Optimal Deployment of Robotic Teams for Autonomous Wilderness Search and Rescue

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***Abstract*—This paper presents a novel method for the optimal deployment of multi-robot teams for autonomous, coordinated wilderness search and rescue. The new concept of iso-probability curves, used to represent the time-varying prediction of a lost person's probable location within the search area, is utilized to effectively distribute the search effort. The proposed method can be used for initial deployment, as well as subsequent on-line re-deployment to address the dynamic nature of the search for a moving lost person in a growing search area with varying terrain. The modularity of the proposed method allows the user to define and utilize different objective functions and weigh them according to the goal at hand. The two specific objective functions considered in this paper are (minimizing) search time and (maximizing) the probability of success. A simulated realistic wilderness search scenario demonstrates the integration of optimal deployment within the overall search methodology.**

***Index Terms*—Optimal deployment, multi-robot coordination, wilderness search and rescue (WiSAR)**

I. Introduction

Wilderness Search and Rescue (WiSAR) deals with the problem of locating mobile lost persons in unbounded, inland environments with varying and often complex terrains [e.g., 1, 2]. The use of robotic teams in WiSAR has been a topic of recent interest, with the primary focus being on developing effective search strategies. In contrast to WiSAR, research efforts in Urban Search and Rescue (USAR), where the aim is to find stationary survivors amidst collapsed structures, continue to be mainly on the development of specialized robots [e.g., (3-5)]. Furthermore, search strategies developed for USAR are not readily applicable to WiSAR.

Search methodologies, as formulated in Search Theory literature, determine the optimal allocation of search effort to locate a stationary or moving target [6-9]. Their dependence on optimization modeling and analytical solutions [8, 9] make it difficult to address real-life factors that influence a WiSAR search scenario, such as varying terrain, finding clues, and different target physiologies and psychologies. Some works [8, 10-13] do consider a limited number of additional factors, but do not present a comprehensive, on-line method suitable for automation with multiple robots. Thus, the purpose of our recent research has been to develop an effective multi-robot coordination (MRC) methodology for autonomous search in WiSAR applications [14, 15]. This paper addresses one specific issue in this endeavor, namely, optimal deployment of multi-robot teams.

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Deployment problems in the literature have generally either referred to multi-agent formations [16-18] or to coverage of a bounded area via the dispersion of multiple agents [10, 19, 20]. An example of the former is [17], where a user specifies the deployment locations and a general deployment strategy for a team of multiple heterogeneous robots. A lowest-cost assignment (in terms of route-length and time) of robots to locations is determined based on hierarchical task network planning and constraint reasoning techniques. In [18], uncertainty is considered in the deployment of a network of mobile robots towards a fixed, steady-state spatial configuration. A stochastic gradient descent algorithm guides the robots and a potential function is suitably chosen such that the goal configuration corresponds to its minimum value.

As a coverage task, for example, the deployment problem in [10] involves determining the number and size of robot-groups that should be unloaded from a carrier, and the initial robot locations. A solution that can cover the deployment area within the maximum coverage time allowed is determined iteratively by varying the number and sizes of groups based on heuristics. In [19], the time required to decrease uncertainty density of the environment below a specified level (through effective coverage) is compared for both combined and sequential deploy-and-search strategies with random and greedy searches. Deployment is conducted by performing a centroidal Voronoi partition of the search space. However, the approach used to update the probabilistic information is applicable only to static, bounded environments.

In summary, existing deployment methods account for a limited scope of factors when determining deployment solutions. The problem is one of either attaining a particular formation, or of covering an area under robot sensors as completely as possible, neither of which considers optimal positioning of robots with respect to metrics important for a WiSAR search operation. Furthermore, incorporation of uncertainty is only in terms of an unknown, static environment with an *a priori* known, continuous 2D uncertainty distribution. In WiSAR, however, robot deployment requires initially assigning multiple robots to positions that help to optimize the search, based on probabilistic information of a lost target's location. As well, subsequent on-line re-deployment of the robots must be conducted to address the dynamic nature of the search for a moving target in a growing search area, who may leave behind clues and whose motion is influenced by terrain topology and lost-person psychology. The aforementioned deployment methods cannot address these issues, and, thus, a specialized solution, such as the one proposed in this paper, is required.

