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Research Article

Consensus of Multiagent Networks with Intermittent Interaction and Directed Topology

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Intermittent interaction control is introduced to solve the consensus problem for second-order multiagent networks due to the limited sensing abilities and environmental changes periodically. And, we get some sufficient conditions for the agents to reach consensus with linear protocol from the theoretical findings by using the Lyapunov control approach. Finally, the validity of the theoretical results is validated through the numerical example.

1. Introduction

The problem of coordinating the motion of multiagent networks has attracted increasing attention. Research on multiagent coordinated control problems not only helps in better understanding the general mechanisms and interconnection rules of natural collective phenomena but also carries out benefits in many practical applications of networked cyber-physical systems, such as tracking [1], flocking [2, 3], and formation [4]. Consensus, along with stability [5] and bifurcation [6], is a fundamental phenomenon in nature [7]. Roughly speaking, consensus means that all agents in network will converge to some common state by negotiating with their neighbors. A consensus algorithm is an interaction rule on how agents update their states.

To realize consensus, many effective approaches were proposed [8–10]. Since the network can be regarded as a graph, the issues can be depicted by the graph theory. The recent approaches concentrate on matrix analysis [11], convex analysis [12, 13], and graph theory [14]. The concept of spanning tree especially is widely used to describe the communicability between agents in networks that can guarantee the consensus [15]. For more consensus problems, the reader may refer to [16–21] and the references therein.

As we know, sometimes only the intermittent states of its neighbors can be obtained by the agents to the transmission capacity, communication cost, sensing abilities, and the environmental changes. To decrease the control cost, only the intermittent states of its neighbors are obtained [22]. This is mainly because such networks are constrained by the following operational characteristics: (i) they may not have a centralized entity for facilitating computation, communication, and timesynchronization, (ii) the network topology may not be completely known to the nodes of the network, and (iii) in the case of sensor networks, the computational power and energy resources may be very limited. Inspired by the above consideration, the goal in this setting is to design algorithms by exploiting partial state sampling at each node; it is possible to reduce the amount of data which needs to be transmitted in networks, thereby saving bandwidth and energy, extending the network lifetime, and reducing latency. Also, the linear local interaction protocol can guarantee the linear nature of distributed multiagent networks in real world and linear algorithm is simple and easy to implement so as to be widely used in practical engineering especially in the limited transmission environment. Using the Lyapunov control approach, some sententious conditions are obtained in this paper for reaching consensus in multiagent networks.

The rest of this paper is organized as follows. In Section 2, some preliminaries on the graph theory and the model formulation are given. The main results are established in Section 3. In Section 4, a numerical example is simulated to verify the theoretical analysis. Concise conclusions are finally drawn in Section 5.

2. Preliminaries and Model

2.1. Graph Theory. In this subsection, some basic concepts and result of algebraic grapy theory are introduced. Suppose that information exchange among agents in multiagent networks can be modeled by an interaction digraph.

Let $g = (V, \varepsilon, A)$ denote a directed graph with the set of nodes $V = \{1, 2, \ldots, N\}$, where $\varepsilon \subseteq V \times V$ represents the edge set and $A = (a_{ij})_{N\times N}$ is the adjacency matrix with nonnegative elements a_{ij}. A directed edge ε_{ij} in the network g is denoted by the ordered pair of nodes (i, j), where i is the receiver and j is the sender, which means that node i can receive information from node j. We always assume that there is no self-loop in network g. An adjacency matrix A of a directed graph can be defined such that a_{ij} is a nonnegative element if $\varepsilon_{ij} \in \varepsilon$, while $a_{ij} = 0$ if $\varepsilon_{ij} \notin \varepsilon$. The set of neighbors of node i is denoted by $N_i = \{j \in V : (i, j) \in \varepsilon\}$. A sequence of edges of the form $(i, j_1), (j_1, j_2), \ldots, (j_m, j) \in \varepsilon$ composes a directed path beginning with i and ending with j in the directed graph g with distinct nodes j_k, $k = 1, 2, \ldots, m$, which means the node j is reachable from node i. A directed graph is strongly connected if for any distinct nodes i and j, there exists a directed path from node i to node j. A directed graph has a directed spanning tree if there exists at least one node called root which has a directed path to all the other nodes [16]. Let (generally nonsymmetrical) Laplacian matrix $L = (l_{ij})_{N\times N}$ associated with directed network g be defined by

