Sensor Fusion and Decision-making in the Cooperative Search by Mobile Robots

Barouch Matzliach[1,3], Irad Ben-Gal[1,3] and Evgeny Kagan[2,3]
[1]Dept. Industrial Engineering, Tel-Aviv University, Israel
[2]Dept. Industrial Engineering, Ariel University, Israel
[3]LAMBDA Laboratory, Tel-Aviv University, Israel

Keywords: Probabilistic Search, Bayesian Scheme, Multi-robot Systems, Sensor Fusion, Swarm Dynamics, Mobile Robots.

Abstract: The paper addresses the problem of probabilistic search and detection of multiple targets by the group of mobile robots that are equipped by a variety of sensors and are communicating with each other at different levels. The goal is to define the trajectories of the robots in the group such that the targets are chased in minimal time. The suggested solution model follows the occupancy grid approach, and sensor fusion is implemented using a general Bayesian scheme with varying sensitivity of the sensors. The created control algorithm was verified in three settings with different levels of communication and information sharing between the robots and different levels of sensors' sensitivity. The suggested algorithms were implemented in a software simulation to analyze and compare the different policies.

1 INTRODUCTION

The problem of search for a hidden object is one of the oldest mathematical problems that attract both theoretical and practical interest (Nahin, 2007). In its basic formulation, this problem deals either with the distribution of the search efforts or with the trajectory of the searcher, such that provides a maximal probability of detecting the target in a given time or minimal time of certain detection of the target (Stone, 1975).

Practical studies of the search problem were initiated in 1942 as a result of the quest for the detection of the submarines in Atlantic (Koopman, 1946). Then, the considerations were distributed to the search of hidden moving targets (Washburn, 1983), and in most settings, there were suggested optimal or near-optimal solutions of the problem; for the overview, see, e.g. (Frost & Stone, 2001; Kagan & Ben-Gal, 2013; Kagan & Ben-Gal, 2015; Washburn, 1989).

However, with the development of mobile robots and multi-robot systems, the problem of the search was extended to the groups of autonomous agents searching for single or multiple targets. In such a setting, the activities of the agents strongly depend on the communication between the agents and decisions regarding the target made by each agent.

In the paper, we consider the problem of probabilistic search and detection of multiple targets by the group of mobile robots. Such a problem was considered in (Pack, DeLima, Toussaint & York, 2009) in the framework of search by unmanned aerial vehicles that required sophisticated navigation and prediction techniques for control of the vehicles' motion. In the earlier work (Vidal, Shakeria, Kim, Shim & Sastry, 2002) in the field considered the pursuit-evasion game of the team of the ground and aerial vehicles that required to explore the terrain and build its map.

We assume that the robots are equipped with different sensors that can signal with both false positive and false negative errors. The robots communicate with each other and share information regarding detected targets. In the paper, we consider different levels of communications: from complete sharing of the obtained date up to purely independent activity without sharing information. The aim of the research is to construct such control procedures that provide detection of the targets in minimal time.

The suggested solution follows the simultaneous location and mapping techniques (see, e.g. Siegwart & Nourbakhsh, 2004), in particular – the occupancy

Matzliach, B., Ben-Gal, I. and Kagan, E.
Sensor Fusion and Decision-making in the Cooperative Search by Mobile Robots.
DOI: 10.5220/0008840001190126
In *Proceedings of the 12th International Conference on Agents and Artificial Intelligence (ICAART 2020) - Volume 1*, pages 119-126
ISBN: 978-989-758-395-7; ISSN: 2184-433X
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grid approach, where the map of the targets' candidate points is created simultaneously with the detection process and the robots' motion (Elfes, 1987; Elfes, 1990). The implemented sensor fusion follows the general Bayesian scheme (Stone, Barlow & Corwin, 1999). However, in order to bound the influence of the false-positive detection errors, the sensitivity of the sensors is specified dynamically with respect to the status of the search.