II. Problem description

The primary difficulty in any WiSAR search scenario is the probabilistic representation of a target's location as a function of time. An effective representation must address the following real-life factors for the optimal deployment of resources: target physiology and psychology, irregular terrain, and found clues. Prior to the formulation of the deployment problem in Sub-Sections B and C below, our novel target-location prediction model reported earlier in [14, 15] is first summarized in Sub-Section A.

A. Proposed Search Methodology for Autonomous WiSAR

A typical robotic WiSAR scenario is assumed to proceed as follows: first, a notification arrives of a missing person (i.e., the target). The last known position (LKP) coordinates of the target at time t = 0 s are given. Next, to initially deploy the robots and start the search process, the target motion behavior is predicted using a key construct developed in our research: the *iso-probability curves*.

1) Construction of Iso-Probability Curves

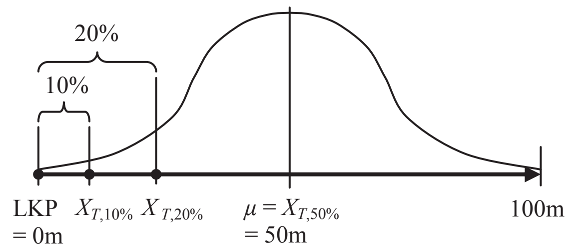
Iso-probability curves represent the probabilistic information about the target's location within the search area at any given time. They are constructed using a one-dimensional target-location probability density function (PDF) for the likely location of the target along a single line of travel. It is assumed, herein, that the target can move in any direction, $\theta\in[0°, 360°]$, from his/her LKP = (x_0, y_0). Given a PDF, $p(v, \theta)$, $v\in\Re$, $v \geq 0$, for all the possible mean target speeds [21], a target-location PDF, $p(r, \theta, t)$, for the distance, $r\in\Re$, $r \geq 0$, along a given direction (ray) emanating from the current LKP can be obtained. Assuming a bounded normal distribution for the (nominal) mean target-speed PDF, the target-location PDF, $p(r, \theta, t)$, also becomes a normal distribution (see [14] for more details), Fig. 1(a).

Each ray emanating from the LKP is sub-divided at key cumulative-probability points for the target location. The loci of all common points form contours, referred to hereafter as *iso-probability curves*. A curve formed from the locus of X% points bounds the region that has an X% chance of containing the target. Fig. 1(b) illustrates the formation of iso-probability curves for 8 rays with identical PDFs on all rays. Methods have also been devised to scale the PDFs to incorporate the effect of varying terrain and obstacles, so that in general, the curves would have irregular shapes, [14].

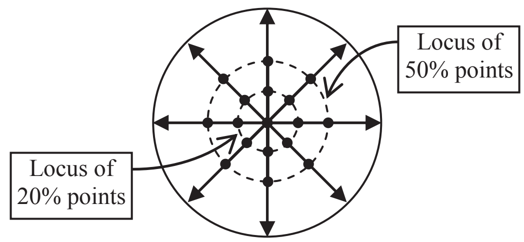
2) Propagation of Iso-Probability Curves

As search time passes, the iso-probability curves need to be propagated outwards to account for the possible continued target motion. Making the conservative estimate that the target moves at constant speed in a fixed direction outward from the LKP, this propagation is accomplished by multiplying the mean target-speed PDF corresponding to each ray by the total time passed since the target was at the LKP.

The effect of clues is addressed by taking the coordinates of the newly-found clue as the new LKP, and reconstructing the iso-probability curves based on the elapsed time since the target dropped the clue. For clues that only indicate position, conservative speed and path estimates can be made for the time the clue was dropped, and the additional time for which the target would have been moving.



(a) Side-view: a single ray



(b) Top-view: locus of points

Fig. 1. Iso-probability curves.

3) A Search Strategy

A basic search strategy that utilizes the iso-probability curves could require each robot to: (*i*) start on its assigned curve; (*ii*) move in a direction tangent to it in a clockwise manner at a predetermined constant speed for a fixed short amount of time; (*iii*) change direction to move on a new line, tangent to an imaginary circle centered at the current LKP, with a radius equal to the distance from the LKP to the current position of the robot; and, (*iv*) return to its respective curve via the shortest path and restart the basic motion strategy whenever the curves are propagated outward.

