Multi-Agent Based Adaptive Swarm Robotics Control in Dynamically Changing and Noisy Environments*

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During the past decades, the coordination of multi-robot systems has become a special focus of research due to the growing number of their applications. Formally, a collection of large number of autonomous mobile robots working together is termed as a swarm of mobile robots. Such systems are faced with various tasks including flocking, which we focus on in this paper. The flocking problem is described as forming of large groups of individuals moving together toward a common target location. We study the possibility of multi-agent technologies application to this problem and propose a consensus-based algorithm to control a swarm in dynamically changing and noisy environments. A simulation is presented to validate the effectiveness of the suggested method.

Keywords: multi-agent technologies, flocking, adaptive control, swarm control, swarm intelligence, local voting protocol, self-organizing systems.

1. Introduction

The technology of multi-agent systems is a new paradigm of IT, focused on sharing of technological and technical achievements and the benefits that the opportunities and methods of artificial intelligence, hardware and software support for distribution and openness. In this connection, we see now actively developing methods for the formation and construction of complex adaptive systems based on multi-agent techniques and technologies [1]. Such systems are often used to control the ensembles (swarms; flocks) of dynamic plants [2], performing a common task or a task with multiple objectives under conditions of significant uncertainties. Such systems use robotic devices as actuators for different purposes. They may act simultaneously in three environments: on the ground (fixed, wheeled and tracked device) under water (miniature unmanned submarines) and air (drones, UAVs).

During the past decades, the coordination of multi-robot systems has become a special focus of research due to the growing number of their applications in unmanned autonomous vehicles, spacecraft, sensor networks, etc. [3–5]. Indeed, there are many potential advantages of such systems over a single robot, including scalability, flexibility and robustness. One of the paradigms behind the cooperative robotic control is based on biological inspirations such as the collective motion of animal social groups (e.g. schools of fish, bird flocks, mammal herds).

Swarm intelligence is a widely observed natural phenomena, which can lead simple agents (robots) interacting locally with each another and with their environment without centralized control to arising an emergent global behaviour. A typical swarm consists of a large number of homogeneous agents with limited abilities compared to the difficulty of the collective objectives. Swarm robotics systems are faced with a various tasks including aggregation, flocking, foraging, object clustering and sorting, navigation, path finding, self-deployment, collaborative manipulation, and so on [6, 7]. In this article we focus on the flocking problem, which is also known as coordinated motion, which means to form large groups of individuals moving together toward a common target location. In practice, understanding a process of flocking in animal groups can help develop many artificial autonomous systems such as formation control of unmanned air vehicles, motion planning of mobile robots, and scheduling of automated highway systems.

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Literature review: Reynolds developed a distributed behavioral model for animal flocks, herds, and schools [8, 9]. He presented three rules by which decisions are made by agents using information only from their nearest neighbors. Reynolds' rules are: collision avoidance (avoid collisions with neighbors); velocity matching (match speed and direction of motion with neighbors); flock centering (stay close to neighbors). Later, in [10] the authors simulated self-propelled particles behaviour in phase transition and showed that by using nearest neighbor interaction rules their motion changes from disoriented to ordered. The Vicsek's model has become a general approach to theoretical research on complex systems.

In [11] a flocking problem was generalized as a network consensus problem. This problem on graphs with noisy measurements of its neighbours states under general imperfect communications is considered in [12,13], where stochastic approximation-type algorithms with decreasing to zero step size are used. Noisy convergence with non-vanishing step size was studied in [14], but the step parameters were chosen differently for different agents and the network scenario considered is a specific one. The stochastic gradient-like (stochastic approximation) methods have also been used in the presence of stochastic uncertainties [11, 15–17]. For the linear case without feedback in stochastic network the problem of achieving an approximate consensus was considered in [18].

