplification purposes and easier comprehension of the results. The main constraints imposed to the robots are that they remain within the terrain's limits, i.e. within $[x_{min}, x_{max}]$ and $[y_{min}, y_{max}]$ in the $x-$ and y-axes, respectively. At the same time they have to satisfy a maximum height requirement while they do not "hit" the terrain, i.e. they remain within $[\Phi(x, y) + d, z_{max}]$ along the z-axis. The scenarios considered are terrains with obstacles with same or uneven heights, while for each scenario different values of the expression α which is responsible for the convergence of the algorithm were tested. Apart from the simulated terrains a realistic scenario was considered by using a map of a real area [13], extracted with the methodology described in detail in [12].

A. Simulated Environments

The first case studies an area sizes 10 by 10 meters, which includes a surface with seven same height randomly placed obstacles. All the team members were placed at starting points adjunct to each other, with initial height 0.6 meters. The maximum allowed flight height was 1 meter for all robots. Different values of the expression α were tested and the respective cost functions are presented in Fig. 1. A sample trajectory of the robotic team in the case of $\alpha = 0.3$ is presented in Fig. 2, while the final configuration in all three test cases is presented in Fig. 3. It should be noted that CAO does not converge always to the same swarm configuration, but it converges always to a swarm configuration with similar

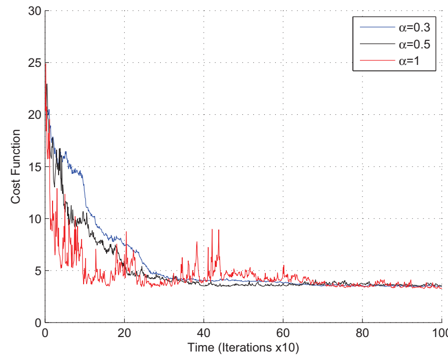

Fig. 1. Cost Functions for $\alpha = 0.3, 0.5, 1$, for the case of area with same height obstacles.

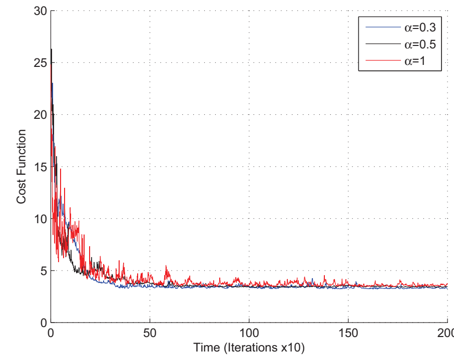

Fig. 4. Cost Functions for $\alpha = 0.3, 0.5, 1$, for the case of area with uneven obstacle height.

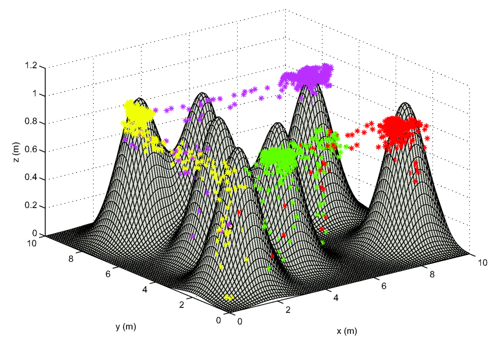

Fig. 2. 3D Path followed by the robot team for $\alpha = 0.3$, for the case of area with same height obstacles.

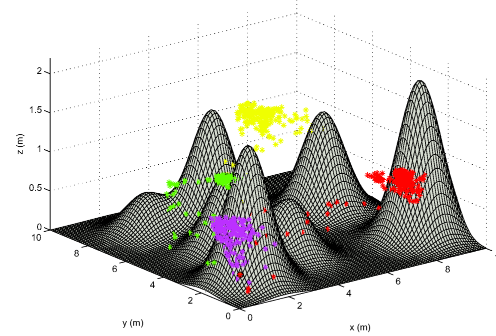

Fig. 5. 3D Path followed by the robot team for $\alpha = 0.5$, for the case of an area with uneven obstacle height.

coverage characteristics which corresponds to similar final J value.

In the second case the area sizes 10 by 10 meters, which includes a surface with seven randomly placed obstacles with uneven height, with maximum value 2 meters. All team members were placed at starting points close to each other, with initial height 0.2 meters. The maximum allowed flight height was 1 meter for all robots. Different values of the expression α were tested and the respective cost functions are presented in Fig. 4. A sample trajectory of the robotic team in the case of $\alpha = 0.5$ is presented in Fig. 5.