The search strategy may also be modified to account for target psychological behavior. For example, 1 to 6 year-old children, when lost, seek out a place of shelter after an initial period of random motion, [21]. Search robots on the nearest iso-probability curves would, thus, make a detour to known shelters for a close-up investigation at regular time intervals.

B. Problem Formulation for Initial-Deployment

In our proposed approach to conducting WiSAR based on the use of iso-probability curves, as introduced above, the first task at hand is the effective initial deployment of search effort. Since iso-probability curve density guides search effort allocation, the deployment problem would, thus, involve determining the optimal number of curves and their optimal positions within the search region. However, one must note that every time the search-engine of the deployment optimization process evaluates the 'goodness' of a set of iso-probability curves, the calculation of the corresponding objective-function value relies on the balanced distribution of robots on these curves, Fig. 2.

Determining the balanced distribution of robots among a given set of iso-probability curves was addressed in our earlier work [14, 15]. It will, thus, be only briefly summarized below, prior to a detailed discussion of the optimization process for determining the optimal number of curves and their locations.

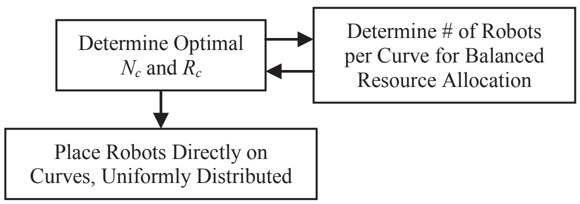


Fig. 2. The initial-deployment problem.

1) Determining Resource Allocation Among Iso-Probability Curves

The metric for the allocation of robots to a set of iso-probability curves in our work aims at achieving a balanced search effort by all sub-sets of robots assigned to individual curves. One can note that curves positioned further out from the LKP would have greater perimeter length and, thus, they must be allocated proportionately more robots compared to curves closer to the LKP. The ratio of the radial distance of each nominal curve from the LKP, relative to that of the *first* nominal curve in the curve-set can be used for the purpose of this allocation-balancing. These ratios would need to be multiplied by a scaling-factor and rounded to the nearest integer to yield a valid number of robots.

2) Determining The Optimal Number of Iso-Probability Curves and Their Positions

For the optimization problem formulated herein, the decision variables are the number of curves, N_c, and the position, R_c, of the center of the curve-set (expressed as the cumulative probability value under the target-location PDF up to the position of the center). To ensure that the optimization is feasible for on-line mode, the problem is simplified by assuming that the inter-curve spacing, D_c, is a constant, user-selected parameter. This spacing is the difference in the position (cumulative probability) values of any two adjacent curves. Given these three quantities, the position value, R_p, of any curve, p, is determined as:

$$R_p = R_c + (2p - N_c - 1)\frac{D_c}{2}. \qquad (1)$$

As often done in Search Theory literature [6, 8], search effectiveness can be quantified in terms of: the total time taken to find the target (*search time*), and the probability of finding the target (*success rate*). These two metrics are detailed next.

a) A Search-Time Metric: Let's assume that the $N_{r,p}$ robots deployed on the p^{th} iso-probability curve are uniformly distributed along its perimeter, and travel clockwise along the perimeter. Thus, if the target happens to be located on one of the curves, the robots assigned to that curve would 'find' the target. A measure of the search time would, then, be equivalent to the distance, on average, that a robot would have to travel on its curve to 'find' the target – defined by half the curve-length between any two adjacent robots on that curve. The average search time metric for any given curve, $p \in [1, N_c]$, with circumference, C_p, is expressed as:

$$T_{s,avg,p} = 0.5\left(C_p / N_{r,p}\right). \qquad (2)$$

This average search time per curve can be normalized by taking its ratio to the average search time for the "100%" curve that has been allocated a single robot (i.e., the worst-case search time, given by half the circumference, $\frac{1}{2} \cdot C_{100}$). Subsequently, averaging the normalized search times of all the curves yields the overall average search time measure as:

$$N_{T_{s,avg}} = \frac{1}{N_c}\sum_{p=1}^{N_c} \frac{C_p}{N_{r,p} C_{100}}. \qquad (3)$$

