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Distributed estimation and control for mobile sensor networks with coupling delays

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ABSTRACT

This paper deals with the issue of distributed estimation and control for mobile sensor networks with coupling delays. Based on the Kalman-Consensus filter and the flocking algorithm, all mobile sensors move to a target to increase the quality of gathered data, and achieve consensus on the estimation values of the target in the presence of time-delay and noises. By applying an effective cascading Lyapunov method and matrix theory, stability analysis is carried out. Furthermore, a necessary condition for the convergence is presented via the boundary conditions of feedback coefficients. Some numerical examples are provided to validate the effectiveness of theoretical results.

1. Introduction

Most recently, a great research attention has been paid on sensor networks, which are composed of several sensors with limited capabilities of data gathering, communication, and computation [1,2]. Due to features of low cost, tiny size, mobility and flexibility, mobile sensor networks have extremely high advantages in applications like target tracking, information processing, and surveillance systems [3–9].

In particular, Olfati-Saber and Jalalkamai have proposed a mobile target tracking method via a combination of a flocking algorithm and the Kalman-Consensus filtering protocol [10]. Flocking is a ubiquitous phenomenon in nature exhibited by flocking of birds, schooling of fish, swarming of bacteria and so forth [11,12]. It portrays the collective behavior derived from interacting individuals using only limited local environmental information and has been continuously studied for its potential application in multi-agent coordination control such as unmanned air vehicles, mobile robots and sensor networks [13,14]. On the other hand, Kalman-Consensus filter is a kind of recursive filter broadly applied in dynamical networks, which can accurately estimate the states from a series of measurements that contain noises [15]. In fact, the problem of distributed estimation and control for mobile sensor networks in [10] has been well solved by a flocking algorithm, in which the measurement of the leader for each mobile sensor is not accurate due to noise interference.

Considering the constrained speed of transmission or spreading together with communication congestions, time-delay is inevitable in control system and it would degrade performance or even result in instability. A great number of literatures focus on its negative effects and corresponding solutions. Experiment results about the states of coupled optoelectronic oscillators with varied time-delays are available in [16]. Issues of time-delay in different control situations like Takagi-Sugeno fuzzy systems [17] and multi-variable systems [18] have been investigated. It is noted that few works about flocking have studied with time-delay up to now [19–22]. In [19], Lu et al. have presented a flocking algorithm for double-integrator multi-agent systems with an active virtual leader and time-delay. In [20], Yang et al. have considered the flocking of multi-agent systems in the presence of time-delay for both leader-free and leader-present scenarios. Delay-dependent rendezvous and flocking of large-scale multi-agent systems in the presence of communication delays have been investigated in [21]. In [22], Hu et al. have studied the flocking in multi-agent systems with nonholonomic wheeled agents and a large communication delay via a distributed low gain feedback control algorithm.

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In this study, we consider the distributed estimation and control for mobile sensor networks with coupling delays. Compared with the highly related existing results, the contribution of this study lies in two aspects. First, this paper extends the previous research results on distributed estimation and control for mobile sensor networks [10] to a more practical situation, that is, the case with coupling delays. Second, compared with the previous literatures on the flocking with a leader and time-delay [19–22], the measurements of the state of the leader are different for all mobile sensors and time-delay exists in the nonlinear couplings.

The remainder of this paper is organized as follows. Section 2 describes preliminaries on graph theory and the problem concerned. Section 3 states the main estimation and control algorithm. Section 4 presents a series of numerical examples to illustrate the effectiveness of the theoretical results. Section 5 concludes the paper and gives discussion on future works.

Notations: Through out this paper, I_m is the $m \times m$ identity matrix, and 1_n stands for $n \times 1$ column vector of all ones. Let diag $(A_1, A_2, \ldots, A_p)$ be the diagonal matrix with A_i, $i = 1, 2, \ldots, p$ on the diagonal position. $\lambda_i(A)$ means the ith eigenvalue of matrix A, while $\lambda_{min}(A)$ and $\lambda_{max}(A)$ are, respectively, the minimum and maximum eigenvalues of the matrix A. $\otimes$ refers to the Kronecker product and $\| \cdot \|$ represents the Euclidean norm.

2. Preliminaries and problem formulation

2.1. Preliminaries

Conventionally, we use $\mathbb{G} = \{\mathbb{V}, \mathbb{E}\}$ to represent the communication topology among N nodes, where $\mathbb{V} = \{1, 2, \ldots, N\}$ is a nonempty finite set of nodes and $\mathbb{E} \subseteq \mathbb{V} \times \mathbb{V}$ is an edge set describing the information exchange. If an edge $(i, j) \in \mathbb{E}$, it means that there is an information flow from node i to node j, that is, node j can directly get information from node i. We exclude the circumstance of self-connection, i.e., $(i, i) \notin \mathbb{E}$. If an edge $(i, j) \in \mathbb{E}$ means the edge $(j, i) \in \mathbb{E}$ simultaneously, the corresponding graph is called undirected graph, otherwise, it is said to be directed. The neighbors set of node i is defined as $N_i = \{j \in \mathbb{V} \mid (i, j) \in \mathbb{E}\}$. A path from node i to node j is a sequence of edges: $(i, v_1), (v_1, v_2), \ldots, (v_{k-1}, v_k), (v_k, j)$, where $v_l \in \mathbb{V}$ for $1 \le l \le k$. The undirected graph is called connected if there is a path between any two nodes.

