

# Iterative Learning Consensus Control for Multi-Agent Systems under Independent Position and Velocity Topologies

Jiaxian Wang Lin Zhang Junmin Li Jinsha Li

School of Mathematics and Statistics, Xidian University, Xi'an 710071, PRC  
E-mail: jmli@mail.xidian.edu.cn

**Abstract:** In this paper, we propose an iterative learning control (ILC) for the consensus of multi-agent systems in a very general framework where the position and velocity interactions among agents are modeled by independent graphs. A class of distributed consensus protocol is constructed as iterative learning algorithm. Assuming that the leader node is globally reachable under independent position and velocity topologies, a sufficient condition to guarantee the multi-agent consensus is derived for the directed communication topologies. Further, the proposed scheme is also extended to achieve the formation control for the multi-agent systems. Simulation results are finally presented to illustrate the performance and effectiveness of our iterative learning protocol.

**Key Words:** multi-agent systems; double-integrator dynamics; consensus algorithm; iterative learning control; formation control; independent position and velocity interactions.

## 1 INTRODUCTION

Over the past decades, the multi-agent system has been being a representative that is used to describe and analyze complex interconnecting behaviors of autonomous individuals. Some important research issues involve the problems of consensus, flocking, formation, rendezvous, coverage and swarming, whose common task is to develop distributed schemes or protocols to ensure the realization of complicated global goals.

Consensus is well accepted as a fundamental paradigm for coordination of multi-agent system, and numerous studies have been published. Based on the algebraic graph theory, Saber and Murray (2003) and Saber and Murray (2004) discussed the consensus problem for networks of the single-integrator agents. With simple linear consensus protocols, the agreements of agents were achieved under the assumption of strong connectivity of digraphs. Later multi-agent systems with double-integrator dynamics were paid great attentions because of their importance in practice. For example, the unmanned aerial vehicles and underwater vehicles are adjusted for their desired motion directly by their acceleration rather than their speed. Ren and Beard (2005) and Ren (2008) generalized the results of Saber and Murray (2004) and presented condition for the double-integrator dynamics with topology of directed networks. Recently, the consensus issue has received increasing attention with many profound results established in Saber, Fax and Murray (2007), Qin and Gao (2012), Li, Liu, Ren and Xie (2013a), Li, Ren, Liu and Fu (2013b).

However, almost all of the existing works concerning double-integrator agents are formulated based on the assumption that the position and velocity interactions among agents are modeled by the same digraph. Qin and

Yu (2013) considered the position and velocity interaction topologies are modeled by independent graphs. And most people may ask what the practical application significance of independent position and velocity topologies is. Actually, in real applications, some interactions existing among agents may be used while the others may be neglected in order to optimize the coordination behavior or reduce the computational complexity. Moreover, it can also reduce the rate of information interception.

On the other hand, iterative learning control (ILC) has been widely employed for the tracking control of periodic dynamic systems. By generating a correct control signal from the previous control execution, it can achieve perfect tracking performance on the finite time interval (Ahn, Chen and Moore 2007). Recently, ILC has been applied to the multi-agent system in Li and Li (2013) and Su and Huang (2012) and Li and Li (2012). And especially the group of Jia, a series of articles were published, Meng and Jia (2012) and Meng, Jia, Du and Yu (2012) considered the ILC approaches to design finite-time consensus protocols for multi-agent systems and tracking control over a finite interval for multi-agent systems, respectively. Liu and Jia (2012), Meng and Jia (2014) and Meng and Jia (2014) considered formation control problem for multi-agent systems by ILC. Different from the ILC literature above, we will study a new problem with ILC.

With this inspiration, the iterative learning control (ILC) for multi-agent systems in a very general framework where the position and velocity interactions among agents are modeled by independent graphs will be considered at the first time. Then, a sufficient condition to guarantee the multi-agent consensus is derived for the independent position and velocity topologies.

The subsequent sections are organized as follows. Some preliminaries and the problem statement are detailed in Section 2. ILC schemes for multi-agent consensus problems and formation control problems are proposed in

---

This work is supported by National Nature Science Foundation under Grant 61573013

Sections 3 and 4, respectively. Illustrative examples are provided in Section 5 to demonstrate the effectiveness of our theoretical findings. Finally, conclusions are drawn in Section 6.

