Smart Targets to Avoid Observation in CTO Problem

Extended Abstract

Thayanne França da Silva, José Luis Alves Leite, Raimundo Juracy Campos Ferro Junior, Leonardo Ferreira da Costa, Raphael Pinheiro de Souza, João Pedro Bernardino Andrade and Gustavo Augusto Lima de Campos
Universidade Estadual do Ceará
{thayanne.silva,luis.alves,junior.ferro,leonardo.costa,raphael.souza,joao.bernardino}@aluno.uece.br,gustavo@larces.uece.br

ABSTRACT

Security is one of the values essential to the common good of society. With population growth and modernity, new challenges have emerged to ensure the safety of a large number of people in circulation with limited resources for observation. The Cooperative Targets Observation (CTO) problem consists of two groups of agents, observers and targets, in which observer agents seek to maximize the Average Number of Observed Targets (ANOT) in environments where there are more targets than observers. In most of the approaches to this problem the behavior of the target agents was modeled very simply, out of reality in competitive multi-agent environments. The objective of this work is to propose and validate four strategies for the team of target agents in the CTO problem, three involving grouping algorithms and two organizational paradigms, and one using neural networks. The approaches were implemented and tested on the NetLogo agent-based simulation platform. Test results showed that target team performance increased considerably when they were modeled as rational agents in an organization.

KEYWORDS

Cooperative Target Observation; Extension of Target's Strategy; Organization; Artificial Neural Network

ACM Reference Format:

Thayanne França da Silva, José Luis Alves Leite, Raimundo Juracy Campos Ferro Junior, Leonardo Ferreira da Costa, Raphael Pinheiro de Souza, João Pedro Bernardino Andrade and Gustavo Augusto Lima de Campos. 2019. Smart Targets to Avoid Observation in CTO Problem. In *Proc. of the 18th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2019), Montreal, Canada, May 13–17, 2019,* IFAAMAS, 3 pages.

1 INTRODUCTION

The CTO is a variant of the Cooperative Multi-Robot Observation of Multiple Moving Targets (CMOMMT) problem, the core of surveillance problems in environments where there are more targets than observers [5]. Differently from the original CMOMMT problem, in the CTO problem the environment is totally observable. In this first approach, the focus was on the rationality of the movement of the observers. The targets were considered to move randomly by the environment. More recent approaches to the problem focused on the targets movement, e.g., considering the straight-line movement and one kind of controlled randomization for the targets [2].

However, in these approaches the observers work in a kind of organization, in which a superior agent receives the position of all targets and observers, and groups the targets into clusters and observers in the center of these clusters. More recently, in a similar approach to the CTO problem the Fuzzy C-means (FCM) algorithm and the notion of organization in Multi-Agents System (MAS) were employed to cluster the targets and to better control the observers' movement [1]. However, the targets remained to move at random.

Just as [2] has used other types of strategies for the targets, the approach in this paper proposes four strategies for the target team, three inspired on clustering algorithms and on organizational paradigms and one on neural networks. Because the organizational clustering approach was proposed only to observers and neural network has proved to be an easy way for mapping data and adaptation for new data [6]. The results showed that modeling the targets as intelligent agents has an impact on the performance of observers, mainly when the targets employed the strategies based on the organizational clustering approach.

2 MODEL DESCRIPTION

Our approach allow targets to act as rational agents during the whole task, different from the approaches proposed by [4] and [2]. The environment task is a continuous, 2D, non-toroidal, obstacle-free rectangular field containing N observers and M targets, with $N < M$ [4]. The coordinator computes the new destination point and sends to each observer every γ time steps. If one reaches its destination point in less than γ time steps, then it waits until a new destination point is computed. The targets have observation sensors similar to the observers [2], and can move in the same manner as them. In the case of an observer, at each γ steps of time, its next position is computed employing the clustering algorithm k-means [4] [2]. This algorithm presented significant results for observers when targets are fast (the hill-climbing search approach seems to be better to employ when targets are slower than the observers). Thus the observer walks toward the computed destination point and continuously wait until a new destination point is forwarded to him.

Focusing on the refinement of each target's movement, this paper proposes two main approaches to compute its next position at each step of time, Organizational Clustering and Decentralized Neural Networks.

Different from the observer's strategy, where the computed position is adopted by its next desired position, in our approach, the computed position for the target is not its next desired position, i.e., the target does not seek to reach this destination, but to avoid

Proc. of the 18th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2019), N. Agmon, M. E. Taylor, E. Elkind, M. Veloso (eds.), May 13–17, 2019, Montreal, Canada.

it, since there may be observers there. The objective of the observers is the same objective defined by [5], that maximizes the average of observed targets during the experiment time. In this case, similar to formalism presented in [3], where at each time step t, the observers compute which targets are monitored, given by the indicator function θ:

$$\theta(\omega) = \begin{cases} 1\,, & if\ \omega\ is\ monitored\ at\ t, \\ 0\,, & otherwise, \end{cases} \tag{1}$$

where ω is any target. Then at each time-step is possible to know the number of targets observed by the observers through a μ value computed by:

$$\mu(t) = \sum_{\omega \in \Omega} \theta(\omega) \tag{2}$$

in which Ω stands the conjunct of the all targets ω. The average value of μ considering all time-steps of the experiment is the function to be maximized by the organization as your objective, defined by:

$$\bar{\mu} = \frac{1}{T} \sum_{t \in T} \mu(t) \tag{3}$$

where T stands the conjunct of the t time-steps, composing the total time of the experiment. We call the $\bar{\mu}$ value of Average Number of Observed Targets (ANOT), and this value will be considered as the performance measure of the observers, as used by [4]. For the purpose of this work, the smaller the ANOT the more efficient the strategy adopted by the target proves to be. The next subsections describes the two main approaches to compute each target's next position.