The control algorithm implements three different levels of communication and information sharing:

- each robot had complete information about the data available to the other robots;
- the robots shared partial information;
- the robots acted independently without sharing information.

As was expected, the independent actions of the robots lead to the worst results in terms of the search time and the best results are obtained in the case of information sharing. In particular, while the robots share complete information, then the search time decreases exponentially with the increasing of the sensors' power down to a specific value and then stays constant. In this case, we found the upper and lower bounds for the probable sensor's reliability such that in these bounds, the search time is nearly constant, and out of these bounds, the search time increases exponentially.

The algorithms were implemented in the Python programming language and the code can be directly used for solving the real-world tasks of search and detection by the groups of mobile robots.

2 THE CONSIDERED SCENARIO OF COOPERATIVE SEARCH

Let us start with a general description of the considered scenario of cooperative search.

Consider the number of mobile robots(agents) searching for several stationary targets hidden in the gridded domain. It is assumed that each searching robot, as well as each target, can occupy only a single cell of the grid. Each searching robot is equipped with a variety of sensors that provide may be erroneous information regarding the targets' locations relative to the robot's location. The robots can communicate and share information about the targets' locations as they have been perceived by the sensors. The goal is to define the trajectories of the robots in the group and their sensing activities such that all the targets will be detected in minimal time.

In order to obtain the formal definition of the presented scenario, including erroneous perception, in addition to true targets that can be detected with a certain probability, we introduce the dummy targets that produce false alarms that can be perceived by the robots' sensors with certain probabilities.

It is clear that the presented scenario follows a general framework of the probabilistic search (Stone, 1975; Stone, Barlow & Corwin, 1999); however, for obtaining a practical solution, it requires several heuristic approaches and reasonable assumptions. In the next section, we start the consideration of particular methods used in the suggested algorithm and present the Bayesian sensor fusion that is used for calculating the probabilities in the presence of false alarms.

An example of the domain with true and dummy targets is depicted in Figure 1.

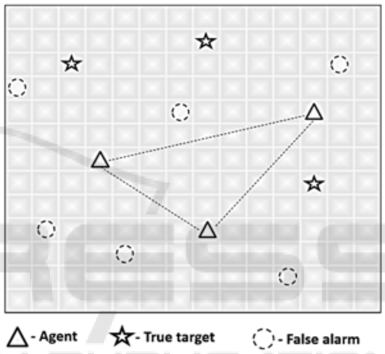

Figure 1: An example of a search grid area with true and dummy targets and several searching robots (agents).

3 UPDATING THE SENSOR PROBABILITY MAP

Following the implemented approach of the occupancy grid (Elfes, 1987; Elfes, 1990), the domain perceived by the sensor is considered as a set of cells $c_i, i = 1, 2, \ldots, n < \infty$. The state $s(c_i)$ of an ith cell is defined as a discrete random variable with the values $s(c_i) = 1$ that stands for the fact that the target is located in the cell c_i or $s(c_i) = 0$ that represents the absence of the target in the cell c_i. It is clear that for the probabilities of these two events in each cell c_i it is assumed that

$$Pr\{s(c_i) = 1\} + Pr\{s(c_i) = 0\} = 1 \qquad (1)$$

In other words, for each cell, it is associated with a probability mass function that is estimated by the sensors.

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As indicated above, following the assumption, the domain includes true targets and dummy targets, and, in each time, t, they broadcast signals that represent true and false alarms. The probabilities of perception of these signals by the sensors are drawn with respect to exponential distribution

$$Pr\{alarm\ percieved \mid alarm\ sent\} = Ae^{-R/\lambda(\mathbb{s})} \quad (2)$$

where R stands for the distance between the cell of the target (true or dummy) and the cell, in which the sensor is located, and $\lambda(\mathbb{s})$ is the sensor's sensitivity.

