I-CMOMMT: A multiagent approach for patrolling and observation of mobile targets with a continuous environment representation

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Abstract

Agent-based modelling has been widely studied for observing moving targets and patrolling. However, in general, the studies are interested either in observation in a continuous environment or patrolling in a graph representation. In order to deal jointly with observation and patrolling, a common representation of the environment is required. In this paper, we firstly proposed a new environment representation's formalism, merging both agent-based distributed patrol and observation method. Secondly, we implemented a new approach called I-CMOMMT to cope with a trade-off between observation and patrolling using our new formalism. The obtained results are compared with other methods to show the efficiency of our approach.

1. Introduction

Multiagent paradigm is widely used for mobile targets observation and patrolling. The observation problem consists in positioning agents to maximize the number of viewed targets by at least one agent. The Cooperative Multi-Robot Observation of Multiple Moving Targets (CMOMMT) is a well defined problem [1]. It is composed by a team of m robots, supervising n targets into an enclosed spatial region, where the number of robots is greater than the number of targets. To maximize the number of viewed targets, the author [1] proposed a distributed solution called A-CMOMMT. This solution is based on local force vector, where each agent is attracted by all the targets within its sensor range, and repulsed by all other agents within a protection range. The authors in [2] proposed the Behavior CMOMMT (B-CMOMMT) to improves the target's distribution among the agents, by adding for instance the ability for the agents to ask for help if they are facing a potential loss of target tracking.

The patrolling problem consists of positioning agents to minimize the idleness, which represents the time difference between two visits of a same location by at least one agent. Idleness was formalized using a graph representation by the authors in [3]. An area is represented by a node and an idleness to be minimized. The authors [4] put forward the use of Long short-term memory (LSTM) to learn a patrolling strategy. In [5], the authors consider an open system, where agents can enter/leave the system. The coordination is based on auctions, where agents can trade their belonging nodes.

On one hand, the observation problem uses a continuous spatial representation to incorporate the motion of targets and agents. On the other hand, the patrolling problem is based on graph representation to evaluate the idleness of a node. To deal with both observation and patrolling problem, we developed a conceptual framework unifying the two representations into a continuous environment representation. Besides, we developed a method called Idleness CMOMMT (I-CMOMMT), to consider both patrolling and observation, and we assess it through new patrolling evaluation tools.

The paper is organized as follows. Section 2 explains our conceptual framework. Section 3 defines our developed method I-CMOMMT. Section 4 describes our experiments and the obtained results. Section 5 concludes our work.

2. Conceptual framework

We define the patrolling and target tracking problem as follows: S is a two dimensional enclosed area, where $S \subset \mathbb{R}^2$. A is a set of m patrolling agents. O is a set of n targets.

Each patrolling agent $a_i \in A$ (with $i \in [1, m]$) is defined by a set of three parameters $(state, obs, com)$: $state$ contains the Cartesian position $p_{a_i} \in S$ of the agent a_i, and the speed v_{a_i}, where $v_{a_i} < v_{a_{max}}$. obs is described by an observed surface $s_o \in S$ and the sensor's description. The sensor's description includes the percentage of false positive and false negative detection and the time processing. com defines the agent's communication capabilities, described by a surface s_c and the communication's limitation. The latter includes the delay and the bandwidth's constraint.

Each target $o_j \in O$ (with $j \in [1, n]$) is defined by a

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$state$. For the whole mission of patrolling and observation, the objective is to minimize the average idleness (eq. (4)), as well as the maximum idleness, defined in eq. (5), and to maximize the target's observation through the A metric (eq. (7)). The following subsections will describe in detail these metrics and our work on changing the environment representation into a continuous one.