$$l_{ij} = \begin{cases} \sum_{k=1,k\neq i}^{N} a_{ik}, & i = j, \\ -a_{ij}, & i \neq j, \end{cases} \tag{1}$$

which ensure the diffusion property $\sum_{j=1}^{N} l_{ij} = 0$. Suppose L is irreducible. Then, $L1_N = 0_N$ and there is a positive vector $\xi = (\xi_1, \xi_2, \ldots, \xi_N)^T$ satisfying $\xi^T L = 0_N$ and $\xi^T \mathbf{1}_N = 1$. In addition, there exists a positive definite diagonal matrix $\Xi = \mathrm{diag}(\xi_1, \xi_2, \ldots, \xi_N)$ such that $\overline{L} = (\Xi L + L^T \Xi)/2$ is symmetric and $\sum_{j=1}^{N} \overline{L}_{ij} = \sum_{j=1}^{N} \overline{L}_{ji} = 0$ for all $i = 1, 2, \ldots, N$ [18].

For simplicity, some mathematical notations are used throughout this paper. $I_n(O_n)$ denotes the identity (zero) matrix with n dimensions. Let $\mathbf{1}_n(\mathbf{0}_n)$ be the vector with all n elements being 1(0). R^n is the n-dimensional real vector space. The notation $\otimes$ denotes the Kronecker product.

2.2. Model Description. The discretization process of a continuous-time system cannot entirely preserve the dynamics of the continuous-time part even small sampling period is adopted. So, we consider the following second-order multiagent networks of N agents in [19] with intermittent measurements. The ith agent in the directed network g is governed by double-integrator dynamics

$$\begin{aligned} \dot{x}_i(t) &= v_i(t), \\ \dot{v}_i(t) &= d(t)\left(\sum_{j=1,j\neq i}^{N} a_{ij}\left(x_j(t) - x_i(t)\right)\right. \\ &\quad \left. + \kappa \sum_{j=1,j\neq i}^{N} a_{ij}\left(v_j(t) - v_i(t)\right)\right), \\ &\qquad i = 1, 2, \ldots N, \end{aligned} \tag{2}$$

where $x_i(t) \in R^n$ and $v_i(t) \in R^n$ are the position and velocity states of the ith agent, respectively. κ denotes the coupling strengths. $d(t)$ denotes the intermittent control as follows:

$$d(t) = \begin{cases} 1, & t_0 + k\varpi < t \leq t_0 + k\varpi + \delta, \\ 0, & t_0 + k\varpi + \delta < t \leq t_0 + (k+1)\varpi, \end{cases} \tag{3}$$

where $\varpi > 0$ is the control period and $\delta > 0$ is called the control width.

Equivalently, model (2) can be rewritten as follows:

$$\begin{aligned} \dot{x}_i(t) &= v_i(t), \\ \dot{v}_i(t) &= -d(t)\left(\sum_{j=1}^{N} l_{ij} x_j(t) + \kappa \sum_{j=1}^{N} l_{ij} v_j(t)\right), \\ &\qquad i = 1, 2, \ldots, N. \end{aligned} \tag{4}$$

In this paper, our goal is to design suitable ϖ, δ such that the network reaches consensus. In the following we present the following lemma and definitions.

Lemma 1 (see [23]). *Suppose that $M \in R^{n\times n}$ is positive definite and $N \in R^{n\times n}$ is symmetric. Then $\forall x \in R^n$, and the following inequality holds:*

$$\lambda_{\max}\left(M^{-1}N\right) x^T M x \geq x^T N x \geq \lambda_{\min}\left(M^{-1}N\right) x^T M x. \tag{5}$$

Definition 2 (see [18]). Let ξ, Ξ, and $\overline{L}$ be defined as in Section 2.1. For a strongly connected network with Laplacian matrix L, let

$$a(L) = \min_{x^T\xi=0, x\neq 0} \frac{x^T \overline{L} x}{x^T \Xi x}, \qquad b(L) = \max_{x^T\xi=0, x\neq 0} \frac{x^T \overline{L} x}{x^T \Xi x}. \tag{6}$$

Definition 3. Periodic intermittent consensus in the second-order multiagent networks (2) is said to be achieved if, for any initial conditions,

$$\begin{aligned} \lim_{t\to\infty} \left\| x_i(t) - x_j(t) \right\| &= 0, \\ \lim_{t\to\infty} \left\| v_i(t) - v_j(t) \right\| &= 0, \quad \forall i, j = 1, 2, \ldots, N. \end{aligned} \tag{7}$$

3. Main Results

In this section, we will focus on consensus analysis of second-order multiagent networks via intermittent control in the strongly connected networks, simply for that a matrix G is irreducible if and only if its corresponding system G is strongly connected [24].

