Stability of linear multiagent systems with guaranteed steady-state performance
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Abstract—Gradual advancement of control technology gives rise to the studies of the stability of linear systems. The stability of the linear multiagent system is motivated by increasing utilization of agent dynamics together with the number of control protocols associated with each agent. To that respect, in this report, the idea of event-triggered control and the stability of the linear multiagent system under steady-state performance conditions will be presented. By applying a steady-state condition, the state of an agent in the closed-loop linear system will be discussed using fixed network topology both in discrete-time and continuous-time. Moreover, the system is also analyzed via employing the Lyapunov function methods, and then an average consensus of will also be realized. Finally, we will verify the system's average consensus and stability via a simulation example.

Keywords: stabilization, multiagent system, Laplacian matrix, steady-state performance, Lyapunov function method, average consensus.
1. Introduction

The rapid development of computer technology, such as the advent of embedded systems, can be observed in the last few decades. This means that the discrete-time has reached its highest level. The advantages of these analog devices are that they are small and flexible, reduce energy consumption, and save installation costs. In this way, they become part of a wide range of applications. For discrete-time systems, only the sampling signal at the instant of the discrete-time is used, even if it is difficult to select the appropriate sampling interval. For these small and highly integrated embedded systems, the limited space in the power modules meant that the energy supply could not be inexhaustible.

Moreover, recent technological advances in computing and communication resources have facilitated distributed control of large multiagent systems. More recent references [1] and [2] show some results on coordinated multiagent control. Consensus or consensus algorithm [3], [4], [5], formation control [6-9].

Traditionally, the system used a timed control method to adjust the actuator state at each sample time. Such time-controlled adjustment mechanisms can cause significant and frequent changes in the actuator state, leading to unnecessary energy consumption and actuator damage. Therefore, various researchers have been studying event-driven control mechanisms to overcome these shortcomings. This means that in event-driven control mechanisms, the agent is modulated after the system meets certain conditions specified in the control system. In other words, each agent's control protocol changes after each agent's state approach a particular measurement or condition. In this case, stable system performance and energy utilization efficiency are guaranteed. Consider an event-driven control issue where an agent is kept at the agent state at specific state intervals over time. This means that the agent's control signal is triggered only when the states are separated by a given interval. Otherwise, the agent dynamics (state and controller) do not change.

The resulting model of the system can be converted into a time-delay system with different delays between agents and its neighbor. This is in contrast to the first-order response models with constant delay [10-11] and the first-order response models with varying delays that do not consider self-delay. Consider the state of the agents or the equal delay between each agent and its neighbors [12]. Note that in the absence of self-delay, convergence is guaranteed even with heterogeneous delays and asynchronous updates [13].

Author [14] provided a systematic stabilization approach for closed nonlinear systems with output control error dynamics. It is affected by nonlinear rational numbers with steady-state and internal
conditions. Since the output error dynamics were eliminated via the differential algebra form, a numerical optimization technique was implemented to take into account the controller design parameters under the inequality of the bilinear matrix. The event-triggered control of the stabilization technique can be used for the small gain theorem. This indicates that the controlled system has certain characteristics of input-to-state stability (ISS). Therefore, the author [15] proposed a new event-driven control mechanism for stabilization technology. This requires the control system to achieve a certain level of input state stability, and the proposed method is output control of a linear system. The main purpose of introducing both the event-triggered control strategy and stability theory of the system is that to reduce the error among communication channels of the states of each agent. In that case, a considerable system performance such as stabilization and consensus agreement will be reached.

