Robotics and Autonomous Systems 83 (2016) 243–250

Contents lists available at ScienceDirect

Robotics and Autonomous Systems

journal homepage: www.elsevier.com/locate/robot

Constrained clustering for flocking-based tracking in maneuvering target environment

Samaneh Hosseini Semnani [a,*], Otman A. Basir [a], Peter Van Beek [b]

[a] Electrical and Computer Engineering department, University of Waterloo, Waterloo, Canada
[b] Cheriton School of Computer Science, University of Waterloo, Waterloo, Canada

ARTICLE INFO

Article history:
Received 30 April 2015
Received in revised form
13 February 2016
Accepted 12 April 2016
Available online 18 May 2016

Keywords:
Surveillance systems
Mobility control
Constrained clustering
Maneuver target
Biologically inspired computing
Sensor coordination
Sensor networks

ABSTRACT

Self-organizing ability is one of the most important requirements of modern sensor networks; particularly for tracking maneuvering targets. Flocking-based approaches are biologically inspired methods that have recently gained significant attention to address the control and coordination problem in self-organizing sensor networks. These approaches are exemplified by the two well-known algorithms, namely, the Flocking and the Semi-Flocking algorithms. Although these two algorithms have demonstrated promising performance in tracking linear target(s), they have deficiencies in tracking maneuvering targets.

This paper introduces a constrained clustering approach that uses a novel extension of K-means algorithm to provide better coverage over maneuvering targets. This extension clusters the sensors based on certain background knowledge, then uses the information about the clusters to improve coverage. The performances of flocking-based algorithms, both with and without the proposed approach, are examined in tracking both linear and maneuvering targets. Experimental results demonstrate how constrained clustering yields better tracking of maneuvering targets, and how applying constraints on the clustering process improves the quality of clustering and increases the speed of convergence.

1. Introduction

Throughout the last decade, mobile sensor networks have been attracting significant attention for possible use in a wide range of applications, including environmental monitoring, habitat tracking, military command and control, security, manufacturing and transportation activities. Mobile surveillance systems are one of the applications in which sensor networks are well studied and efficiently used [1–4].

Surveillance applications involve self-organized mobile sensors. Such sensors cooperate and coordinate their activities to detect and track targets and events in a given volume of interest (VOI) and fuse the collected information to create a complete picture of the situation of interest. In a surveillance application, targets are normally classified into two classes based on their motion type: maneuvering (non-linear) and non-maneuvering (linear). A non-maneuvering target has a constant velocity. All other targets (those with non-constant velocity) are categorized as maneuvering targets [5].

One key challenge in large-scale surveillance systems is mobility control and coordination, which deals with the optimal movement of a set of mobile sensors. Maximizing target coverage is one of the main objectives in mobility control of many surveillance applications [6]. This problem is even more challenging when sensors are dealing with maneuvering targets that change their speed and direction frequently and suddenly [7,8]. Extensive research has focused on this problem in recent years [9–12]. The Flocking algorithm [9] is a well-cited example of this research work [6,13–18]. Flocking is a type of group behavior of large numbers of autonomous agents that cooperate and coordinate to reach common objectives.

Flocks' self-organizing feature and their ability to benefit from local communication make them suitable for use in sensor networks. Flocking [13], Anti-Flocking [15] and Semi-Flocking [6] are examples of flocking-based algorithms that have been applied in management of sensors in sensor networks. Although flocking-based algorithms have demonstrated promising performance in tracking mobile targets, they are not able to cover maneuvering targets as well as non-maneuvering ones, particularly when there is a small flock around a maneuvering target.

* Corresponding author.
E-mail addresses: s29hosse@uwaterloo.ca, samane.hossayni@gmail.com (S. Hosseini Semnani), obasir@uwaterloo.ca (O.A. Basir), vanbeek@cs.uwaterloo.ca (P. Van Beek).

http://dx.doi.org/10.1016/j.robot.2016.04.004
0921-8890/

This paper discusses two flocking-based algorithms, namely, Flocking [13] and Semi-Flocking [6]. The effectiveness of these two algorithms in tracking maneuvering and non-maneuvering targets is evaluated. The paper discusses the deficiencies of both algorithms when it comes to their ability to maintain robust target coverage over maneuvering targets, then presents a novel constrained clustering approach that facilitates improved target coverage performance under complex target maneuvering conditions.

Constrained clustering is an approach that can be applied in applications in which some background knowledge about data sets is available. Traditional clustering approaches make no use of this information even if it does exist [19]. This prior information provides increased evidence as to which instances should or should not be placed in the same cluster. This information provides indispensable insight for forming more-precise clusters and/or increasing the rate of convergence in a clustering algorithm. In this paper we maintain that cluster precision and clustering convergence are key requirements for dynamic multi-target tracking.

The outline of the paper is as follows. Section 2 briefly explains two flocking-based algorithms (Flocking and Semi-Flocking) for mobility control of sensors in surveillance applications. Section 3 highlights the drawbacks of flocking-based methods for tracking maneuvering targets and introduces a constrained clustering based approach that addresses these drawbacks. Section 4 introduces the evaluation criteria, the experimental setup, and the simulation results and analysis. Finally concluding remarks and future directions are given in Section 5.