b) A Success-Rate Metric: Let us assume that each robot has a sensing range of r_d, and follows curve, p, located at $r = L_{p,i}$ from the LKP on a ray, $i \in [1, N_{rays}]$. Then, the success rate for that curve from the perspective of this ray can be taken as the area (probability) under the target-location PDF on that ray between $L_{p,i} - r_d$ and $L_{p,i} + r_d$. Averaging the probability values over all rays and summing this average probability over all curves, gives the overall search success rate measure. Assuming a normal distribution, $N_i(r_i, \mu_{Di}, \sigma_{Di}^2)$, for the target-location PDF on each ray, i, the overall search success rate becomes:

$$P_s = \sum_{p=1}^{N_c}\left\{\frac{1}{N_{rays}}\sum_{i=1}^{N_{rays}}\left[\int_{L_{p,i}-r_d}^{L_{p,i}+r_d} N_i(r_i, \mu_{Di}, \sigma_{Di}^2)\, dr_i\right]\right\}. \qquad (4)$$

c) A Multi-Objective Metric: An overall objective function can quantify search effectiveness as a weighted sum of multiple objective functions, such as the above two metrics, weighted by w_{T_s} and w_{P_s}, respectively:

$$Minimize: Z_1 = f(N_c, R_c) = w_{T_s} N_{T_{s,avg}} - w_{P_s} P_s. \qquad (5)$$

The constraints for this formulation are the upper and lower bounds on the two decision variables. With respect to curve-set position, R_c, since an iso-probability curve must have some finite distance from the LKP, the user must specify a minimum position, R_{min}. However, a target-location PDF with infinite range, such as the normal distribution, does not have a finite 100% cumulative probability point, and must be truncated. We define the 100% iso-probability curve position as the point on the ray corresponding to $r = (\mu_D + 3\sigma_D)$. Thus, R_c can range from R_{min} to the cumulative probability value, R_{max}, corresponding to $r = (\mu_D + 3\sigma_D)$:

$$R_c \geq R_{min} \quad (\textit{User-specified}), \qquad (6)$$

$$R_c \leq \int_{-\infty}^{(\mu_D + 3\sigma_D)} N(r, \mu_D, \sigma_D)\, dr \quad (= R_{max}). \qquad (7)$$

The lower bound on N_c is 1 curve, but the upper bound depends on two considerations. First, given values for R_c and D_c, the maximum number of curves is limited by the available space in the range [R_{min}, R_{max}]. Secondly, the available number of robots, N_r, must be allocated to each curve following the resource allocation method mentioned earlier. Thus, an iterative process must be used to determine the upper bound, N_{c_max}, where curves are added symmetrically about R_c until any one of the above two conditions cannot be satisfied:

$$N_c \geq 1 \, , \tag{8}$$

$$N_c \leq N_{c\_max} \, . \tag{9}$$

C. Problem Formulation for Re-Deployment

Since the environment, target-state, and probabilistic target information are dynamically changing in the WiSAR problem, on-line re-deployment of the iso-probability curves and the robots assigned to them, beyond the initial first deployment, is also required during the search process to maintain the optimality of the search. As summarized in Fig. 3, at a given time instant, the re-deployment problem is identical to initial deployment in determining the optimal number of iso-probability curves and their locations, except for an additional task of re-assigning robots to new curves.

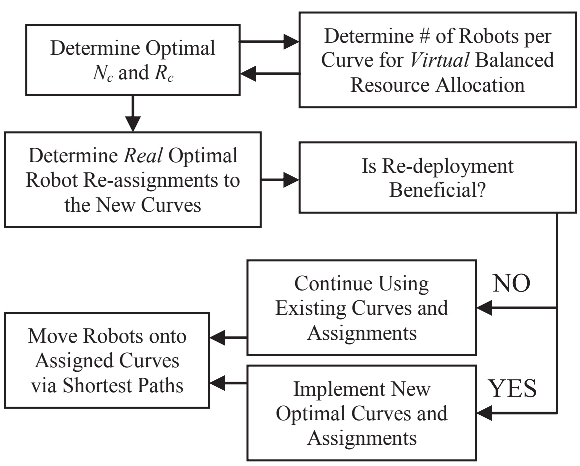


Fig. 3. The re-deployment problem.