2.1. From a graph to a continuous environment representation In a graph representation, we define $i_k(t)$ the idleness of a node n_k at a time t. At each time step Δt: $i_k(t+1) = i_k(t) + \Delta t$. If, at a time t, the node n_k is observed by at least one agent a_i, then $i_k(t) = 0$. However, the graph representation is not suitable for agents and targets evolving in a continuous environment. We propose to create a continuous idleness function called $I_t(x, y)$. This function returns the idleness of a position in two dimensions (x, y) defined by: $\mathbb{R}^2 \rightarrow \mathbb{R}^+ \mid x, y \mapsto I_t(x, y)$. At the beginning of the mission, the idleness of the whole map is equal to 0:

$$I_{t=0}(x, y) = 0 \tag{1}$$

Then, at each time step Δt, the idleness of each position changes such as:

$$I_{t+1}(x, y) = I_t(x, y) + \Delta t \tag{2}$$

When a patrolling agent a_i observes an area s_o, then the region's idleness changes to 0:

$$\forall (x, y) \in s_o : I_t(x, y) = 0 \tag{3}$$

2.2. Evaluation criteria In order to compare different developed approaches for patrolling and observation, several evaluation criteria need to be defined. In the following sections, we define them for the patrolling and then for the observation context.

2.2.1. Patrolling problem In [3, 6], the authors propose several criteria resulting from the notion of idleness. They are represented on the left side of the table 1. In order to lighten the memory of the agent, we propose to discretize the continuous idleness function into multiple cells. Let d_f be the discretization factor and M_e the chosen metric (e.g. meter, km). Then each surface M_e^2 is transformed into d_f^2 cells.

The discretization factor d_f has to take into account the surface's observation s_o of the agents. We propose to choose a d_f such as s_o covers at least 3×3 cells. The size of d_f must also be dimensioned considering the processing capacity of the agent. This discretized representation is on the right side of the table 1.

The objective of a patrolling method is to minimize the idleness's average, which can be done in the continuous representation case with the defined equation (4). However, this criterion is an average, and does not reflect whether a region has been neglected for a long time.

Graph	Discrete map
Worst graph's idleness $i_G^m(t) = max_{n_k \in N} i_k(t)$ with $i_k(t)$ the idleness of the node n_k and N the set of nodes in the environment.	Worst map's idleness $i_M^m(t) = max_{c_k \in C} i_k(t)$ with $i_k(t)$ the idleness of the cell c_k and C the set of cells in the environment.
Instantaneous graph idleness $i_G(t) = \frac{1}{\lvert N \rvert} \sum_{n_k \in N} i_k(t)$ with $\lvert N \rvert$ the number of nodes in the environment.	Instantaneous map idleness $i_M(t) = \frac{1}{\lvert C \rvert} \sum_{c_k \in C} i_k(t)$ with $\lvert C \rvert$ the number of cells in the environment.
Graph idleness $i_G^{av} = \frac{1}{\lvert N \rvert \times T} \sum_{t \geq 0}^{T} \sum_{n_k \in N} i_k(t)$ with T, the mission duration.	Idleness map $i_M^{av} = \frac{1}{\lvert C \rvert \times T} \sum_{t \geq 0}^{T} \sum_{c_k \in C} i_k(t)$ (4) with T, the mission duration.

Table 1: Idleness's definition using a graph (left) and a discrete map (right) representation.

In [7], the author underlined other different patrolling evaluation criteria, in particular to consider the maximum idleness of a node during the whole duration T: $i_G^{max} = max_{t \in [0,T]} i_G^m(t)$ We propose to use the same definition in the context of a discrete map as follows:

$$i_M^{max} = max_{t \in [0,T]} i_M^m(t) \tag{5}$$

However, this criterion is still not significant. Indeed, by using a discretized map idleness, a node (which represents an area) cannot be compared to a cell (which represents the smallest surface unit). Therefore, the maximum cell idleness (eq. 5) can easily reach the mission duration T. Thus, instead of evaluating the maximum idleness of a cell, we propose in this paper to consider a new criteria: the maximum idleness of a set of cells, called region. In order to fit the aggregation of cells with the agent's observation capabilities, we set the region's surface equals to the observation surface s_o. As mentioned in [8], for the image processing field, getting the average intensity of pixels in an area is performed by filtering. This transformation is done by using a two-dimensional convolution, based on a kernel ω. By analogy, the map M is a matrix, composed by intensities (in this case, idleness), that we can filter using the following equation: $M_r = \omega * M$. With M_r the regional map, containing the region's idleness $ir_k(t)$ for the cell c_k. Then, we can compute the maximum region idleness $i_{M_r}^{max}$ by:

$$i_{M_r}^{max} = max_{t \in [0,T]} \, max_{c_k \in C} \, ir_k(t) \tag{6}$$

In order to perform an average, the kernel ω is a square matrix, with the size of the observation surface in the discrete representation, made only by ones over the sum of element.