2.1 Organizational Clustering

The Organizational Clustering approach encompasses in its structure an organizational paradigm and the clustering algorithms. In this paper, we used the hierarchy and the holarchy as organizational paradigms. In this approach, depending on the structures used, hierarchical or holarchical, the targets can be subordinated to one or more coordinators. Each coordinator is committed to compute with the clustering algorithms the next position of a group of targets, i.e., the positions that the targets should avoid. We developed three approaches in this strategy: a hierarchical approach with k-means, a hierarchical approach with fuzzy c-means and a holarchical approach.

2.1.1 Hierarchical Approach with K-means (KM). We propose a two-level hierarchy, in which the targets team has a coordinator agent who is on the level above them. This agent has the overview of the observation scenario, while the targets have a local view based on their range sensor. The coordinator of targets receives the positions of all targets and observers, and through the KM each observer is the centroid of a cluster. The coordinator sends these centroids to the targets forcing them to move away from these points.

2.1.2 Hierarchical Approach with Fuzzy C-means (FCM). Similar to the hierarchical approach with k–means. In this approach there is only one general coordinator and all targets are subordinate to it. The operation remains the same, but the calculation of the positions that the targets must move away is performed by the FCM.

2.1.3 Holarchical Approach. In this approach, the targets were divided into two hierarchical groups with the same number of members, each with its coordinator, and each one subordinated to a general coordinator. The coordinator of one group has no relation to the members of one other different group. The coordinator calculates the position that his subordinates must move away, one with KM and the other with the FCM, using the information provided by the general coordinator. The holarchical approach is the union of the hierarchical with KM and FCM approaches.to avoid, rotates 90° and moving away in straight line.

2.2 Decentralized Neural Networks

In this paper, we model a neural network to predict the behavior of observer agents. The main goal of this neural network is to establish a decision-making strategy for target agents. By doing that, the targets will have a better rationale when trying to move or escape from observers, and each one will have its own network coupled within itself. The reason of the use of neural networks in the targets, besides testing another type of approach for this team, was the same one used by the organizational approach, i.e., not only to make the strategic targets but rational throughout the simulation period.

The development of this model was divided into two phases: training and data collecting. To train a neural network, first, we need to provide a dataset that has some meaning for the problem. In this project, we collect data by monitoring all the agents when the simulation is running. This is done by a central agent that has access to all information of the given simulation, e.g., coordinate positions, direction, speed, etc. By having access to all these data, what remains is to define what features are going to be chosen.

By trial and error, we determine that a better approach to predict observer behavior is to see which targets agents are close to each one of them. In this example, we pick five targets closest to each observer agent. For instance, we see that agent 1 has five targets pointed out by the arrows as well as agent 2.

3 CONCLUSIONS

This paper examined two approaches to the target team in the Cooperative Target Observation problem, one based on organizational paradigms and clustering algorithms, and another one based on neural networks. Both allowed a better performance for the targets, with emphasis on organizational approaches, making the task of the observer more difficult and complex, which caused in the fall of its performance. At one extreme, the observer had ANOT less than 1.

As future work is intended to use other types of algorithms in the organizational approach to avoid empty grouping, such as search algorithms. In addition to defining and implementing other neural networks.

4 ACKNOWLEDGEMENTS

The present work was carried out with the support of the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brazil (CAPES) - Financing Code 001.

REFERENCES

[1] Joao PB Andrade, Robson Oliveira, Thayanne F da Silva, José E Bessa Maia, and Gustavo AL de Campos. 2018. Organization/fuzzy Approach to the CTO Problem. In *2018 7th Brazilian Conference on Intelligent Systems (BRACIS)*. IEEE, 444–449.

[2] Rashi Aswani, Sai Krishna Munnangi, and Praveen Paruchuri. 2017. Improving surveillance using cooperative target observation. In *Thirty-First AAAI Conference on Artificial Intelligence*.

[3] Jacopo Banfi, Jérôme Guzzi, Francesco Amigoni, Eduardo Feo Flushing, Alessandro Giusti, Luca Gambardella, and Gianni A Di Caro. 2018. An integer linear programming model for fair multitarget tracking in cooperative multirobot systems. *Autonomous Robots* (2018), 1–16.

[4] Sean Luke, Keith Sullivan, Liviu Panait, and Gabriel Balan. 2005. Tunably decentralized algorithms for cooperative target observation. In *Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems*. ACM, 911–917.

[5] Lynne E Parker. 1999. Cooperative robotics for multi-target observation. *Intelligent Automation & Soft Computing* 5, 1 (1999), 5–19.

[6] Ivan Nunes Silva, Danilo Hernane Spatti, Rogério Andrade Flausino, Luisa Helena Bartocci Liboni, and Silas Franco dos Reis Alves. 2018. *Artificial Neural Networks: A Practical Course*.