## 2. Preliminaries and problem formulation

### 2.1 Preliminaries

The interactions among agents can be modeled by a weighted directed graph (digraph). Let  $G = (V, \mathcal{E}, A)$  be a weighted graph consisting of a node set  $V = \{1, 2, \dots, N\}$ , a set of edges  $\mathcal{E} \in V \times V$ , and a weighted adjacency matrix  $A = [a_{ij}] \in R^{N \times N}$ , which is defined as  $a_{ij} > 0$  if  $(j, i) \in \mathcal{E}$  and  $a_{ij} = 0$  otherwise. Moreover, we assume  $a_{ii} = 0$  for all  $i \in V$ . The Laplacian matrix  $L = [l_{ij}]$  of a weighted graph is defined by

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

Leader-following multi-agent dynamics will be studied in this paper, let  $D = \text{diag}\{d_1, d_2, \dots, d_N\}$  be a diagonal matrix where  $d_i > 0$  if there exists a directed edge from node 0 to node  $i$  in  $G$  and  $d_i = 0$  otherwise. We mean  $\bar{G}$  as an induced digraph from  $G$  and matrix  $D$ , i.e.,  $\bar{G}$  is the digraph comprising  $G$ , node 0, and the directed edges from 0 to the nodes in  $G$ .

In what follows,  $G_p = (V, \mathcal{E}_p, A_p = [a_{ij}])$  and  $G_v = (V, \mathcal{E}_v, A_v = [b_{ij}])$  are employed to represent, respectively, the position and velocity interaction topologies; the Laplacian matrices of  $G_p$  and  $G_v$  are denoted by  $L_p$  and  $L_v$ , respectively. Furthermore, from the previous section, we let  $\bar{G}_p$  be the digraph induced from  $G_p$  and  $D_p$ ; and  $\bar{G}_v$  from  $G_v$  and  $D_v$ .

**Lemma 1:** (Hu and Hong 2007) The matrix  $H = L + D$  is positive stable if and only if the leader node 0 is globally reachable in  $\bar{G}$ .

**Remark 1:** From the Lemma 1, we can easily get that all the eigenvalues of  $H$  have positive real parts, that is to say  $H$  is a nonsingular matrix.

**Assumption 1:** The leader (that is, node 0) is globally reachable in  $\bar{G}_p$  and  $\bar{G}_v$ .

**Assumption 2:** The initial resetting condition is assumed for all agents, i.e.

$$x_0(t_0) = x_i(t_0, k), v_0(t_0) = v_i(t_0, k), k = 0, 1, \dots$$

**Definition 1:** Given a matrix  $A \in R^{n \times n}$ , its 2-norm is defined by:  $\|A\| = \sqrt{\lambda_{\max}(A^T A)}$ , where  $\lambda_{\max}(\cdot)$  denotes the matrix maximum eigenvalue.

**Definition 2:** Given a vector function  $f: [0, T] \rightarrow R^n$ , its  $\lambda$ -norm is defined by:

$$\|f\|_{\lambda} = \sup_{0 \leq t \leq T} \{\|f(t)\| e^{-\lambda t}\}$$

### 2.2 Double-integrator dynamics

This paper attempts to introduce the ILC approach to deal with the consensus problem for the double-integrator MAS, and the dynamic of the  $i$ th agent at the  $k$ th iteration is given by:

$$\begin{aligned} \dot{x}_i(t, k) &= v_i(t, k) \\ \dot{v}_i(t, k) &= u_i(t, k) \end{aligned} \quad (1)$$

Where  $x_i(t, k) \in R^n$  is the position state,  $v_i(t, k) \in R^n$  is the velocity state, and  $u_i(t, k) \in R^n$  is the coordination algorithm (also denoted control law) of agent  $i$ .

Define the consensus error of the multi-agent system:

$$\delta_{1i}(t, k) = x_i(t, k) - x_0(t), \delta_{2i}(t, k) = v_i(t, k) - v_0(t) \quad (2)$$

$$\delta(t, k) = \begin{pmatrix} \delta_1(t, k) \\ \delta_2(t, k) \end{pmatrix} = \begin{pmatrix} x(t, k) - 1_N x_0(t) \\ v(t, k) - 1_N v_0(t) \end{pmatrix} \quad (3)$$

where  $\delta_{1i}(t, k)$  represents the disagreement of the leader and the agent  $i$ , and  $k$  denotes the iterative time. The perfect consensus problem for the leader-following multi-agent system is to find an appropriate control input sequence  $\{u_i(t, k), t_0 \leq t \leq T, i = 1, 2, \dots, N; k \in Z_+\}$  such that the follower agents can track the leader  $[x_0(t), v_0(t)]^T$ , i.e.,  $\delta(t, k) \rightarrow 0$  and  $k \rightarrow \infty$  for all  $t \in [t_0, T]$ .

Where  $T$  is a finite positive constant.