2. Preliminaries

2.1. Algebraic Graph Theory

For a directed communication graph \( G = (V, E, A) \) with \( N \) number of connected nodes (agents), the adjacency matrix of the \( A = A(G) = (a_{ij}) \), where \( A \) is an \( NxN \) matrix with \( a_{ij} = 1 \) if the node \( j \) is a neighbor of node \( i \) and there is a connected edge between them and \( a_{ii} = 0 \), \( V = \{1, ..., N\} \) and \( E \subseteq V \times V \), is the node-set of edges of the graph. The set of the neighbors of the node \( i \) is denoted by \( Ni = \{ j \in V \mid (j, i) \in E \} \) where \( i \) and \( j \) are neighbors to each other. It has been considered that \( |Ni| \) is the cardinality of the set \( Ni \). If all the elements of graph \( G \) are non-isolated or there is a path between any vertices (i.e., \( i = j \) there is a cycle), the graph is connected.

For a directed graph(digraph), \( G \) is said to be strongly connected if and only if all the nodes have an equal number of incoming and outgoing information signals among the communication graph. For the nodes of graph \( G \), if there exists node \( i \) that has the direct edges to all the other neighboring nodes(vertices), graph \( G \) has characteristics of a spanning tree.

The given interaction topology \( G \), the Laplacian matrix of the digraph, will be given by

\[
l_{ij} = \begin{cases} 
-a_{ij}, & \text{if } j \neq i \\
\left|N_i\right|, & \text{if } j = i 
\end{cases}
\] (1)

The degree matrix of the corresponding communication graph \( G \) is indicated by \( \Delta = diag\{d1, d2, ..., dN\} \), where \( di = \sum_{j=1}^{N} a_{ij} \) is the total number of the incoming neighboring information signal to the nodes \( i \) or agent \( i \). From the weighted adjacency matrix, \( A \), and the
corresponding diagonal matrix of the in-degree matrix, the Laplacian matrix of graph $G$ will be characterized as follows.

$$L = \Delta - A$$  \hspace{1cm} (2)

For a directly connected graph, the Laplacian matrix has one single zero eigenvalue with one $v = 1^T = (1,1,\ldots,1)^T$ left eigenvector. The corresponding eigenvalues of the Laplacian matrix $L$ are given by $0 = \lambda_1(G) \leq \lambda_2(G) \leq \lambda_3(G) \leq \cdots \leq \lambda_N(G)$ and all the nonzero real eigenvalues of the matrix $L$ is positive ($\lambda_2(G) \geq 0$).

The distributed control linear multiagent system (MAS) considered in this paper includes an $N$ intelligent group of agents named from 1 to $N$. Each agent in this regard is a single integrator dynamic, and these agents communicate with each other to meet at the desired point of common interest-driven and triggered by appropriate control protocol. Event-trigger control is a mechanism that has been employed to update or trigger the control protocol whenever the state of the closed-loop system reaches its predefined threshold value. The typical, predefined value is displayed as the equilibrium point or the average state value of the initial information state of each agent under the given communication networks. In order to achieve consensus among the networked agents, the infinite triggering of the controller in short instants of time will be neglected. This common characteristic of agent dynamics to facing a frequent triggering in instants of time is called Zeno-behavior. In this work, we assume that the Zeno-behavior is ignored, and the network dynamics achieved consensus agreement cooperatively. Early literature [16] based on this event condition did not consider a strategy for recurring event checking. Every time the system meets the requirements, the state of each agent will be updated. That means once the state of each agent is too close to a certain value, the state of the agent will be broadcast in a distributed fashion. In that case, all the agents in the network access the status of their neighbor, and they update their state as well. In this configuration, each agent is equipped with an event detector that periodically evaluates the event trigger state. If this condition is violated, the current status of agent $i$ should be updated and broadcast.

**A. Assumption:** The interaction graph $G = (V,E,A)$ is assumed to be directed, weighted, strongly connected, and has a spanning tree.