The re-assignment of robots to the new set of curves is a secondary optimization problem. As search progresses, the robots move and become distributed throughout the search area. If and when re-deployment becomes necessary, the robots would not necessarily be on their assigned curves. This requires the secondary task for optimal re-deployment: decide how to re-assign robots to the new optimal curves.

The time spent by robots in trying to achieve a re-deployment is time taken away from conducting the search. As a result, the optimality of the iso-probability curves, and of the search endeavor, could be compromised. Therefore, the objective of the optimal re-assignment problem is to minimize the distance travelled by the *last* robot to reach its assigned deployment position on a new curve.

In order to ensure that re-deployment is achieved as quickly as possible, the optimization needs to assign robots to curves, and the robots take the shortest path to get there. The point at which they reach their assigned curve in this manner becomes their deployment position coordinates. Given an optimal solution to this re-assignment problem, the time taken for the last robot to reach its deployment position (i.e., the return-time) is compared to a user-specified maximum return-time threshold to see if the decision variables, N_c and R_c, are valid.

Since there are always as many assigned positions on curves as there are robots, we define the binary decision variables, $x_{ipj} \in [0, 1]$, representing the yes/no decision to assign robot $i \in [1, N_r]$ to deployment position $j \in [1, N_{r,p}]$ on curve $p \in [1, N_c]$. A cost matrix is defined with a column for each position on each curve that must be filled (i.e., Curve 1 requiring $N_{r,1}$ robots is associated with the first $N_{r,1}$ columns of this matrix; Curve 2 with the next $N_{r,2}$ columns, and so on). This produces an $N_r \times N_r$ cost matrix, where each element, c_{ipj}, represents the shortest-path distance between robot r_i and curve p_j. The objective is to select the robot re-assignments that minimize the maximum return-distance among all the robots:

$$Min.: Z_2 = f(x_{ipj}) = \max_{1 \leq i \leq N_r} \left\{ \sum_{p=1}^{N_c} \sum_{j=1}^{N_{r,p}} \left[x_{ipj} \cdot c_{ipj} \right] \right\} . \tag{10}$$

Four constraints are required: each robot is assigned to only one deployment position (Eq. 11); each deployment position of each curve must have one robot assigned to it (Eq. 12); the total number of assignments must equal the total number of robots (Eq. 13); and, the decision variables must be integers that can only take on the values '0' or '1' (Eqs. 14 and 15):

$$\sum_{p=1}^{N_c} \sum_{j=1}^{N_{r,p}} x_{ipj} = 1, \quad \forall i \in [1, N_r] \, , \tag{11}$$

$$\sum_{i=1}^{N_r} x_{ipj} = 1, \quad \begin{matrix} \forall p \in [1, N_c] \\ \forall j \in [1, N_{r,p}] \end{matrix} \, , \tag{12}$$

$$\sum_{i=1}^{N_r} \sum_{p=1}^{N_c} \sum_{j=1}^{N_{r,p}} x_{ipj} = N_r \, , \tag{13}$$

$$x_{ipj} \in [0,1], \forall i \in [1, N_r]; \; \forall p \in [1, N_c]; \; \forall j \in [1, N_{r,p}], \tag{14}$$

$$x_{ipj} \in \mathbb{Z}, \quad \forall i \in [1, N_r]; \; \forall p \in [1, N_c]; \; \forall j \in [1, N_{r,p}] \, . \tag{15}$$

III. Integrated Re-Deployment Solution Methodology

We propose an integrated approach to solving the re-deployment problem, Fig. 3, by simultaneously considering the selection of the optimal curve-set and the optimal robot re-assignments. Initial deployment, Fig. 2, is just a sub-problem for the determination of the optimal curve set.

The proposed integrated solution method combines: (*i*) a non-linear optimization technique, to determine the optimal iso-probability curves (Eqs. 5-9), with (*ii*) a method that solves the constrained optimization formulation (Eqs. 10-15) of the re-assignment problem, for any given parameter set value, $\underline{x_i} = \{N_{ci}, R_{ci}\}$, that is being evaluated.