Equation (2) forms a basis for the calculation of the probability

$$p^{sensor}_{s(c_i)=1}(j,k,t) = Pr\{\mathbb{s}^k(\mathbb{A}_j)\ identifies\ true\ target\ in\ c_i\ at\ time\ t\}$$

where $\mathbb{s}^k(\mathbb{A}_j)$ is a sensor of type k installed on the jth agent $\mathbb{A}_j$ and scanning the cell c_i at time t. This calculation is as follows.

According to the Bayesian approach, the states $s(c,t)$ of the cells c at time t are estimated based on information read by the sensor as follows. Denote by $\tilde{s}(c_i,t)$ the signal received by the sensor (more precisely: by the sensor $\mathbb{s}^k(\mathbb{A}_j)$ of the agent $\mathbb{A}_j$) at time t. Since in the considered scenario, the cell c_i at time t can be either occupied ($s(c_i,t)=1$) or not ($s(c_i,t)=0$), we say that $\tilde{s}(c_i,t)=1$ if the sensor receives information that c_i is occupied and $\tilde{s}(c_i,t)=0$ otherwise. Then, the state probabilities of the cell c_i are:

$$Pr\{s(c_i,t)=1 \mid \tilde{s}(c_i,t)=1\} = \frac{Pr\{s(c_i,t-1)=1\}\cdot Pr\{\tilde{s}(c_i,t)=1 \mid s(c_i,t)=1\}}{\sum_{s(c_i)} Pr\{s(c_i,t-1)\}\cdot Pr\{\tilde{s}(c_i,t)=1 \mid s(c_i,t)\}}, \quad (3)$$

$$Pr\{s(c_i,t)=1 \mid \tilde{s}(c_i,t)=0\} = \frac{Pr\{s(c_i,t-1)=1\}\cdot Pr\{\tilde{s}(c_i,t)=0 \mid s(c_i,t)=1\}}{\sum_{s(c_i)} Pr\{s(c_i,t-1)\}\cdot Pr\{\tilde{s}(c_i,t)=0 \mid s(c_i,t)\}}. \quad (4)$$

These equations define the updating of the probabilities map using new observations.

In addition, the signals received by the sensors can be true or false alarms. Denote the positive alarm received from the cell c_i by $\tilde{a}(c_i)=1$ and negative alarm receives by the cell c_i by $\tilde{a}(c_i)=0$. Alarm $\tilde{a}(c_i)=1$ means, truly or not, that the cell c_i is occupied, and alarm $\tilde{a}(c_i)=0$ means, truly or not, that the cell c_i is empty.

Using the probability of receiving such alarms defined equation (2), from the equations (3) and (4) we obtain:

$$Pr\{s(c_i,t)=1 \mid \tilde{s}(c_i,t)=1\} = \frac{Pr\{s(c_i,t-1)=1\}\cdot Pr\{\tilde{a}(c_i,t)=1 \mid s(c_i,t)=1\}\cdot Ae^{-\frac{R}{\lambda(\mathbb{s})}}}{\sum_{s(c_i,t-1)} Pr\{s(c_i,t-1)\}\cdot Pr\{\tilde{a}(c_i,t)=1 \mid s(c_i,t)\}\cdot Ae^{-\frac{R}{\lambda(\mathbb{s})}}}, \quad (5)$$

$$Pr\{s(c_i,t)=1 \mid \tilde{s}(c_i,t)=0\} = \frac{Pr\{s(c_i,t-1)=1\}\cdot \left(1-Pr\{\tilde{a}(c_i,t)=1 \mid s(c_i,t)=1\}\cdot Ae^{-\frac{R}{\lambda(\mathbb{s})}}\right)}{\sum_{s(c_i,t-1)} Pr\{s(c_i,t-1)\}\cdot \left(1-Pr\{\tilde{a}(c_i,t)=1 \mid s(c_i,t)\}\cdot Ae^{-\frac{R}{\lambda(\mathbb{s})}}\right)}. \quad (6)$$

These equations allow calculating the occupation probabilities at each time t, given the probabilities at the previous time $t-1$ and the information obtained by the sensors at time t. At the initial time $t=1$, the probabilities are defined based on topographic data and prior information or, in the worst case, can be specified by a uniform distribution of the occupancy grid.