**2.2. Model setup**

The distributed linear closed-loop multiagent system is given by a dynamic equation

$$\dot{x}_i(t) = u_i(t), \quad i = 1,2,\ldots,N$$  \hspace{1cm} (3)
\[ u_i = -\sum_{j \in N_i} a_{ij}(x_i(t) - x_j(t)) \]  

(4)

Where the \( x_i(t) \in R \) is the state of agent \( i \) and \( u_i(t) \in R \) is a control protocol corresponding to agent \( i \). The strongly connected digraph \( G \) is said to achieve consensus if and only if \( \lim_{t \rightarrow \infty} |x_i(t) - x_j(t)| = 0 \), \( i, j = 1, 2, ..., N \), \( x_i(t) \) is state of agent \( i \), and \( x_j(t) \) is state of neighboring agent \( i \) (i.e., state of agent \( j \)). Therefore, for any agents state starts from the initial state \( x_i(0) \), the system is asymptotically stable, and it is converged to its average initial state. Using the matrix theory, the general dynamics equation of the closed-loop system for the (3) and a control law (4), will be given in terms of the Laplacian matrix \( L \) where \( x(t) = (x_1(t), ..., x_N(t))^T \) and \( \dot{x}(t) = (\dot{x}_1(t), ..., \dot{x}_N(t))^T \) as shown in equation (5).

\[ \dot{x}(t) = u \]  

(5)

\[ u = -Lx(t) \]  

(6)

The disagreement among the state measurements of the closed-loop system is calculated by measuring the difference between the last broadcasted state of agent \( i \), \( \bar{x}_i(t) \) and the current state of agent \( i \), \( x_i(t) \) to be \( \delta_i(t) \). Moreover, the closed-loop system of the (5) and the last broadcasted state of agent \( i \) will be given by (7) and (8), respectively.

\[ \delta_i(t) = \bar{x}_i(t) - x_i(t) \]  

(7)

\[ \dot{x}(t) = -L\bar{x}(t) \]  

(8)

Let an error \( e(t) = [e_1(t), ..., e_N(t)]^T \) and substituting error equation in (8), we will get

\[ \dot{x}(t) = -L(x(t) + \delta(t)) \]  

(9)

So, if the Laplacian matrix \( L \) satisfies the assumption given in (2.1). A, and the matrix \( L \) is a positive semidefinite together with all its none zero eigenvalues are greater than zero and can be indicated as \( 0 = \lambda_1 \leq \lambda_2 \leq \lambda_3 \leq ... \leq \lambda_N \). For both undirected and directed graphs, the zero is a simple eigenvalue of the Laplacian matrix, with \( 1_N \) eigenvector. The common property of \( L \) is that the sum of all the entries of each row of \( L \) is equal to zero, where \( 1_N \) is the column vector, which has all its entries are equal to 1.

\[ L1^T = \lambda_1 = 0 \]
Let the dynamics of the disagreement function in (7) and (8) between states of each agent, $x_i(t) \rightarrow 1^T \alpha$, as $t \rightarrow \infty$ and is given by

$$1^T \alpha = \frac{\sum_{j=1}^{N} x_i(0)}{N}$$

(10)

$$\dot{\delta} = -L \dot{x}(t) = -L(x(t) + \delta(t))$$

(11)

Then, substituting the for $x_i(t) \rightarrow 1^T \alpha$ into (10), where $\alpha$ is the average of the initial states of all the agents, the dynamics equation of the disagreement vector is given by

$$\dot{\delta} = -L \dot{x}(t) = -L(1^T \alpha + \delta(t)) = -L1^T \alpha - L\delta(t), \quad L1^T \alpha = 0$$

(12)

The main objective of the disagreement vector in the situation is to reduce the exploitation of communication networks (i.e., $\delta \rightarrow 0$). The solution of the dynamic equation (12) is $\|\delta(t)\| = \|\delta(0)\| e^{-L t}$, the proof of the continuous-time consensus problem in (10) is illustrated by

$$\lim_{t \rightarrow \infty} \delta(t) = \lim_{t \rightarrow \infty} e^{-L t} \delta(0) = 1^T \delta(0)$$

From the proof above, then, as time goes by, an error function converges to its initial value, and in the case of the initial error measurement for the states of each agent (7) $\delta_i(0) = \bar{x}_i(0) - x_i(0) = 0$, the system converges to its equilibrium point, which satisfies that the system is asymptotically stable.