Let $\overline{x} = \sum_{k=1}^{N} \xi_k x_k(t)$, $\overline{v} = \sum_{k=1}^{N} \xi_k v_k(t)$ represent the average position and velocity of agent. Naturally, $\widehat{x}_i(t) = x_i(t) - \overline{x}$ and $\widehat{v}_i(t) = v_i(t) - \overline{v}$ represent the position and velocity vectors relative to the average position and velocity of the agents in network. Then the error dynamical system can be rewritten in a compact matrix form as

$$\dot{y}(t) = \left(\widehat{L} \otimes I_n\right) y(t), \tag{8}$$

where $\widehat{L} = \begin{pmatrix} 0_N & I_N \\ -\alpha d(t) L & -\beta d(t) L \end{pmatrix}$.

Theorem 4. *Suppose that the agent network is strongly connected; then the linear consensus in the multiagent networks* (2) *via periodic intermittent interaction is achieved if the following conditions are satisfied:*

(1) $a(L) > 1/\kappa^2$,

(2) $\gamma(\varpi - \delta) + \eta\delta < 0$, $\gamma > 0$, $\eta < 0$,

where

$$\gamma = 2\lambda_{\max}\left(B^{-1}E\right) > 0, \qquad \eta = 2\lambda_{\max}(C)/\lambda_{\max}(D) < 0,$$
$$B = \begin{pmatrix} 2\kappa a(L)\Xi & \Xi \\ \Xi & \kappa\Xi \end{pmatrix}, \qquad C = \begin{pmatrix} -a(L)\Xi & O_N \\ O_N & \Xi - \kappa^2 a(L)\Xi \end{pmatrix},$$
$$D = \begin{pmatrix} 2\kappa b(L)\Xi & \Xi \\ \Xi & \kappa\Xi \end{pmatrix},$$
$$E = \begin{pmatrix} O_N & (\kappa/2)\left(\Xi L + L^T\Xi\right) \\ (\kappa/2)\left(\Xi L + L^T\Xi\right) & \Xi \end{pmatrix}. \tag{9}$$

Proof. The potential Lyapunov function is defined to be

$$V(t) = \frac{1}{2}y^T(t)\left(\Omega \otimes I_n\right)y(t), \tag{10}$$

where $\Omega = \begin{pmatrix} 2\kappa\overline{L} & \Xi \\ \Xi & \kappa\Xi \end{pmatrix}$. Computing by the Definition 2, one obtains

$$\begin{aligned} V(t) &= \frac{1}{2}\hat{x}^T(t)\left(\left(2\kappa\overline{L}\right)\otimes I_n\right)\hat{x}(t) + \frac{1}{2}\hat{x}^T(t)\left((\Xi)\otimes I_n\right)\hat{v}(t) \\ &\quad + \frac{1}{2}\hat{v}^T(t)\left((\Xi)\otimes I_n\right)\hat{x}(t) + \frac{1}{2}\hat{v}^T(t)\left((\kappa\Xi)\otimes I_n\right)\hat{v}(t) \\ &\geq \frac{1}{2}y^T(t)\left(B\otimes I_n\right)y(t), \\ V(t) &\leq \frac{1}{2}y^T(t)\left(D\otimes I_n\right)y(t), \end{aligned} \tag{11}$$

where $B = \begin{pmatrix} 2\kappa a(L)\Xi & \Xi \\ \Xi & \kappa\Xi \end{pmatrix}$, $D = \begin{pmatrix} 2\kappa b(L)\Xi & \Xi \\ \Xi & \kappa\Xi \end{pmatrix}$.

$B > 0$ is equivalent to $\Xi > 0$ and $2\kappa a(L)\Xi - (1/\kappa)\Xi > 0$ by Schur Complement Lemma. And it is clear that $a(L) > 1/2\kappa^2$; thus $B > 0$. So $V(t) \geq 0$ and $V(t) = 0$ if and only if $y = 0$.