4 SENSORS FUSION

As indicated above, it is assumed that each mobile agent $\mathbb{A}_j$ is equipped with several sensors $\mathbb{s}^k(\mathbb{A}_j)$ of different types of k, and each sensor obtains information from the cell c_i independently. Then, sensors fusion allows filtering the events resulting in false alarms and increasing the quality of detecting real targets.

In the framework of the occupancy grid, sensor fusion is conducted as follows. Consider two sensors $\mathbb{s}_1=\mathbb{s}^{k_1}(\mathbb{A}_j)$ and $\mathbb{s}_2=\mathbb{s}^{k_2}(\mathbb{A}_j)$ of the type k_1 and k_2, respectively, installed at the same agent $\mathbb{A}_j$. The signals received by these sensors denote by $\tilde{s}_1(c_i,t)$ and $\tilde{s}_2(c_i,t)$. Using these signals, the probability that the state $s(c_i,t)$ of the cell c_i at time t is $s(c_i,t)=1$ is defined as follows:

$$Pr\{s(c_i,t)=1 \mid \tilde{s}_1(c_i,t)=1, \tilde{s}_2(c_i,t)=1\} = \frac{Pr\{\tilde{s}_2(c_i,t)=1 \mid s(c_i,t)=1\}\cdot Pr\{s(c_i,t)=1 \mid \tilde{s}_1(c_i,t)=1\}}{\sum_{s(c_i,t-1)} Pr\{\tilde{s}_2(c_i,t)=1 \mid s(c_i,t)\}\cdot Pr\{s(c_i,t) \mid \tilde{s}_1(c_i,t)=1\}}. \quad (7)$$

If the agent $\mathbb{A}_j$ is equipped with independent sensors $\mathbb{s}_1=\mathbb{s}^1(\mathbb{A}_j)$, $\mathbb{s}_2=\mathbb{s}^2(\mathbb{A}_j)$, …, $\mathbb{s}_m=\mathbb{s}^m(\mathbb{A}_j)$ that perceive completely different types of signals, for example, light, sound, ultrasound, and so far, then the probability that the agent $\mathbb{A}_j$ on which these sensors are installed detects the target in the cell c_i is

$$p^{agent}_{s(c_i)=1}(j,t) = \frac{\prod_{k=1}^{m} P_k}{\prod_{k=1}^{m} P_k + \prod_{k=1}^{m}(1-P_k)}, \quad (8)$$

where $P_k = p^{sensor}_{s(c_i)=1}(j,k,t) = Pr\{s(c_i,t)=1\}$ is the probability defined by equations (5) and (6).

The presented equation is based on the approach known as “independent opinion pool” under the assumption that the sensors are independent and that their reliabilities and accuracies are equivalent.

By the same manner can be fused the sensors installed on different agents that result in global probability.

$$p^{global}_{s(c_i)=1}(t) = \frac{\prod_{j=1}^{l} p^{agent}_{s(c_i)=1}(j,t)}{\prod_{j=1}^{l} p^{agent}_{s(c_i)=1}(j,t)+\prod_{j=1}^{l}\left(1-p^{agent}_{s(c_i)=1}(j,t)\right)}. \tag{9}$$

As a result, over the cells c_i, $i = 1,2,\dots,n$, the probabilities $p^{sensor}_{s(c_i)=1}(j,k,t)$ form the sensor probabilities map for each sensor $\mathbb{s}^k\left(\mathbb{A}_j\right)$ of the agent $\mathbb{A}_j$. The map is obtained by real-time updating of the sensor's probabilities. The probabilities $p^{agent}_{s(c_i)=1}(j,t)$ form the agent $\mathbb{A}_j$ probabilities map, and the probabilities $p^{global}_{s(c_i)=1}(t)$ form the global probability map.