Therefore, a good patrolling strategy tends to minimize the idleness of regions through the minimization of the equation (6).

2.2.2 Observation problem The observation evaluation criteria has already been defined in the formalization of the CMOMMT [1]. We propose to use the same notation and definition. The metric A represent the number of targets seen on average by at least one agent during evaluation time T. Therefore, the objective of an observation strategy is to maximize the metric A.

3. I-CMOMMT Proposal

We propose to combine observation and patrolling by developing a distributed method called Idleness CMOMMT (I-CMOMMT), based on the force field of the A-CMOMMT. In this method, an agent a_i, at a time t, undergoes a force from each target j under its observation surface (weighted by ω_{ik}) and from each other agent k within its communication range :

$$F(a_i, t) = \sum_{j=1}^{n} \omega_{ij} f_{ij}^{t} + \sum_{k=1}^{m} f_{ik}^{r} \tag{7}$$

The magnitudes of f_{ij}^t and f_{ik}^r are defined in the figure 2 and 3 of the paper [1], alongside with the parameter $do_1, do_2, do_3, dr_1, dr_2$ and the concept of predictive tracking range. The weights ω_{ik} depends on the strategy design.

Based on the equation (7), we propose to add a force f_i^p related to the patrol problem. This force is weighted by the value $\lambda(t) \in [0; 1]$, implying that $\lambda(t)$ is the patrolling level priority over the observation at a time t. Then, the sum of the force is defined by :

$$F(a_i, t) = (1 - \lambda(t)) \sum_{j=1}^{n} \omega_{ij} f_{ij}^{t} + \sum_{k=1}^{m} f_{ik}^{r} + \lambda(t) f_i^p \tag{8}$$

If the agent a_i has no target under its observation surface s_o at a time t, then a_i is doing only patrolling with $\lambda(t) = 0$. Besides, we consider the weights $\omega_{ij} = 1$.

Because each scenario is unique, we let the experimenter define the idleness's indicator σ (in seconds) from which the idleness of a region is considered to be high. The desired agent's behavior of the I-CMOMMT is to perform observation as long as the idleness of regions is low. When the idleness of at least one region approaches the σ value, λ (t) increases to prioritize the patrolling.

Therefore, λ (t) has to evolve according to the maximum idleness of region at a time t : $max_{c_k \in C}\, ir_k(t)$. We propose the following definition, by using the $tanh$ function to keep $\lambda(t) \in [0; 1]$: $\lambda(t) = tanh \left(\frac{max_{c_k \in C}\, ir_k(t)}{\sigma} \right)$

With $ir_k(t)$ the region's idleness at the cell k and C the set of cells in the environment. The force f_i^p is directed toward the highest region's idleness only, with a constant magnitude of 1. This direction is changed when another region has a greater idleness. In case of multiple regions having the same idleness, the agent randomly selects only one among them.

To improve the patrolling strategy, we propose that each agent shares its own map with all the others agents belonging to its communication surface. During the reception, the agent updates its map by choosing the most up to date information, which is the minimum between its own cells and the ones received.

4. Experimentation

Several simulations have been carried out to evaluate the effectiveness of our proposed I-CMOMMT method in the context of patrolling and observation mission. For this purpose, we defined a random target's behavior. The target is randomly choosing a position from the environment S with a constant velocity, and then randomly selects a new position. We also suppose that there is no communication between the targets, nor collision consideration.

The experiments have the following configuration: An environment's surface of $75m \times 75m$, which is discretized by a factor $d_f = 3$ cells/m. The experiment duration is $T = 1\ 800s$. Agents have an observation's range of 4m and a communication's range of 5m. Besides, the target's maximum speed $v_{o_{max}} = 0.5m/s$ and the agent's maximum speed $v_{a_{max}} = 1m/s$. Finally, we set $\sigma = 0.8 \times T$, $do_1 = 1m$, $do_2 = 2m$, $do_3 = 4m$, $dr_1 = 1m$, $dr_2 = 2m$ and a predictive tracking range of 5m.