3. System stability analysis

When discussing the stability of a closed-loop system, this includes a particular level of performance that the system can achieve under certain conditions or design parameters. Ultimately, the main purpose of designing a controller in a control design is to achieve a certain level of closed-loop system performance. This closed control loop system can be divided into a time-invariant system and a time-invariant system. A time-invariant system is a system that relies on an external time-invariant signal, but a time-invariant system does not change over time. The stability of a nonlinear control loop system depends on its equilibrium point (origin). It is also categorized as overall stability, asymptotic stability, and global asymptotic stability to support stable system performance ideas. The steady-state performance of highly networked nonlinear systems is based on stabilization, tuning, and synchronization issues. A nonlinear closed-loop system with equilibrium points at the origin, zero control input, and absorption of specific disturbances, the
system reaches exact stabilization when the system is asymptotically stable globally at the equilibrium point. The network state of a closed-loop system begins with the initial state in the convergent region of the system. Over time, the state of the system gradually converges to the equilibrium point or origin point. In this case, stabilization of the nonlinear system is easy to achieve. In [17,], to investigate the global stabilization of neutral and stable linear closed-loop control using actuator saturation, we proposed event-triggered linear feedback control. When evaluating the history of system status, control inputs, and event-driven controls, the status of the system can converge to an equilibrium state. This ensures that global asymptotic stabilization is achieved over time.

Let us recall the control protocol in (4)

\[ s_i = -u_i = \sum_{j \in N_i} a_{ij}(x_i(t) - x_j(t)) \]  

(13)

Let us consider the Lyapunov function of the form

\[ V = \frac{x^T L x}{2} \]  

(14)

Where \( V \geq 0 \). The Lyapunov function \( V = 0 \), if and only if \( x = 0 \) is the equilibrium point of the dynamic equation (1), then \( V \) is positive semidefinite. So, in this regard, the system is said to be stable if all the nonzero eigenvalues of the matrix \( L \) are positive and where \( L \) is the Laplacian matrix of the communication graph \( G \). The dynamics of the Lyapunov function via incorporating (9) into derivative of (14) is given as follows:

\[ \dot{V} = \frac{x^T L (Lx) + x^T L x}{2} = \frac{x^T L (Lx) + x^T L (Lx + L\delta)}{2} = \frac{-s_i^T s_i - \frac{s_i^T L \delta}{2}}{2} < 0 \]

Where \( s_i = Lx \), and \( s_i^T = x^T L \), from the dynamics of the Lyapunov function, \( \dot{V} < 0 \), indicating that the \( \dot{V} \) is negative semidefinite, which verify that is the sufficient condition of the linear multiagent system holds, and the asymptotic stability is achieved.

Based on the assumption section (2.1). A, in the case of the strongly connected graph, the information states of each agent concentrate on the average of the initial states of each agent. Considering Lemma 1 [18]: for closed-loop system (8), the agent's average information state remains constant, which proved that the linear system achieved consensus with the convergence value is the average of all agent's initial state. In general, the steady-state property of the linear
multiagent system is defined as the analysis of the system's stability[19-21], output regulation, and output synchronization. However, in this article, we will be focused only on the stability of the linear closed-loop system under fixed topology, time-varying, and both continuous-time and discrete-time.

The proof of (10) using continuous-time interval:

Let us take $\bar{x}(t)$ be the average state and be expressed as follows.

$$\bar{x}(t) = \frac{\sum_{i=1}^{N} x_i(t)}{N}$$

By taking derivative, both sides give,

$$\dot{\bar{x}}(t) = \frac{\sum_{i=1}^{N} \dot{x}_i(t)}{N} = -\frac{1}{N} L \bar{x}(t)$$