An example of a global probabilities map is depicted in Figure 2. Dark color represents a higher probability for target location.

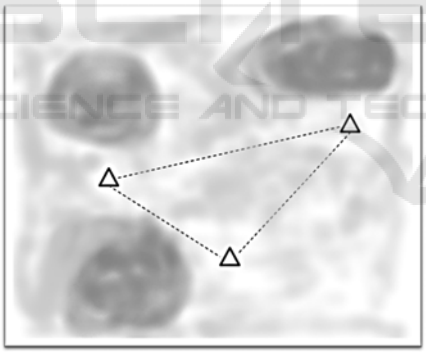

Figure 2: Global probabilities map example.

5 PROBLEM FORMULATION

Now we are ready to formulate the considered problem of search in the exact terms. As indicated in the introduction, the goal is to define the trajectories of the agents such that they detect the targets in minimal time.

In general, such a problem can be considered from two different directions:

1. The agents have to detect the targets and to reach them. The search is terminated when all the targets have been reached. In other words, the problem is considered as the path-planning problem widely accepted in the considerations of a search for moving targets (Kagan & Ben-Gal, 2015).
2. The agents have to allocate the targets without reaching them. The search process is terminated when the positions of all the targets were achieved. Such formulation follows classical considerations of the search and screening problem that result in the distribution of search efforts over the domain (Stone, 1975).

Below, we focus on the first formulation. In this scenario, the step of the search process is outlined as follows.

1. At time t, the agent $\mathbb{A}_j$ is located in the cell $c(t)$ and percepts the signals (that receives true and false alarms) from the cells, in which the targets can be located. The quality of sense depends on the sensitivities λ of the agent’s sensors $\mathbb{s}^k\left(\mathbb{A}_j\right)$ and the distances $R(c(t), c_i)$ between the agent’s cell $c(t)$ and the cells c_i, from which the alarms are sent.
2. After receiving the signals, the sensor probability maps $p^{sensor}_{s(c_i)=1}(j,k,t)$, $i = 1,2,\dots,n$, are updated.
3. The resulting sensor probability maps are combined into the agent’s probability map $p^{agent}_{s(c_i)=1}(j,t)$, $i = 1,2,\dots,n$.
4. Following the considered control algorithms, there are three possible scenarios:

   4.1. If the agents act independently without communication, the further decision about the next step is obtained, based on the agent’s probability map $p^{agent}_{s(c_i)=1}(j,t)$, $i = 1,2,\dots,n$.

   4.2. If the agents can communicate, they can share their maps with the other agents. In the case of complete information sharing, each agent creates a global probability map $p^{global}_{s(c_i)=1}(t)$, $i = 1,2,\dots,n$, and makes a decision basing on this map.

   4.3. Otherwise, following partial maps obtained from the other agents, the agent creates a local probability map and makes a decision using this map.

Thus, the problem consists of two questions:

1. What kind of communication (complete information sharing, partial information sharing, or independent activity) is better?
2. Given the probability map (global, partial or individual), how the agent should choose its next location?

In addition, we can allow the updating of the sensors' sensitivity λ that allows decreasing the influence of false alarms.

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6 SEARCH POLICIES

Let us start with the scenario in which the agents can share complete information. In this case, at each time t each agent $\mathbb{A}_j$ is aware of its location $c(t)$ and the probability map $p^{agent}_{s(c_i)=1}(j,t)$, and about the global probability map $p^{global}_{s(c_i)=1}(t)$, $i=1,2,\dots,n$.

Since for each cell in the grid (except boundary cells) the agent has 9 possibilities: to stay in the current cell or make a step to one of 8 neighboring cells, the agent's goal is to choose a possibility such that it results in reaching the targets in minimum time.