In our experiments, we consider that communication and observation are only limited by the range (implying no delay, nor bandwidths constraint and perfect target's detection). We compare the I-CMOMMT method with the observation's strategy A-CMOMMT and three other patrolling strategies. Inspired by the work of [3], we adapt these strategies in our continuous idleness function case:

Random Reactive (RR) : The agent randomly selects a position, goes there, and randomly selects a new one. In [3], the agent randomly selected a node.

Closest Idleness (CI) : The agent chooses, among the surrounding cells, the one with the highest idleness. The agent can perform a map sharing with other agents under its communication range. In [3], the agent selected the surrounding nodes, without communication. The behavior was called the Conscientious Reactive.

Highest Idleness (HI) : The agent chooses, among all the cells, the one with the highest idleness. The agent can per-

form a map sharing with other agent under its communication range. In [3], the agent selected among all the nodes, without communication. The behavior was called the Conscientious Coordinated.
We have run 15 experiments for each set of agents and targets configuration. The statistical obtained results of the evaluation criteria are shown in Figure 1 and Figure 2.

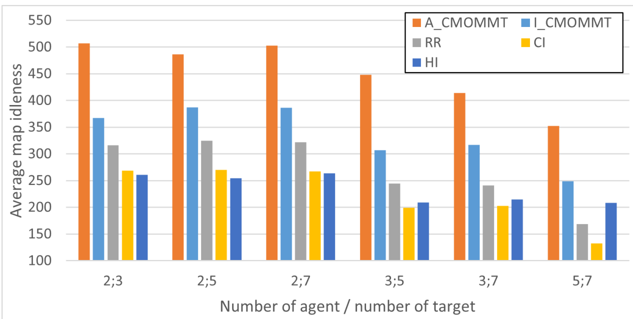

Figure 1: Illustration of the obtained results from the Map idleness and the ratio number of agents and targets.

The map idleness for the aforementioned five methods are shown in Figure 1. Through this figure, we can see that the highest average idleness is obtained from the A-CMOMMT. In contrast, we obtained a better minimization from the patrol-oriented methods (such as CI and HI). The I-CMOMMT method is an in-between, it improves the map idleness compared to the A-CMOMMT, but it is not as efficient as the patrol-oriented methods.

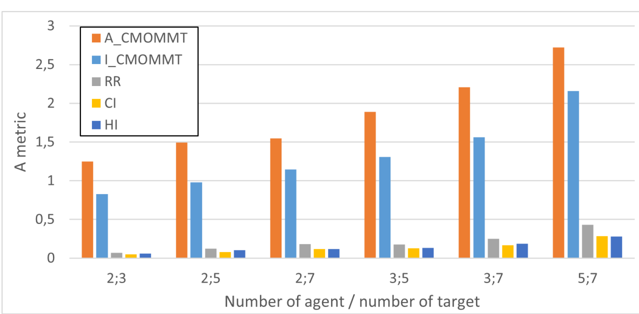

Figure 2: Illustration of the obtained results comparing A metric according to agent and target ratio.

Figure 2 compares the A metric for the aforementioned five methods. On one hand, the patrol-oriented methods have no interest in the observation objective, leading to a low value of A. On the other hand, A-CMOMMT is focusing on the observation, with a high value of the metric A. Therefore, the I-CMOMMT is an in-between method, by considering observation as well as patrolling. In our scenarios, on average, the I-CMOMMT reaches 71% of the A-CMOMMT observation's efficiency. While it reduces, still in comparison with the A-CMOMMT, 25% of the average map idleness.

From these experiments we can consider I-CMOMMT as a method that makes a compromise between both observation and patrolling problem.

5. Conclusion and future work

In this paper we are interested on combining approaches related to observation and patrolling. The patrolling representation and analysis tools are based on graph whereas the observation problem uses a continuous representation. In this work, we proposed to merge both representations into a uniform continuous representation. This transformation has been achieved through the use of a continuous idleness function $I_t(x, y)$.

A new patrolling and observation method called Idleness CMOMMT (I-CMOMMT) was proposed. This method weights patrolling and observation forces to find a good balance between the two problems. We evaluate I-CMOMMT with different methods. Our result shows that the I-CMOMMT approach is successfully achieving its goal to consider both patrolling and observation, by being more efficient for patrolling than observation-oriented method and observing more targets than patrolling-oriented methods.

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