Because the control gain $d(t)$ works intermittently by the control period and the control width, the consensus is discussed in the two different intervals, respectively.

Firstly, for $t_0 + k\varpi < t \leq t_0 + k\varpi + \delta$ and $\widehat{L} = \begin{pmatrix} 0_N & I_N \\ -L & -\kappa L \end{pmatrix}$, taking the derivative of $V(t)$ along the trajectories of (8), it can be obtained that

$$\dot{V}(t) = \frac{1}{2}y^T(t)\left[\left(\Omega\widehat{L} + \widehat{L}^T\Omega\right)\otimes I_n\right]y(t). \tag{12}$$

In addition,

$$\begin{aligned} \Omega\widehat{L} &= \begin{pmatrix} 2\kappa\overline{L} & \Xi \\ \Xi & \kappa\Xi \end{pmatrix}\begin{pmatrix} O_N & I_N \\ -d(t)L & -\kappa d(t)L \end{pmatrix} \\ &= \begin{pmatrix} -\Xi L & 2\kappa\overline{L} - \kappa\Xi L \\ -\kappa\Xi L & \Xi - \kappa^2\Xi L \end{pmatrix}, \\ \widehat{L}^T\Omega &= \begin{pmatrix} -L^T\Xi & -\kappa L^T\Xi \\ 2\kappa\overline{L} - \kappa L^T\Xi & \Xi - \kappa^2 L^T\Xi \end{pmatrix}. \end{aligned} \tag{13}$$

Thus, one obtains that

$$\frac{\Omega\widehat{L} + \widehat{L}^T\Omega}{2} = \begin{pmatrix} -\overline{L} & O_N \\ O_N & \Xi - \kappa^2\overline{L} \end{pmatrix}. \tag{14}$$

Therefore, from (12) to (14), one obtains

$$\dot{V}(t) \leq \|y\|^T C\|y\|, \tag{15}$$

where $C = \begin{pmatrix} -a(L)\Xi & O_N \\ O_N & \Xi - \kappa^2 a(L)\Xi \end{pmatrix}$.

Using $a(L) > 1/\kappa^2$ in condition (2), C is a negative-definite matrix.

Thus,

$$\dot{V}(t) \leq \lambda_{\max}(C)\, y^T(t)\, y(t), \quad \left(\lambda_{\max}(C) < 0\right). \tag{16}$$

And, on the other hand,

$$\begin{aligned} V(t) &= \frac{1}{2}y^T(t)\left(\Omega\otimes I_n\right)y(t) \leq \frac{1}{2}y^T(t)\left(D\otimes I_n\right)y(t) \\ &\leq \frac{1}{2}\lambda_{\max}(D)\, y^T(t)\, y(t). \end{aligned} \tag{17}$$

Consequently,

$$\begin{aligned} \dot{V}(t) &\leq \eta V(t), \quad \eta = \frac{2\lambda_{\max}(C)}{\lambda_{\max}(D)} < 0, \\ & t_0 + k\varpi < t \leq t_0 + k\varpi + \delta. \end{aligned} \tag{18}$$

Thus, we can obtain

$$V(t) \leq V\left(t_0 + k\varpi\right)e^{\eta(t - t_0 - k\varpi)}, \quad t_0 + k\varpi < t \leq t_0 + k\varpi + \delta. \tag{19}$$

Then let us consider the period $t_0 + k\varpi + \delta < t \leq t_0 + (k+1)\varpi$. For $\widehat{L} = \begin{pmatrix} O_N & I_N \\ O_N & O_N \end{pmatrix}$, we can derive

$$\begin{aligned} \dot{V}(t) &= y^T(t)\left(\Omega\otimes I_n\right)\left[\left(\widehat{L}\otimes I_n\right)y(t)\right] \\ &= \frac{1}{2}y^T(t)\left[\left(\Omega\widehat{L} + \widehat{L}^T\Omega\right)\otimes I_n\right]y(t), \end{aligned} \tag{20}$$

where

$$\begin{aligned} \Omega\widehat{L} &= \begin{pmatrix} 2\kappa\overline{L} & \Xi \\ \Xi & \kappa\Xi \end{pmatrix}\begin{pmatrix} O_N & I_N \\ O_N & O_N \end{pmatrix} = \begin{pmatrix} O_N & 2\kappa\overline{L} - \kappa\Xi L \\ O_N & \Xi \end{pmatrix}, \\ \widehat{L}^T\Omega &= \begin{pmatrix} O_N & O_N \\ 2\kappa\overline{L}^T & \alpha\Xi \end{pmatrix}. \end{aligned} \tag{21}$$