The most information about the targets' locations is provided by the global probability map, and the agent decides to move toward the highest probability $p^{global}_{s(c_i)=1}(t)$, $i=1,2,\dots,n$. In addition, since the movements' time is equivalent to the distance that the agent moved, the agents' choice should minimize this distance. The simplest implementation of these two assumptions is:

$$c(t+1) = \underset{i=1,\dots,n}{\operatorname{argmax}} \left\{ p^{global}_{s(c_i)=1}(t) / R(c(t), c_i) \right\}, \tag{10}$$

where $R(c(t), c_i)$ is the distance between the current cell $c(t)$ occupied by the agent and the cell c_i.

The usage of a global probability map with reasonable search policy, for example – with the policy defined by equation (10), provides the best results in terms of minimal search time than the usage of partial or individual probability maps. However, the usage of a global probability map requires either transfer of all available information to a central station and then broadcasting it to the agents or transfer of all information to each agent and processing it by the on-board computer. Obviously, both options are rather problematic.

In order to decrease the quantity of transferred information and of the computations, instead of a global probability map, the partial or individual maps can be used. In the first scenario, we assume that the agent shares only those positions of the cells in which the probabilities of detecting the targets are relatively high. Such a technique allows decreasing uncertainty in target locations and excluding some of the false alarms. Formally, such sharing is implemented as follows. The data are transferred among the sensors $\mathbb{s}^k(\mathbb{A}_j)$ of the same type installed on different agents $\mathbb{A}_j$, $j=1,2,\dots,m$, and for this type k the threshold probability P^*_k is specified. Over the agents we find

$$p^{max}_{s(c_i)=1}(k,t) = \max_{j=1,\dots,m} \left\{ p^{sensor}_{s(c_i)=1}(j,k,t) \right\}, \tag{11}$$

and if $p^{max}_{s(c_i)=1}(k,t) > P^*_k$, then the for each agent $\mathbb{A}_j$ the probability $p^{sensor}_{s(c_i)=1}(j,k,t)$ of the sensor of the type k is updated by:

$$p^{sensor}_{s(c_i)=1}(j,k,t) = \frac{p^{max}_{s(c_i)=1}(k,t) \cdot p^{sensor}_{s(c_i)=1}(j,k,t)}{p^{max}_{s(c_i)=1}(k,t) \cdot p^{sensor}_{s(c_i)=1}(j,k,t) + \left(1 - p^{max}_{s(c_i)=1}(k,t)\right) \cdot \left(1 - p^{sensor}_{s(c_i)=1}(j,k,t)\right)}. \tag{12}$$

Such partial data sharing enhances the agent probability map that allows better decisions even using the simples rule defined by equation (10).

Finally, the same decision rule (10) was applied to the individual agent's probability map $p^{agent}_{s(c_i)=1}(j,t)$, $i=1,2,\dots,n$. Such maps are created individually by each agent and do not require communication between the agents. Since such a scenario does not imply information transfer and so is based on decisions made using restricted data, it leads to the longer search time.

7 SIMULATION RESULTS

The indicated three scenarios were studied by numerical simulations. The methods and algorithms were implemented using basic tools of the Python programming language and the trials were run on regular PC Intel I5 8265U.

In the simulations, the search is conducted over the gridded domain of the size 80×80 cells and both searchers and the targets can occupy one cell. In the illustrations below, we consider the group of 3 agents searching for 3 targets. Each agent is equipped with the sensors of 2 types. The starting positions of the searchers are: $(5,5)$, $(8,8)$ and $(62,62)$, and the locations of the targets are: $(65,76)$, $(75,70)$ and $(75,78)$.

In order to obtain the lower bound of search time, we consider the scenario in which all the agents have complete information about the targets' locations and move directly toward the targets. In this case, the overall search time by three agents is $T_{min} = 158$. Since this is the minimal possible time of the agents' motion toward the targets, the other search scenarios were compared with this time T_{min}.

In the first series of simulations, we considered the search with constant sensors' sensitivity $\lambda(\mathbb{s}) = 20$ and different ratios of false alarms. The implemented threshold probability is $P^*_k = 0.75$ for each type k of the sensors. The results of the simulations are summarized in Table 1.