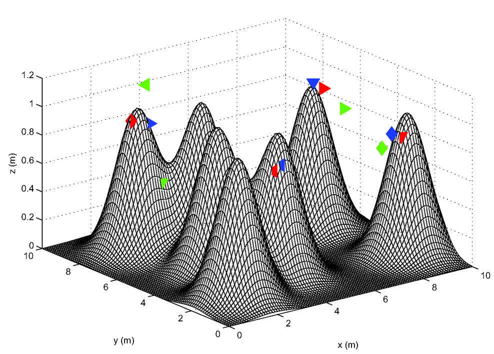

Fig. 3. Final positions of the robotic teams in the case of $\alpha = 0.3$ (blue markers), $\alpha = 0.5$ (red markers), $\alpha = 1$ (green markers), for the case of area with same height obstacles.

B. Birmensdorf area

To validate our approach in a realistic environment, we used the data which were collected with the use of a miniature quadrator helicopter specially designed for the needs of the European project sFLY (www.sfly.org).

These data correspond to the Birmensdorf area presented in Fig. 6. More details about the data and the methodology used, are presented in [12] and [13]. The main constraints imposed to the robots are that they remain within the terrain's limits, i.e. within $[x_{min}, x_{max}]$ and $[y_{min}, y_{max}]$ in the $x-$ and y-axes, respectively. At the same time they have to satisfy a maximum height requirement while they do not "hit" the terrain, i.e. they remain within $[\Phi(x, y) + d, z_{max}]$ along the z-axis. The value of α was equal to 0.3. Several initial configurations for the robot team were tested. The values of the cost function for three different configurations are presented in Fig. 8. Sample trajectories for a robot team with initial coordinates for *Robot 1* $(0.1, 9, 1.7)$, for *Robot 2* $(0.2, 9, 1.7)$, for *Robot 3* $(0.3, 9, 1.7)$ and for *Robot 4* $(0.4, 9, 1.7)$ are presented in Fig. 7.

V. Discussion and Conclusions

A new method for dealing with the problem of performing surveillance coverage in unknown terrain of arbitrary morphology has been proposed. The proposed approach has the following advantages:

Fig. 6. Outdoor flight path through the Birmensdorf area.

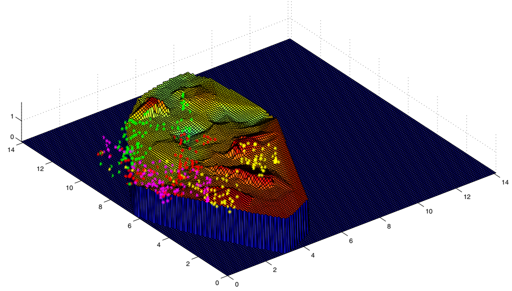

Fig. 7. 3D Path followed by a robot team in a coverage scenario in Birmensdorf area.

- it does not require any a priori knowledge on the environment;
- it works in any given environment, without the necessity to make any kind of assumption about its topology;
- it can incorporate any kind of constraints;
- it does not require a knowledge about these constraints since they are learnt during the task execution;
- its complexity is low allowing real time implementations.

The advantages of the proposed methodology make it suitable for real implementations and the results obtained through numerical simulations give us the motivation to adopt the CAO also in other frameworks. We are also interested into formulating the same problem in a distributed manner by using different cost functions for any robot in the team. This approach is closer to real world applications since it will not depend into a centralized scheme with all the known disadvantages. Apart from that a decentralized approach will allow us to include communications constraints. Our aim is to develop a strategy for the surveillance of an unknown urban-like environment with a real MAV swarm.

We expect that many important tasks in mobile robotics can be approached by CAO-based algorithms: for example coordinated exploration, optimal target tracking, multi-robot localization, and so on. This is basically due to the fact that the CAO approach does not require an a priori knowledge of the environment and it has low complexity. Both these issues are fundamental in mobile robotics.

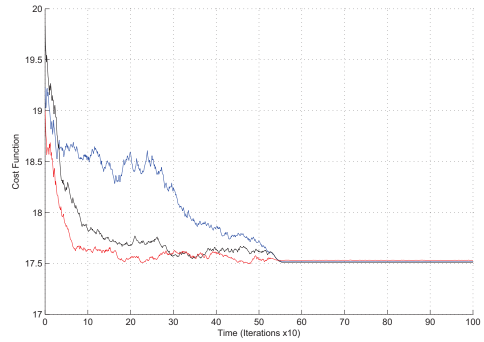

Fig. 8. Comparative cost functions for different initial robot team configurations in Birmensdorf area.

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