The adjacency matrix $\mathbb{A} = [a_{ij}] \in R^{N \times N}$ related to undirected graph $\mathbb{G}$ is defined as

$$a_{ij} = \begin{cases} 1, \text{if } j \in N_i, \\ 0, \ \text{otherwise}. \end{cases}$$

The Laplacian matrix $\mathbb{L} = [l_{ij}] \in R^{N \times N}$ associated with $\mathbb{G}$ is defined as

$$l_{ij} = \begin{cases} \sum_{j \in N_i} a_{ij}, \text{if } i = j, \\ -a_{ij}, \ \text{otherwise}. \end{cases}$$

It is well known that $\mathbb{L}$ has eigenvalues ordered as $0 = \lambda_1(\mathbb{L}) \le \lambda_2(\mathbb{L}) \le \cdots \le \lambda_N(\mathbb{L})$. Further, if $\mathbb{G}$ is connected, $\lambda_2(\mathbb{L})$ is the smallest nonzero eigenvalue.

2.2. Problem formulation

Consider a mobile sensor network composed of N sensors labeled as $1, 2, \ldots, N$, and one target moving in an n-dimensional Euclidean space. The dynamics of the ith sensor is described by

$$\begin{cases} \dot{q}_i(t) = p_i(t), \\ \dot{p}_i(t) = u_i(t), \quad i = 1, 2, \ldots, N, \end{cases} \tag{2.1}$$

where q_i, $_{pi}$, $u_i \in R^n$ are the position vector, velocity vector, and control input of the ith sensor, respectively.

The mobile target has the following dynamics:

$$\dot{x}(t) = Ax(t) + B\omega(t), \quad x(t) \in R^d, \tag{2.2}$$

and sensor agents measure the target with the dynamics

$$z_i(t) = H_i x(t) + v_i(t), \quad z_i(t) \in R^m, \quad i = 1, 2, \ldots, N, \tag{2.3}$$

in which A, B and H_i are of appropriate dimensions, $\omega(t)$ and $v_i(t)$ are input zero-mean Gaussian noise and measurement zero-mean Gaussian noise, respectively. In practice, $\omega(t)$ primarily results from the embedded microprocessors in the sense of electron devices such as thermal noise, shot noise and induction noise, while $v_i(t)$ is generated by unreliable sensing environment. Both of them can corrupt the control performance, but fortunately the distributed Kalman-Consensus filter proposed in [10] achieves unbiased estimation.

Our main task in this paper is to design an effective estimation and control algorithm so as to achieve the flocking of mobile sensor networks with coupling delays, and guarantee achieving consensus on target estimates by all mobile sensors.

3. Main results

In [10], Olfati-Saber and Jalalkamai have proposed a continuous Kalman-Consensus filtering (KCF) algorithm on mobile sensor networks described in the following and have demonstrated its validity and feasibility theoretically.

Theorem 3.1. [10] *Consider a sensor network with a continuous-time linear sensing model in (2.3).Suppose that each node applies the following distributed estimation algorithm*

$$\begin{cases} \dot{\hat{x}}_i = A\hat{x}_i + K_i(z_i - H_i\hat{x}_i) + \mu P_i \sum_{j \in N_i} (\hat{x}_j - \hat{x}_i) \\ K_i = P_i H_i^T R_i^{-1}, \quad \mu > 0 \\ \dot{P}_i = AP_i + P_i A^T + BQB^T - K_i R_i K_i^T \end{cases} \tag{3.4}$$

with a Kalman-Consensus estimator and initial conditions $P_i(0) = P_0$ and $\hat{x}_i(0) = x(0)$. Then, the collective dynamics of the estimation errors $\eta_i = x - \hat{x}_i$ (without noise) is a stable linear system with a Lyapunov function $\hat{V}(\eta(t)) = \sum_{i=1}^{N} \eta_i^T(t) P_i^{-1} \eta_i(t)$. Moreover, $\dot{V}(\eta(t)) \le -2\mu[\eta^T(t)(\mathbb{L}(t) \otimes I_m(\eta(t)] \le -2\mu \min(\lambda_2(\mathbb{L}(t))) \|\eta(t)\|^2$, where $\min(\lambda_2(\mathbb{L}(t)))$ is the minimum value of $\lambda_2(\mathbb{L}(t))$.

In the above estimation algorithm, $\hat{x}_i$ denotes the estimated value on target from sensor i, z_i is the measurement value of the target, μ signifies the feedback coefficient from neighbor sensors, $_{Pi}$ stands for estimate state covariance matrices, and Q, R_i are respectively the variance matrices of random vector ω, v_i.

Remark 3.1. In [10], Olfati-Saber and Jalalkamai have proposed an information value of sensor measurement and have proved that the aggregate information value improves as emergence of flocking, thus the flocking algorithm is information-driven. In this paper, we reserve the definition of information value $I_i = f(\rho_i)$ to depict the information-driven flocking algorithm, where ρ_i denotes the distance between the sensor i and the target.

Assumption 3.1. Suppose that the communication topology of sensor networks is initially connected.

Define that every sensor agent shares the same limited sensing radius r_0, then $\mathbb{E}$ (hence $\mathbb{G}$) is time-varying as topology evolution. Here the frequently-used connectivity-preserving rules [23] are adopted to maintain the connectivity of the proximity graph. The time-varying set of links among mobile sensors is denoted by $\mathbb{E}(t) = \{(i, j) | i, j \in \mathbb{V}\}$ which follows the rules below.