Using the property of the Laplacian matrix, $1_N^T L = 0$, then we will find that $\dot{\bar{x}}(t) = 0$. This terminology verifies that the state of the system is time-invariant, and therefore

$$\bar{x}(t) = \bar{x}(0) = \frac{\sum_{i=1}^{N} x_i(0)}{N}$$

Let us consider an agent dynamic with continuous-time and discrete-time below:

$$\dot{x}(t) = f(x(t), 0, t), \text{ continuous-time} \quad (17)$$

$$x(k + 1) = f(x(k), 0, k), \text{ discrete-time} \quad (18)$$

For the agent dynamics (17) and (18), considering $\bar{x} = 0$, is the equilibrium point of the (17) and (18) if and only if $\dot{x}(t) = f(\bar{x}(t), 0, t) = 0$, and $x(k + 1) = f(\bar{x}(k), 0, k) = \bar{x}$.

Proof: if $f(\bar{x}) = 0$, then $\bar{x} = f(x)$. Demonstrating this concept, let use the stack disagreement vector (7), and verify the proof of this terminology.

$$\delta(t) = \bar{x}(t) - x(t)$$

$$\dot{\delta}(t) = \dot{x}(t) - \dot{x}(t) = \dot{x}(t) - 0 = f(\bar{x}(t), 0, t)$$

$$= f(\delta(t) + x(t), 0, t) \rightarrow \text{new function } g$$

$$= g(\delta(t), 0, t), \text{ where } x(t) = 0$$

$$\Rightarrow g(0, 0, t) = f(x(t), 0, t) = 0$$

where $\delta(t) = 0$ validate that the function $g$ has an equilibrium point at $\delta(t) = 0$. Generally, for a linear closed-loop system with guaranteed steady-state performance, the state trajectory of the
system converges to an equilibrium point or the origin point, satisfying that the system is stable. We have also employed a Lyapunov function method to ensure the asymptotic stability of this linear multiagent system. After all, the linear system achieved an average consensus with the consensus value, which is equal to the average of all the agent's initial states. For a multiagent system that achieves average consensus, if all the initial states of each agent are zero, then the system achieves the average consensus at its equilibrium point. Thus, the linear system satisfies the assumption provided in section (2.1). A, then the system is asymptotically stable and also achieved stabilization. The term stabilization realizes the overall system performance in the existence of external disturbances with a predefined appropriate control protocol to meet a certain level of system performance.

4. Simulation results

In this section, we illustrate the simulations of the distributed linear multiagent system to show the efficiency of the presented methods and ensure both stability and consensus agreement among the networked agents. For this purpose, we consider a weighted, directly connected and network with fixed topology satisfying (1), whose network topology is given in Figure 1. As depicted in Figure 1, the communication topology has 1,…,6 agents that are strongly connected digraph and a balanced graph that has a spanning tree. The agents are randomly distributed among the connected graph.

![Figure 1: Directed communication graph](image-url)

Therefore, the corresponding weighted adjacent matrix, degree matrix, and Laplacian matrix of the given topology will be given below.

$$A = \begin{bmatrix}
0 & 1 & 1 & 0 & 0 & 1 \\
0 & 0 & 1 & 1 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 1 & 1 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 \\
\end{bmatrix}$$
Applying the network dynamics (1) and the control protocol (2), we will use two cases. The discrete-time control protocol for this simulation will be issued by incorporating the (1), (2), and (21).

\[
\Delta = \begin{bmatrix}
3 & 0 & 0 & 0 & 0 & 0 \\
0 & 2 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 3 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

\[
L = \Delta - A = \begin{bmatrix}
3 & -1 & -1 & 0 & 0 & -1 \\
0 & 2 & -1 & -1 & 0 & 0 \\
-1 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & -1 & 3 & -1 & -1 \\
0 & 0 & 0 & -1 & 1 & 0 \\
0 & -1 & 0 & 0 & 0 & 1
\end{bmatrix}
\]

Applying the network dynamics (1) and the control protocol (2), we will use two cases. The discrete-time control protocol for this simulation will be issued by incorporating the (1), (2), and (21).

