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Flocking algorithm with multi-target tracking for multi-agent systems

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ABSTRACT

This paper investigates a flocking algorithm with multi-target tracking for multi-agent systems. It is supposed that every target can accept a certain number of agents. Which target is chosen by an agent is determined by the distances from the agent to the targets and the number of agents accepted by targets. Based on whether agents move toward the same target or toward separate targets, two kinds of potential functions are presented to carry out the flocking algorithm. Then the inputs of the dynamic system can be obtained. Under the driving of the inputs, agents with the same target can make a flocking during the tracking process, and the agents with different targets separate from each other. A time-varying parameter is designed to control the maximum velocity of agents in the proposed algorithm. Lyapunov stability theorem is applied to prove the stability of the dynamic system. Finally, simulation results verify the effectiveness of the proposed algorithm.

1. Introduction

Flocking is a form of collective behavior of a large number of interacting agents with a common target. It is a common phenomenon in nature such as fish, ants, penguins, and so on. Over the last few decades, scientists from different disciplines including animal behavior, computer science, biophysics, physics have studied flocking, swarming and schooling in groups of agents with local interactions (Reynolds, 1987; Okubo, 1986; Vicsek, 1995; Toner and Tu, 1998; Shimoyama, 1996; Mogilner and Edelstein-Keshet, 1999; Parrish et al., 2002; Tanner et al., 2003; Olfati-Saber and Murray, 2003; Tanner, 2004).

A multi-agent dynamic system is a distributed network with many agents. Agents in the system can only have interactions with their neighbors in a bounded workspace. In nature, mobile sensors, satellites, UAVs, and so on can be regarded as agents.

In 1987, Reynolds described the coordinated motion in bird flocks as the combined result of three heuristic rules. That is, each agent should obey the following rules: (1) Cohesion: attempt to stay close to nearby flockmates; (2) Separation: avoid collisions with nearby flockmates; and (3) Alignment: attempt to match velocity with nearby flockmates. In 1995, Vicsek proposed a flocking model in which mobile agents regulate their headings to match the average of the headings of their nearest neighbors. After that, Levine et al. (2001), Mogilner and Edelstein-Keshet (1996) and Topaz and Bertozzi (2004) proposed some models of swarms, respectively. Spears and Gordon (1999) and Spears (2004) provided distributed control of large collections of agents using "Artificial Physics", achieving self-assembly, fault-tolerance, and self-repair.

Recently, two kinds of decentralized navigation functions for formation control were proposed in (Gennaro and Jadbabaie, 2006; Dimarogonas et al., 2006). Some kinds of artificial potential functions were presented in (Baras et al., 2003; Kim et al., 2004; Olfati-Saber, 2006). Olfati-Saber (2006) presented a theoretical framework for design and analysis of distributed flocking algorithms, and gave a definition of flocking for particle systems with similarities to Lyapunov stability. Shi et al. (2007) considered the flocking problem of a group of autonomous agents moving in the workspace with a virtual leader. However, most existing studies about flocking have not considered the multi-target flocking problem (i.e., Olfati-Saber, 2006; Shi et al., 2007). This problem requires that the agents in the workspace choose their targets automatically and move toward their targets to form several flocks. But the study of the problem will be helpful to research such problems as saving life in accidents, doing dangerous and complex work cooperatively by using automatic robots, and so on. The greatest challenge to solving this problem is deciding how to choose targets effectively for agents and flocking toward a certain target at the same time.

In this paper the flocking problem of multi-target tracking for multi-agent systems is studied, and a flocking algorithm is proposed. In the algorithm we suppose that each agent has interactions with its mates within a desired bounded workspace and knows the position and velocity of each target. The purpose is that every agent can find an appropriate target and come into being a flock to track its target with other agents that have the same target. In this way a group of agents can do more work at the same time. The main contributions in the paper include: (1) the models of the

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collective potential function and repulsive potential function are presented, respectively. The advantage of these two models is that they have only one parameter to be designed, which is fewer than that of the potential functions in existing works; (2) the proposed algorithm can make a group of agents flock toward multiple targets at the same time; (3) during the flocking process the velocity of every agent is constrained by the algorithm such that it cannot exceed the maximum value; and (4) Lyapunov stability theorem is applied to prove stability of the dynamic system. In the end of this paper, two simulation examples in the plane are given to illustrate the effectiveness of the proposed flocking algorithm.

The remainder of the paper is organized as follows. In Section 2 the problem of flocking is described and some necessary notions of *Graph Theory* (Godsil and Royle, 2001) are given. In Section 3 we give a method to choose the targets. Potential functions are constructed in Section 4. The flocking algorithm is presented in Section 5. Simulation results are given in Section 6. Section 7 concludes the paper.