M. Huang in [19] proposed a stochastic approximation type algorithm for solving consensus problem and justified for the group of cooperating agents that communicate with imperfect information in discrete time, under the conditions of dynamic topology and delay. Under some general assumptions a necessary and sufficient condition was proved for the asymptotic mean square consensus when step size tends to zero and only with a sufficiently simple dynamics. However, under time-varying environment (e.g., feeding new jobs) using step sizes that decrease to zero may greatly affect convergence. In [20], the authors focus on a more general case of nonlinear functions, which describe dynamics of agents, and nondecreasing to zero step sizes.

Statement of contributions: Despite a large number of publications, satisfactory solutions have been obtained mostly for a restricted class of problems. Factors such as presence of noise, delays and another similar uncertainties in measurements of agents' states may significantly complicate the solutions. As discussed in the latest Vicsek's model analysis [21], the collective behavior of self-organized systems is affected by noise through the interplay of deterministic laws and randomness. The authors showed that under noisy conditions self-organized systems can spontaneously produce turn, vortex, bifurcation, and flock merging phenomena. Therefore, it is important to minimize the effects of noise to improve system stability. In this paper, we propose a generalized consensus-based control algorithm of swarm of agents and assess its performance using simulations. To solve the flocking problem under uncertain conditions, we adopt stochastic approximation, which was studied for stochastic networks in [20]. In contrast to the existing stochastic approximation-based swarm control algorithms, local voting protocol with noisy measurements is described. In [22] authors considered the flocking problem in a noisy environment, however they used a modification of Olfati-Saber's algorithm [23].

Organization: The rest of this paper is organized as follows: In Section II, the problem statement is described, and basic concepts of a graph theory that are used hereinafter are introduced. In Section III, the floacking control strategy is considered. In Section IV, we present the results of simulations. Section V contains conclusions.

2. Problem formulation

Consider a system composed of $N = \{1, 2, \ldots, n\}$ agents (robots) with discrete-time dynamics. The agents move in the m-dimensional space (e.g., $m = 2, 3$) with the same speed but with different headings. At each time instant $t \in [0, T]$ the motion of each agent $i \in N$ is described by the following characteristics:

- q_t^i is the potential function that defines the possibility of completion of the goal s while maintaining the heading x_t^i. For instance, with a determined direction to the target s_t^i for an agent i in the moment of time t we assume that $q_t^i = q_t^i(x_t^i) = \langle x_t^i, s_t^i \rangle$;

- $x_t^i \in R$ is the heading of agent i at time instant t;
- $p_t^i \in R^m$ is the position of agent i at time instant t.

Here and below, an upper index of agent i is used as a corresponding number of an agent (not as an exponent).

We assume that the agents can communicate with each other. The communication graph can be represented by an undirected graph $G = (V, E)$ with the vertex set $V = \{1, ..., N\}$ and the edge set $E \subseteq V \times V$ where $(i, j) \in E$ if and only if agents i and j can communicate. Let two agents i and j can communicate when their relative Euclidean distance is smaller than certain radius R, i.e., $\|p_t^i - p_t^j\| \leq R$. We associate a weight $a^{i,j} > 0$ with each edge $(j, i) \in E$. A graph can be represented by *an adjacency matrix* $A = [a^{i,j}]$ with weights $a^{i,j} > 0$ if $(j, i) \in E$, and $a^{i,j} = 0$ otherwise. Assume, that $a^{i,i} = 0$. Let $N^i = \{j : a^{i,j} > 0\}$ be a "neighbors" set of agent $i \in N$, $|N^i|$ is a corresponding number of "neighbors".

The operator supplies each agent $i \in N$ with a potential map, which provides the directions required to achieve mission objectives. However, the agents do not have information about the presence of obstacles along the way. As they move, each agent creates its own potential map of the world based on sensors data, computer vision methods, information received from its neighbors, etc.

Each agent while determining the direction of motion tries to choose a route so as to avoid collisions. For example, it is possible to define a function $\varphi(x_t^i)$, which shifts the direction in a random fashion in case of an agent i detecting an obstacle in the heading x_t^i at a distance closer than r.