A. Optimal Iso-probability Curves

The primary optimization issue can be expressed as a general non-linear programming problem involving the minimization of Z_1 (Eq. 5), with only inequality constraints $g_i(\underline{x}) \geq 0$ (Eqs. 6-9), where $\underline{x} = \{N_c, R_c\}$ is a given solution point vertex. Although any non-linear programming method may be used to solve it, the Flexible Tolerance Algorithm (FTA) [22] was adopted in our work.

B. Optimal Re-Assignment of Robots

The formulation of this secondary optimization problem given by Eqs. 10-15 produces a Linear Bottleneck Assignment Problem (LBAP). The optimal objective function value yields the minimized maximum robot-return-distance. Dividing this value by the velocity of a search robot gives a time value, which is compared to the maximum return-time threshold to determine if a penalty should be applied. The LBAP can be solved efficiently via the Threshold Algorithm given in [23].

C. Decision-Making Threshold

The optimal re-deployment solution must be computed at regular time intervals for an intended future search time point, T_f. Upon obtaining this solution, the curves corresponding to the *existing* deployment solution being used at that time must be propagated up to T_f, and the objective function values (Eq. 5) for these two alternatives must be computed and compared. The new optimal solution is only used if the percentage difference between these two objective function values exceeds a user-specified threshold (i.e., if re-deployment is deemed to be beneficial).

IV. Illustrative Example of Deployment in WiSAR

The proposed autonomous MRC method for WiSAR is applied to a realistic search scenario to demonstrate when and how optimal initial deployment, and re-deployment, would be beneficial. In this scenario, a 1 to 6 year old child is lost in a forest-type terrain that only allows for ground search. The search commander decides to perform an equally time- and success-critical search, assigning equal weights of $w_{Ts} = w_{Ps} = 0.5$. The simulator chooses a random target speed of 0.14 m/s (from the assumed mean target-speed PDF) and a 20° travel direction. The target is assumed to be moving outward without stopping (i.e., worst-case scenario), with random variations of ±3σ of ±0.014 m/s and ±15°, respectively, every 120 s, to mimic drift. The target also 'drops' clues every 600 s. The nominal mean target-speed PDF is scaled on-line during the search according to calculated instantaneous terrain slope along 8 rays.

The target is assumed to have an 1800 s head-start, representing time taken for the search robots to be initially deployed around the LKP. After 2700 s, the target starts to seek shelter, which he/she can detect from a distance of 10 m. If shelter is found, the target takes the shortest path to the shelter and remains there for the rest of the time.

A total of 19 search robots, moving at constant speed, are available, 18 of which are assigned to iso-probability curves, while the 19th is restricted to search the area bounded by the innermost curve. The robots can detect the target within a 10 m radius, and clues within a 3 m radius.

Before starting the search, the optimal initial deployment solution is computed and utilized. At 300 s time intervals thereafter, the optimal re-deployment solution is computed and compared to the existing one. Re-deployment is implemented if the difference in objective function values between the two exceeds a threshold – set arbitrarily to 4% in our example. The return-time threshold (T_{r_max}) is 300 s.

Figure 4 shows the initial optimal deployment solution (N_c = 6, R_c = 0.432). The small dots on the curves are the cumulative probability points on the rays and the large dark dots are the robots. The circles with solid and dashed lines represent the randomly placed (circular) terrain obstacles that are *a priori* known and unknown, respectively. The squares represent shelter locations, the large lighter-shaded dots are the clues, and the '×' indicates the target.

Figure 5 shows a re-deployment triggered at t = 2400 s (N_c = 7, R_c = 0.445), where the objective function value differs by ΔOB = 4.6% compared to the existing deployment solution. A second re-deployment (N_c = 7, R_c = 0.415, ΔOB = 5.8%) is triggered at t = 4500 s (Fig. 6).