2. Preliminaries and problem statement

In the paper a dynamic system with n agents and m targets operating in the same workspace $W \subset R^2$ is considered. Let q_i, $p_i \in R^2$ denote the position and velocity of agent $i \in \{1,2,\ldots,n\}$, and q_{tk}, $p_{tk} \in R^2$ denote the position and velocity of target $k \in \{1,2,\ldots,n\}$, respectively. u_i is the control input of agent i, in other words, u_i can also be regarded as the input command of agent i. Then the motion of each agent is described by the following equation:

$$\begin{cases} \dot{q}_i = p_i \\ \dot{p}_i = u_i. \end{cases} \quad i \in \{1,2,\ldots,n\} \tag{1}$$

For the dynamic system, we make the following assumptions:

(1) Each agent i has the knowledge of the positions and velocities of only those agents located in a cyclic neighborhood of specific radius r;
(2) Each agent i has knowledge of the positions and velocities of all targets;
(3) The velocities of agents cannot exceed the given upper value;
(4) Each target can only accept a certain number of agents.

Remark 1. For the range constraints of sensors, agents cannot always know the information with respect to all other agents; in a multi-target system, agents need to know the information of all targets to choose the appropriate targets; every kind of agent such as UAV, robot, and so on has velocity constraint in nature; in fact, a certain number of agents are enough to do one complex task. Therefore, the four assumptions are necessary and reasonable for the real multi-agent systems.

In this paper we present some changes to the flocking rules of Reynolds (1987). (1) *Cohesion*: agents with the same target attempt to stay close to nearby flockmates, and the different ones will separate from each other. (2) *Alignment*: agents with the same target attempt to match velocity with nearby flockmates, but different ones donot have to match velocity.

In this paper the interactions between agents are mutual. Therefore, the topology of the multi-agent system can be denoted by an undirected graph. An *undirected graph* G is a pair (v,ε) that consists of a set of vertices $v = \{1,2,\ldots,n\}$ and edges $\varepsilon \subseteq \{(i,j): i,j \in v, j \neq i\}((i,j) = (j,i))$.

The set of *neighbors* of node i is defined by $N_i = \{j \in v:(i,j) \in \varepsilon\}$. The *adjacency matrix* $A = [a_{ij}]$ of an undirected graph is a matrix with elements satisfying the properties that if $(i,j) \in \varepsilon$, $a_{ij} = 1$; Otherwise $a_{ij} = 0$. In the multi-agent systems, if two agents have interaction, we say they are neighbors and connected in the topology. As the definition of the set of neighbors of node i in graph, the set of *spatial neighbors* of agent i in the workspace is defined by

$$N_i = \{j \in v : \|q_j - q_i\| < r\} \tag{2}$$

where r is the maximal range of the interaction between two agents.

Consider a graph G with n nodes, the adjacency matrix $A = [a_{ij}] \in R^{n\times n}$. The *degree matrix* of G is a diagonal matrix $\Delta = \Delta(A)$ with diagonal elements $\sum_{j=1}^{n} a_{ij}$. The *graph Laplacian* $L = [l_{ij}] \in R^{n\times n}$ is defined as $L = \Delta(A) - A$. In this paper, we mainly use the *m-dimensional graph Laplacians* (Olfati-Saber, 2006) defined by

$$\widehat{L} = L \otimes I_m, \tag{3}$$

where $\otimes$ denotes the Kronecker product. $I_m \in R^{m\times m}$ is an m-dimensional identity matrix.

3. Strategy of choosing target

In this section we present a method to choose the appropriate target for each agent. Here, m targets are considered. We suppose that target k can accept s_k agents (where $\sum_{k=1}^{m} s_k = n$). Let P_{ik}^d denote the probability term about distance from agent i to target k and P_{ik}^ρ denote the term of probability density to show whether target k can still accept agent i. ω_1, ω_2 are weight coefficients, $\omega_1 = \omega_2 = 0.5$. The values of P_{ik}^d are shown in Table 1.

where the line of D_i denotes the order of the distances between agent i and all targets. If target k can still accept agent i, $P_{ik}^\rho = 1$; Otherwise, $P_{ik}^\rho = 0$. We define P_{ik} to choose appropriate target.

$$P_{ik} = \omega_1 P_{ik}^d + \omega_2 P_{ik}^\rho. \tag{4}$$

Then the process of choosing target is described as follows:

(1) A recorder is used to store the number of agents that belong to any target. There are m recorders to store the number of agents with respect to m targets. The initial value of each number is set as 0.
(2) The record process starts from agent 1. We can obtain the values of P_{1k}^d through calculating the distances between agent 1 and all targets, and$P_{1k}^\rho = 1$. We calculate P_{1k} in Eq. (4) to choose the biggest value that may be P_{1j}. Then target j is the target of agent 1. The number to target j in the recorder adds 1.
(3) The rest can be deduced by analogy. Finally, the target of every agent is determined.

4. Potential functions

In this section, two simple models of potential functions are set up, and the definitions of collective potential function and repulsive potential function are given, respectively, according to the different actions during the moving of agents. Compared with the existing studies, the models of potential functions set up in this paper have fewer parameters.

Table 1
Values of P_{ik}^d.

D_i	$D_{i1} \geqslant D_{i2} \geqslant \cdots \geqslant D_{im}$
P_{ik}^d	$1/m \quad 2/m \quad \cdots \quad 1$