Then,

$$\frac{\Omega\widehat{L}+\widehat{L}^T\Omega}{2}=\begin{pmatrix} O_N & \kappa\overline{L} \\ \kappa\overline{L}^T & \Xi \end{pmatrix}. \tag{22}$$

Based on the above, one obtains

$$\dot{V}(t)\le y^T(t)Ey(t), \tag{23}$$

where $E=\begin{pmatrix} O_N & (\kappa/2)(\Xi L+L^T\Xi) \\ (\kappa/2)(\Xi L+L^T\Xi) & \Xi \end{pmatrix}$.

From Lemma 1, we obtain

$$\begin{aligned}\dot{V}(t)&\le y^T(t)Ey(t)\le\lambda_{\max}\left(B^{-1}E\right)y^T(t)By(t)\\&\le 2\lambda_{\max}\left(B^{-1}E\right)V(t).\end{aligned} \tag{24}$$

We set $\gamma=2\lambda_{\max}(B^{-1}E)>0$, so as to obtain

$$\begin{aligned}&V(t)\le V\left(t_0+k\varpi+\delta\right)e^{\gamma(t-t_0-k\varpi-\delta)},\\&t_0+k\varpi+\delta<t\le t_0+(k+1)\varpi.\end{aligned} \tag{25}$$

Now, we can obtain from (19) and (25) that

$$\begin{aligned}V\left(t_0+(k+1)\varpi\right)&\le V\left(t_0+k\varpi+\delta\right)e^{\gamma(\varpi-\delta)}\\&\le V\left(t_0+k\varpi\right)e^{\gamma(\varpi-\delta)+\eta\delta}\\&\le\cdots\le V\left(t_0\right)e^{[\gamma(\varpi-\delta)+\eta\delta](n+1)}.\end{aligned} \tag{26}$$

It is clear that there is a constant $n_0\ge 0$ satisfying $t_0+n_0\varpi<t\le t_0+(n_0+1)\varpi$ for any $t>t_0$. Thus we get that for $t_0+n_0\varpi<t\le t_0+n_0\varpi+\delta$,

$$\begin{aligned}V(t)&\le V\left(t_0\right)e^{\eta(t-t_0-n_0\varpi)}e^{[\gamma(\varpi-\delta)+\eta\delta]n_0}\\&\le V\left(t_0\right)e^{[\gamma(\varpi-\delta)+\eta\delta]n_0}\\&=V\left(t_0\right)e^{-[\gamma(\varpi-\delta)+\eta\delta]}e^{[\gamma(\varpi-\delta)+\eta\delta](n_0+1)}\\&\le V\left(t_0\right)e^{-[\gamma(\varpi-\delta)+\eta\delta]}e^{(-(\gamma(\varpi-\delta)+\eta\delta)/\varpi)t_0}e^{((\gamma(\varpi-\delta)+\eta\delta)/\varpi)t}\end{aligned} \tag{27}$$

and for $t_0+n_0\varpi+\delta<t\le t_0+(n_0+1)\varpi$,

$$\begin{aligned}V(t)&\le V\left(t_0\right)e^{\gamma(t-t_0-n_0\varpi-\delta)}e^{[\gamma(\varpi-\delta)+\eta\delta]n_0}\\&\le V\left(t_0\right)e^{((\gamma(\varpi-\delta)+\eta\delta)/\varpi)[\varpi(n_0+1)+t_0-t_0]}\\&\le V\left(\ t_0\right)e^{-((\gamma(\varpi-\delta)+\eta\delta)/\varpi)t_0}e^{((\gamma(\varpi-\delta)+\eta\delta)/\varpi)t}.\end{aligned} \tag{28}$$

Hence, let $K=V(t_0)e^{-[\gamma(\varpi-\delta)+\eta\delta]}e^{-((\gamma(\varpi-\delta)+\eta\delta)/\varpi)t_0}$, and we can conclude the following from the above analysis:

$$V(t)\le Ke^{((\gamma(\varpi-\delta)+\eta\delta)/\varpi)t},\quad t>t_0, \tag{29}$$

which means that the states of agents can achieve consensus. The proof is complete. □

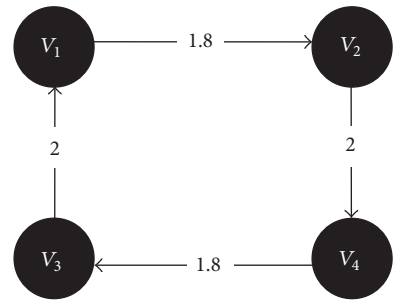

Figure 1: The directed interaction topology of multiagent networks.