Our goal is to show that for any initial set of agent headings, the headings of all agents will converge to the same steady state value x_s despite the presence of obstacles along the way.

3. Distributed control protocol

In this section, we describe a distributed flocking control rule in the dynamically changing and noisy environment based on local voting protocol [24]. We assume that each agent senses its own heading (possibly noisy), and each agent can obtain its neighbors heading (possibly noisy) via sensing or message broadcasting.

Let each agent $i \in N$ at a specific time t has an observation (possibly noisy) of its own heading:

$$y_t{}^{i,i} = g_t^i + \omega_t{}^{i,i}, \tag{1}$$

$$g_t^i = q_t^i x_t^i, \tag{2}$$

and, if $N_t^i \neq 0$, noisy and delayed measurements of its neighbors headings:

$$y_t{}^{i,j} = g^j{}_{t-h_t{}^{i,j}} + \omega_t{}^{i,j}, j \in N_t^i, \tag{3}$$

where $\omega_t{}^{i,j}, \omega_t{}^{i,i}$ are interference (noise), and $0 \leq h_t{}^{i,j} \geq \overline{h}$ is the integer delay, $\overline{h}$ is the maximum possible delay. A heading vector of an agent is multiplied by its current potential value. Assume $\omega_t{}^{i,j} = 0$ and $h_t{}^{i,j} = 0$ for all other pairs (i, j), for which they were not defined. As the system stars its work with $t = 0$, then the implicit requirement for the neighbors is: $j \in N_t^i \to t$ - $h_t{}^{i,j} > 0$.

Local voting protocol application to consensus based multi-agent control problem:

$$u_t^i = \alpha \sum_{j \in \overline{N_t^i}} b_t^{i,j} (y_t^{i,j} - y_t^{i,i}), \tag{4}$$

where α is a step size of control protocol, $\overline{N_t^i} \subset N_t^i, b^{i,j} > 0 \; \forall j \in \overline{N_t^i}$. Let $b_t^{i,j} = 0$ for other pairs (i, j).

Dynamics of changes in the heading of the agent is described by the difference equation:

$$x^i_{t+1} = x^i_t + f(u^i_t, x^i_t) \tag{5}$$

with the control $u^i_t \in R$, the impact of which to the change of heading x^i_t is defined by some function $f(\cdot,\cdot) : R \times R \to R$, which forms the final control in accordance with the procedure of collision avoidance.

The proof of algorithm efficiency (5) under fairly general conditions of statistical uncertainties can be done the same way as in [24].

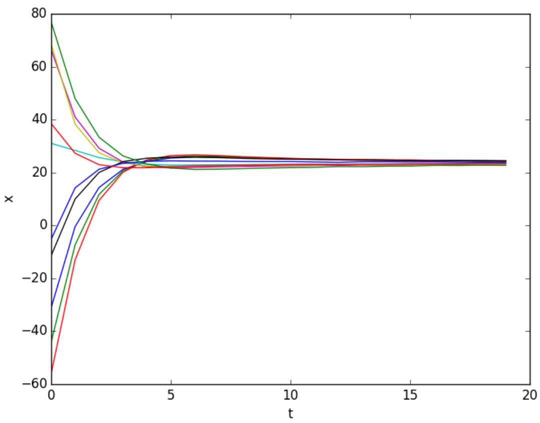
4. Simulation

To show the effectiveness of the proposed control protocol (4), we present the simulation results with a swarm of 10 and 20 agents. At the time $t = 0$, the agents are randomly distributed in a region $[50 \times 50]$. The communication distance is $R = 50$, and we assume that the communication graph is initially connected. We also assume that the headings vary in the interval $[-180; 180]$. An initial value of headings is chosen in a random fashion. Observations of the current headings were made with the backdrop of centered i.i.d noise from the interval $[-0.5; 0.5]$.