Table 1: Search time in different scenarios with respect to the frequency of false alarms.

False alarms per time unit	Search time			
	Lower bound	Global map	Partial data sharing	Individual maps
800	158	166	185	225
1600	158	188	202	321
3200	158	229	274	361

It is seen that, as it was expected, the best results are provided using the global probability map. In this case, the time of search is greater than its lower bound only in 5% (for 800 false alarms per time unit), 19% (for 1600 false alarms per time unit), and 45% (for 3200 false alarms).

The worthier results are obtained by the search with partial information sharing. In this case, the time of search is greater than its lower bound in 17% (for 800 false alarms per time unit), 28% (for 1600 false alarms per time unit), and 73% (for 3200 false alarms).

Finally, the worst results were obtained in the search with the use of individual probability maps without information sharing. In this case, the time of search is greater than its lower bound in 42% (for 800 false alarms per time unit), in 103% (for 1600 false alarms per time unit), and in 128% (for 3200 false alarms).

In all the scenarios, the increasing of search time with the frequency of false alarms represents the reaction of the agents to the greater uncertainty in the data about the targets' locations.

In the other series of simulations with the same agents, we considered the dependence of search time on the threshold probability P_k^* in the scenarios with partial information sharing between the agents. The resulting dependence is shown in Figure 3.

In the figure, it is seen that the minimal time is reached for the threshold's probability $P_k^* = 0.75$ (it was used in the above-described simulations). Notice that for the values $P_k^* > 0.75$, the search time increases exponentially, while for the probabilities $P_k^* < 0.75$ the time increasing is very slow and is close to linear.

Thus, the value of optimal threshold probability P_k^* is crucial for a search by the group of cooperating agents and can completely change the search results. However, in this paper, we do not address this optimization problem and will define the probability P_k^* heuristically based on the convexity of the dependence of search time on this probability.

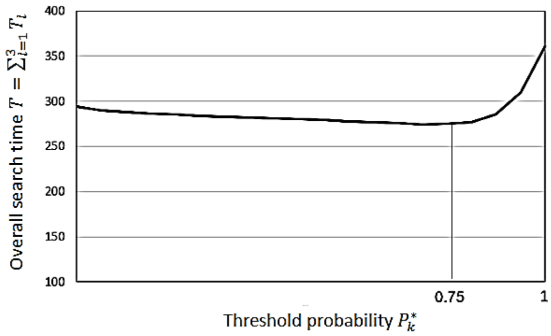

Figure 3: Dependence of the search time T on the threshold probability P_k^*.

8 SENSORS WITH VARYING SENSITIVITY

In the next simulations, we considered the dependence of search time on the sensors' sensitivity $\lambda(\mathbb{s})$ on the search time T.

The greater sensitivity sensors enable to detect more targets on greater distances from the agent. However, more sensitive sensors are more expensive and require more energy. In the case of active sensors, the greater sensitivity also requires broadcasting stronger signals that, especially for the military robots, is not always possible.

Thus, in certain missions, the agents can be equipped not with the best but with cheaper sufficient sensors, that requires an exact definition of the dependence of the search time T on the sensitivity $\lambda(\mathbb{s})$. The resulting dependence obtained in numerical simulations is shown in Figure 4.

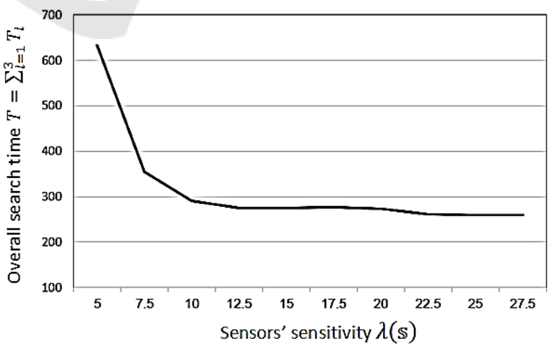

Figure 4: Dependence of the search time T on the sensors' sensitivity $\lambda(\mathbb{s})$.