2. Flocking-based algorithms

This section discuses Flocking and Semi-Flocking algorithms as two flocking-based approaches to mobility control of sensors in surveillance applications. Flocking-based algorithms have several advantages that make them suitable for use in sensor management. Distributed problem solving, local communications, low computation overhead for the sensors, high flexibility and scalability are just a few examples of the advantages of these algorithms. The following assumptions have been made in this paper about the surveillance system and mobile sensors:

- The surveillance system consists of n mobile sensors deployed in a two-dimensional geographical region with width w and length l.
- Communication ability: each sensor can communicate with all its neighboring sensors by exchanging messages through a communication network.
- Sensing ability: each sensor can sense precise position and velocity of all the targets that are placed within distance r from the sensor. Therefore, the sensing range of each sensor is a circle with radius r around it. Targets that come within this range are always detected, while targets outside are never detected. The problem in which the sensors cannot make accurate measurements is addressed in another paper [20] using distributed Kalman-Consensus filtering. Therefore in this paper we assume that sensors can make accurate measurements avoiding complication.
- Motion ability: each sensor motion is controlled independently but coordinated with the motion of other sensors. Let $q_i, p_i \in \mathbb{R}^2$ denote the position and velocity of sensor i, respectively. The motion of sensor i is governed by the following equation:

  $$\begin{cases} \dot{q}_i = p_i \\ \dot{p}_i = u_i \end{cases} \quad \text{where } \in q_i, p_i, u_i\, \mathbb{R}^2.$$

  See below for definition of u_i.
- The surveillance system consists of m mobile targets ($n > m$) randomly entering and leaving the area of interest (AOI). Let $q_{tj}, p_{tj} \in \mathbb{R}^2$ denote the position and velocity of target j respectively. All targets follow the following equation of motion:

  $$\begin{cases} \dot{q}_{tj} = p_{tj} \\ \dot{p}_{tj} = u_{tj} \end{cases} \quad \text{where } q_{tj}, p_{tj} \in, u_{tj}\, \mathbb{R}^2.$$

  If target j is a non-maneuvering target then $u_{tj} = 0$ [5].
- Knowledge of sensors about targets is limited to targets positions and velocities.

2.1. Flocking algorithm

The Flocking algorithm, which is inspired from the collective behavior of birds, is based on three main Reynold's rules: flock centering, collision avoidance and velocity matching [21]. Flock centering aims to keep each particle close to its nearby flock-mates. Collision avoidance tries to avoid collisions between nearby flock-mates, and velocity matching aims to match the velocity of each particle with that of all nearby flock-mates.

Olfati-Saber proposed a famous theoretical framework for Flocking algorithm based on these three rules [13]. In this framework, each sensor applies a control input vector: $u_i = f_i^g + f_i^d + f_i^\gamma$ where f_i^g is a gradient-based term, f_i^d is a velocity consensus term and f_i^γ is navigational feedback due to a group objective. In this method $u_i = u_i^\alpha + u_i^\gamma$ in which:

$$u_i^\alpha = \underbrace{\sum_{j \in N_i} \emptyset_\alpha \left(\left\|q_j - q_i\right\|_\sigma\right) n_{ij}}_{\text{Gradient-based term}} + \underbrace{\sum_{j \in N_i} a_{ij}(q)\left(p_j - p_i\right)}_{\text{Consensus term}} \tag{1}$$

where, N_i represents the set of neighbors of sensor i, and $\emptyset_\alpha(z)$ is an action function that is defined in [13] as follows:

$$\emptyset_\alpha(z) = \rho_h(z/r_\alpha)\,\emptyset(z - d_\alpha) \tag{2}$$

$$\emptyset(z) = \frac{1}{2}\left[(a+b)\,\sigma_1(z+c) + (a-b)\right]. \tag{3}$$

In the above, r_α and d_α are constant parameters of α-lattice; $\sigma_1(z) = z/\sqrt{1+z^2}$ and $\emptyset(z)$ is an uneven *sigmoidal function* with parameters that satisfy $0 < a \le b$, $c = |a-b|/\sqrt{4ab}$; and $\rho_h(z)$ is a *bump function* that smoothly varies between 0 and 1 and is defined in Eq. (4) [13]:

$$\rho_h(z) = \begin{cases} 1, & z \in [0, h) \\ \frac{1}{2}\left[1 + \cos\left(\pi \frac{(z-h)}{(1-h)}\right)\right], & z \in [h, 1] \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

One can show that $\rho_h(z)$ is a C^1-smooth function with the property that $\acute{\rho}_h(z) = 0$ over the interval $[1, \infty)$ and $\left|\acute{\rho}_h(z)\right|$ is uniformly bounded in z [13]. The other parameters of the Eq. (1) are defined as follows:

$\left\|q_j - q_i\right\|_\sigma$ represents the σ-norm of a vector that connects q_i to q_j defined as in [13]:

$$\|z\|_\sigma = \frac{1}{\varepsilon}\left[\sqrt{1+\varepsilon\|z\|^2} - 1\right] \tag{5}$$

$$n_{ij} = \nabla\left\|q_j - q_i\right\|_\sigma = \frac{q_j - q_i}{\sqrt{1+\varepsilon\left\|q_j - q_i\right\|^2}} \tag{6}$$

where n_{ij} is a vector along the line connecting q_i to q_j, and $\varepsilon \in (0, 1)$ is a fixed parameter of σ-norm.