\[
\dot{x}_i = \lim_{\Delta t \to \infty} \frac{x_i((K + 1)\Delta t) - x_i(k\Delta t)}{\Delta t} = u_i(k\Delta t) \quad (21)
\]

From equation (21), we will get a discrete-time agent I state trajectory by

\[
x_i(k + 1) = x_i(k) + u_i(k).\Delta t \quad (22)
\]

In (23) and (24), the state trajectories and control protocols for each agent have been depicted.

\[
\begin{cases}
x_1(k + 1) = x_1(k) + u_1(k).\Delta t \\
x_2(k + 1) = x_1(k) + u_2(k).\Delta t \\
x_3(k + 1) = x_2(k) + u_3(k).\Delta t \\
x_4(k + 1) = x_3(k) + u_4(k).\Delta t \\
x_5(k + 1) = x_4(k) + u_5(k).\Delta t \\
x_6(k + 1) = x_5(k) + u_6(k).\Delta t \\
\Delta t \geq 0
\end{cases}
\]
\[
\begin{align*}
    u_1 &= -(3x_1(k) - (x_2(k) + x_3(k) + x_6(k))) \\
    u_2 &= -(2x_2(k) - (x_3(k) + x_4(k))) \\
    u_3 &= -(x_3(k) - x_1(k)) \\
    u_4 &= -(3x_4(k) - (x_3(k) + x_5(k) + x_6(k))) \\
    u_5 &= -(x_5(k) - x_4(k)) \\
    u_6 &= -(x_6(k) - x_2(k))
\end{align*}
\]

In case one, we demonstrate the stability of the system with zero initial information state of each agent, and in case two, the average consensus of the multiagent system will be analyzed via selecting random numbers for each agent’s initial state.

**Case 1:** The stability of the linear multiagent system is analyzed by employing the state of all agents starting from initial states converge to zero as time goes by. \( x_i(t) \rightarrow 0 \), in continuous-time and \( x_i(k) = 0 \), in discrete-time. Then, the average of the initial states of each agent, in this case, will \( \text{Average} = \frac{\sum_{j=1}^{6} x_i(0)}{6} = 0 \), (CT), and \( \text{Average} = \frac{\sum_{j=1}^{6} x_i(1)}{6} = 0 \), (DT) and the simulation time is 15 seconds.

![State trajectories of communication networks](image)

Figure 2: State trajectories of six agents

From Figure 2, it was shown that the average consensus of the multiagent system is achieved, and the
consensus value is an equilibrium point of all agent states. The convergence rates of each agent are also significantly high, which allows all states to converge to zero in almost 2 seconds. So, this linear multiagent system satisfies the predefined state dynamics and control protocol. The system is stable at its origin.

**Case 2:** The linear closed-loop multiagent system is said to achieve stabilization if and only if each state of all agents starting from its initial values converge to a certain common value or agreed trajectory, then the linear system achieved average-consensus problem satisfying together with stabilization. To that respect, the initial states are taken randomly from random distribution. The simulation of state trajectories of each agent was performed in 15 seconds, and results will be shown below.

![State trajectories of communication networks](image)

**Figure 3:** State trajectories of six agents

![Command Window](image)

**Figure 4:** Results of the average initial states and final state values of each agent
As can see from Figures 3 and 4, the state's trajectories of each agent starting from random initial states converged to its agreed trajectory or the average initial information states. Consequently, the system achieved average consensus.

5. Conclusions
In this paper, the stability of a linear multiagent system with guaranteed steady-state performance is analyzed. Distributed control of the closed-loop system was realized utilizing a single integrator dynamic and an appropriate control protocol. A controller, in this case, performed well that the system is able to achieve both an average consensus and stabilization. Basically, a common steady-state performance of a closed-loop system characterizes the system's stability. Additionally, the stability of the system, in general, is demonstrated via applying Lyapunov function methods, and it has been proved that a linear system with fixed communication topology and satisfying the given assumption could become stable at the origin and asymptotically stable as well. Generally, the overall system analysis was verified by a simulation example.

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