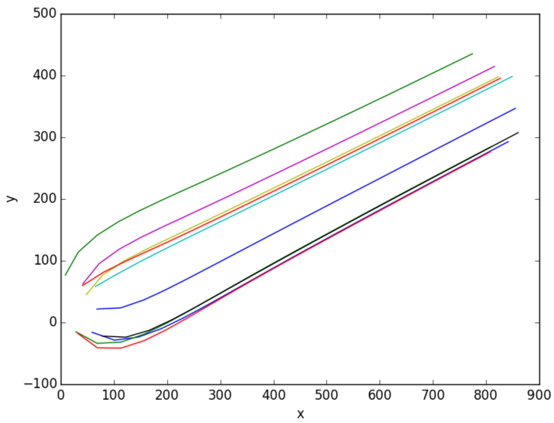
The scenario is to synchronize the headings of the agents, so that the swarm can move in the desired direction. At time step t each agent is provided with its potential value. We use cosine similarity measure between the heading x^i_t of the agent i and the desired direction x_s to calculate the potential value q^i_t as follows:

$$q^i_t = 1 - arccos(\frac{\langle x^i_t, x_s \rangle}{||x^i_t|| \cdot ||x_s||}) \cdot \frac{1}{180} \tag{6}$$

In Fig. 1 and 2 each line indicates how the headings x^i_t evolve over time. These lines also show how the system evolves to reach consensus. During the simulation we have set the coefficient $\alpha = 0.1$.



a)

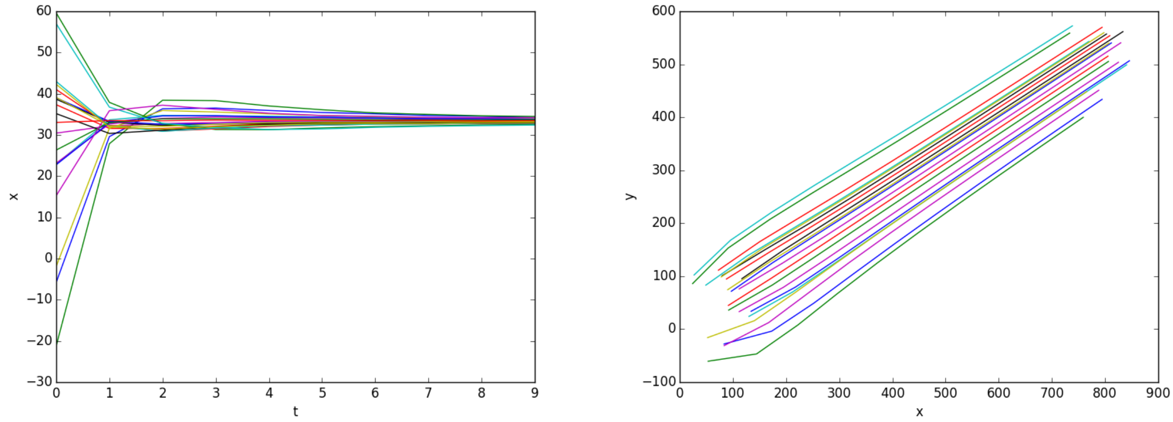


b)

Figure 1. (a) Consensus of headings in a swarm of 10 agents; (b) Motion consensus in (x,y)-plane

5. Conclusions

Finally, we would like to note that control and robotic solutions based on smart embedded systems, equipped with a set of sensors, which act in a group under uncertain conditions and



a) b)

Figure 2. (a) Consensus of headings in a swarm of 20 agents; (b) Motion consensus in (x,y)-plane

control of which is based on described above multi-agent principles could be successfully used for:

- active monitoring of integrity, efficiency, security of critical facilities and networks;
- operational management of incidents in all three environments (land, under water and in the air) with role and local task redistribution in the course of ongoing monitoring and decision-making to solve the common problem.

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