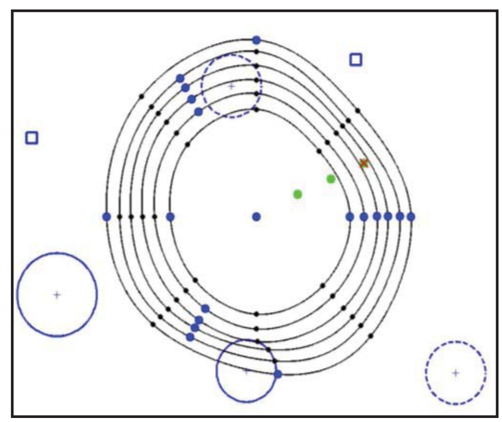


Fig. 4. Optimal deployment solution for $w_{Ts} = w_{Ps} = 0.5$ (t = 1800 s).

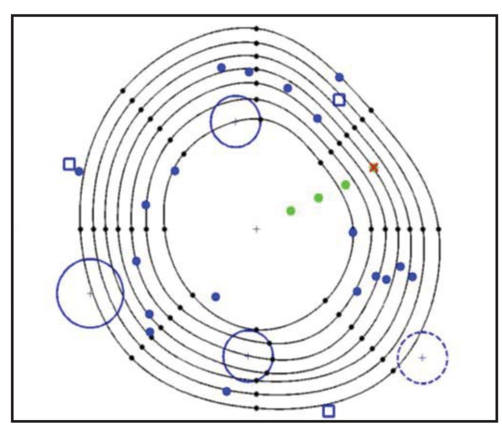


Fig.5. Implementation of new optimal deployment solution (t = 2400 s).

This simulation resulted in a successful search, and the target was found at time t = 4635 s. Figure 7 shows the paths taken by the target (thick, dark line leading to the '×') and by

4 of the robots (thinner lines) throughout the search process. A plot of the percentage change in objective function values used to decide on re-deployment during the re-evaluations every 300 s is given in Fig. 8.

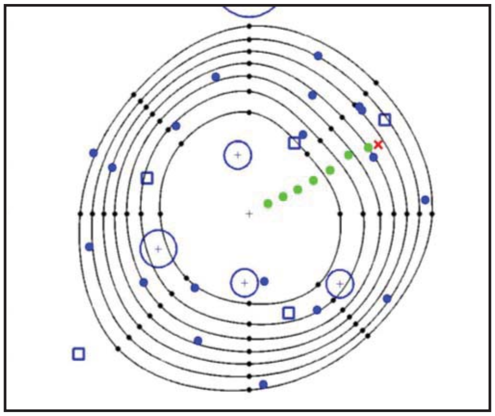


Fig. 6. Implementation of new optimal deployment solution (t = 4500 s).

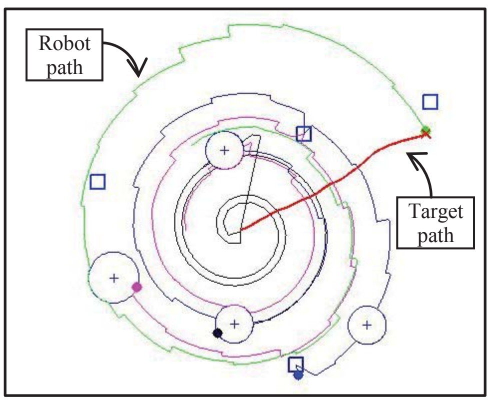


Fig. 7. Paths of target and 4 of the robots throughout the search (t = 4635 s).

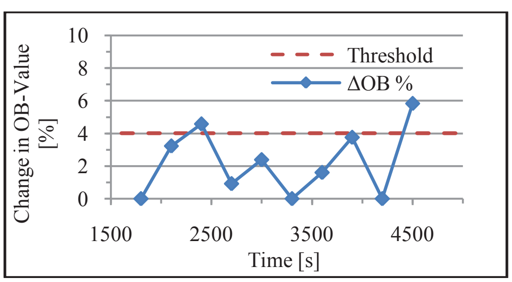


Fig. 8. Plot of percentage difference in objective function values.

V. Conclusions

This paper has presented an optimal deployment methodology for multi-robot teams engaged in autonomous WiSAR. The proposed method utilizes the novel concept of iso-probability curves, which predict and represent a lost person's motion behavior for WiSAR scenarios, in order to properly distribute search effort within a growing search area during initial deployment and subsequent re-deployment, as required. A realistic WiSAR search simulation verified the ability of the method to successfully deploy robots within a dynamically changing environment.

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