4. Numerical Simulations

A multiagent network of four agents is considered as the simulation example. The multiagent network topology is described by a directed network g shown in Figure 1. It can be seen that the network is strongly connected.

Let $\kappa=2$ and $n=3$. With simple calculations, we obtain the $a(L)=1.8>1/\kappa^2$, $\eta=-2.1204$, and $\gamma=3.5980$. From condition (3), we obtain $\delta/\varpi>0.6292$. So if we set $\delta=0.07$ and $\varpi=0.1$, second-order consensus can be achieved in system (2). The initial position and velocity values of agents are $x_1=(3,1,-3)^T$, $x_2=(6,2,-6)^T$, $x_3=(-5,3,-9)^T$, $x_4=(9,4,-12)^T$, $v_1=(2,3,-2)^T$, $v_2=(-5,6,3)^T$, $v_3=(1,-4,2)^T$, and $v_4(3,4,-5)^T$, respectively. Figure 2 shows the linear consensus of position and velocity states of four agents with intermittent control.

5. Conclusions

In this paper, we have considered the linear consensus of multiagent networks with periodic intermittent interaction and directed topology. We choose to show the consensus with linear local interaction protocols, partly for simplifying the problem. On the other hand, it is simple and easy to implement so as to be widely used in practical engineering. The tools from algebraic graph theory, matrix theory, and Lyapunov control approach have been adopted. It is shown that the consensus is determined commonly by the general algebraic connectivity, control period, and control width. And the states of agents converge exponentially.

Conflict of Interests

The author declares that there is no conflict of interests regarding the publication of this paper.

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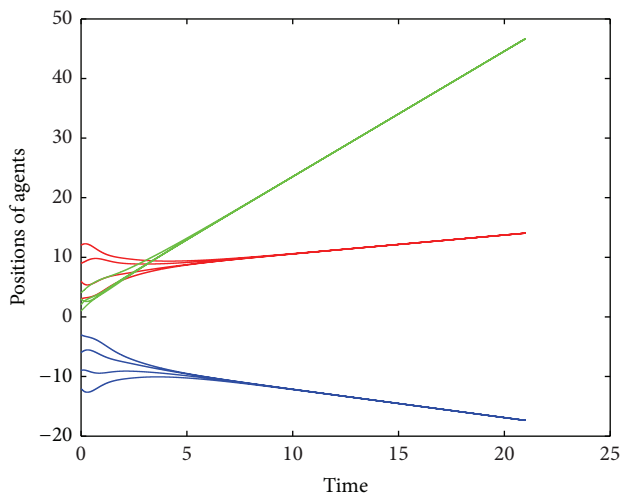
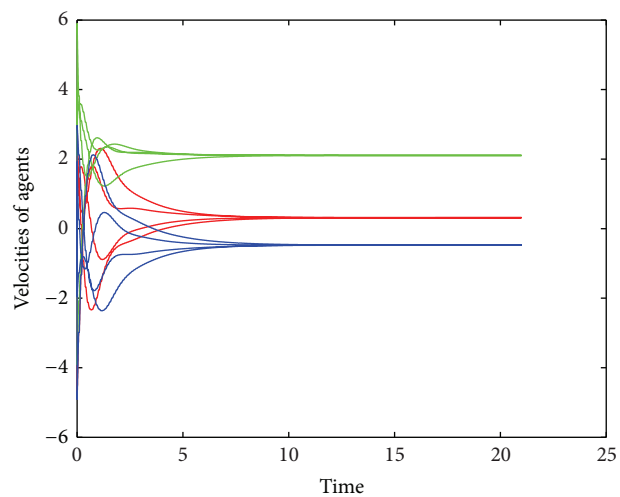


(a)



(b)

Figure 2: Position and velocity states of four agents in the network.

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