It is seen that the search time T decreases exponentially with the sensors' sensitivity $\lambda(\mathbb{s})$ such that for the values $\lambda(\mathbb{s}) > 10$ the greater sensitivity has a minimal influence on the search time. That allows choosing the sensors with the sensitivity $\lambda(\mathbb{s})\sim 10$ without loss of the search efficiency.

Finally, let us consider the real-time update of the sensors' sensitivity. Such updating enables tuning the sensitivity with respect to the updates of the probability map. Sensitivity updating is conducted as follows.

Recall (see equation 11) that $p^{max}_{s(c_i)=1}(k,t)$ stands for maximum probability (over the agents) of detecting the target at time t by the sensor of type k. Denote by P^k_u and by P^k_l, respectively, the upper and the lower threshold probabilities. Then with respect to these probabilities, the sensors' sensitivity $\lambda^{t+1}(\mathbb{s})$ at time $t+1$ obtains the following value:

$$\lambda^{t+1}(\mathbb{s}) = \begin{cases} \alpha \cdot \lambda^t(\mathbb{s}) & if\ p^{max}_{s(c_i)=1}(k,t) \le P^k_l, \\ \lambda^t(\mathbb{s}) & if\ P^k_l \le p^{max}_{s(c_i)=1}(k,t) \le P^k_u, \\ \lambda^t(\mathbb{s})/\alpha & if\ p^{max}_{s(c_i)=1}(k,t) \ge P^k_u, \end{cases} \quad (13)$$

where $\alpha \ge 1$ is an updating coefficient.

The presented sensitivity updating allows improvement of the search time. The results of simulated search scenarios are summarized in Table 2.

Table 2: Search time in different scenarios with respect to the sensors' sensitivity.

Sensors' sensitivity	Search time			
	Lower bound	Global map	Partial data sharing	Individual maps
const $\lambda = 20$	158	229	274	361
$\alpha = 1.05$	158	195	209	280
$\alpha = 1.10$	158	191	195	220
$\alpha = 1.20$	158	178	182	200

Here all the scenarios were simulated with 3200 false alarms are created per time unit; for the other false alarm frequencies, the results follow the same tends.

The obtained results support the expectation that greater sensitivity results in shorter search time and demonstrate the effectiveness of dynamic sensitivity tuning.

9 CONCLUSIONS

In the paper, we considered a probabilistic search for multiple static targets by a group of agents acting in the gridded domain. In opposite to most of the known algorithms, we considered both false positive and false negative detection errors.

For both types of errors, we considered three levels of communication and information sharing:

- complete information sharing (the agents share complete probability maps available to each of them);
- partial information sharing (the agents share the most robust parts of the available probability maps);
- no information sharing (the agents act using their own probability map).

In addition, in these scenarios, we assumed either constant or varying sensors' sensitivity that can be changed online with respect to the target location probabilities.

For the indicated scenarios, we developed new models of decision making, sensor fusion and information sharing. These models are simple enough for practical implementation but, at the same time, completely represent the data and control flows in the system and include the processing of false positive and false negative detection errors.

The developed models were implemented in the Python software that was used in the simulations. The simulations show that, as it was expected, the shortest search times were demonstrated by the groups of agents with complete information sharing and the longest search times – by the groups without information sharing. Partial information sharing results in the intermediate time searches.

The online tuning of the sensors' sensitivity allows shorting the search times in all three considered cases of information sharing; however, the influence of the levels of information sharing still the same.

The future research will address the problem of building the probability maps, or, in other words, the problem of detecting the targets without reaching them in the grid. In this task, the movements of the agents are governed by the expected information gain for the targets' locations and by their visibility, rather than by detection probabilities. The results of this research will complete the model and will allow using the same terms at all the stages of the search process.

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