In this paper, the general consensus error for agent  $i$  is defined as:

$$\begin{cases} e_{1i}(t, k) = \sum a_{ij}(x_j(t, k) - x_i(t, k)) + c_i(x_0(t) - x_i(t, k)) \\ e_{2i}(t, k) = \sum b_{ij}(v_j(t, k) - v_i(t, k)) + d_i(v_0(t) - v_i(t, k)) \end{cases} \quad (4)$$

or,

$$\begin{cases} e_1(t, k) = -[(L_p + D_p) \otimes I_n](x(t, k) - 1_N x_0(t)) \\ \quad = -[(L_p + D_p) \otimes I_n] \times \delta_1(t, k) \\ e_2(t, k) = -[(L_v + D_v) \otimes I_n](v(t, k) - 1_N v_0(t)) \\ \quad = -[(L_v + D_v) \otimes I_n] \times \delta_2(t, k) \end{cases} \quad (5)$$

**Remark 2:** Compared with the general consensus error (4), the consensus error (2) is a global variable that can't be calculated locally at every node. While the error information designed in (4) is available to agent  $i$  for control purposes.

### 3 ILC consensus algorithms for MAS

The control signal of the  $i$  th agent at the  $(k+1)$ -th iteration is updated as follows:

$$u_i(t, k+1) = u_i(t, k) + \gamma_i \dot{e}_{1i}(t, k) + \kappa_i \dot{e}_{2i}(t, k) \quad (6)$$

Where  $\gamma_i$  and  $\kappa_i$  are proper control gains.

And the control vector is described as

$$u(t, k+1) = u(t, k) + (\Gamma \otimes I_n) \dot{e}_1(t, k) + (\mathbf{K} \otimes I_n) \dot{e}_2(t, k) \quad (7)$$

where  $\Gamma = \text{diag}\{\gamma_1, \gamma_2, \dots, \gamma_N\}$ ,  $\mathbf{K} = \text{diag}\{\kappa_1, \kappa_2, \dots, \kappa_N\}$  are the control gain matrices.

**Theorem 1:** Under Assumptions 1–2, for the systems governed by (1), the ILC control law given in (6) ensures the follower agents can track the leader perfectly if there exist control gain matrices  $\mathbf{K}, \Gamma$  such that  $\|\Lambda\| \leq \bar{\rho} < 1$  hold.

$$\text{Where } \Lambda = \begin{bmatrix} I - (\mathbf{K}H_v) \otimes I_n & 0 \\ -(\Gamma H_p) \otimes I_n & I - (\mathbf{K}H_v) \otimes I_n \end{bmatrix}$$

**Proof:** From (1), (5) and (7), the difference of the consensus errors  $\delta_2$  between two successive iterations can be expressed as

$$\begin{aligned} \delta_2(t, k+1) - \delta_2(t, k) &= v(t, k+1) - v(t, k) \\ &= [v(t_0, k+1) - v(t_0, k)] + \int_{t_0}^t [u(\tau, k+1) - u(\tau, k)] d\tau \\ &= \int_{t_0}^t [u(\tau, k+1) - u(\tau, k)] d\tau \\ &= \int_{t_0}^t [(\Gamma \otimes I_n) \dot{e}_1(t, k) + (\mathbf{K} \otimes I_n) \dot{e}_2(t, k)] d\tau \end{aligned}$$

$$\begin{aligned} &= (\Gamma \otimes I_n) e_1(t, k) + (\mathbf{K} \otimes I_n) e_2(t, k) \\ &= -((\Gamma H_p) \otimes I_n) \delta_1(t, k) - ((\mathbf{K}H_v) \otimes I_n) \delta_2(t, k) \end{aligned}$$

It is noted that the last equality above is obtained from (5)

Thus, we have

$$\delta_2(t, k+1) = -((\Gamma H_p) \otimes I_n) \delta_1(t, k) + (I - (\mathbf{K}H_v) \otimes I_n) \delta_2(t, k) \quad (8)$$

Furthermore, the difference of the consensus errors  $\delta_1$  can be expressed as

$$\begin{aligned} \delta_1(t, k+1) - \delta_1(t, k) &= x(t, k+1) - x(t, k) \\ &= [x(t_0, k+1) - x(t_0, k)] + \int_{t_0}^t [v(\tau, k+1) - v(\tau, k)] d\tau \\ &= \int_{t_0}^t [v(\tau, k+1) - v(\tau, k)] d\tau \\ &= \int_{t_0}^t [-(\Gamma H_p \otimes I_n) \delta_1(\tau, k) - (\mathbf{K}H_v \otimes I_n) \delta_2(\tau, k)] d\tau \\ &= -(\Gamma H_p \otimes I_n) \int_{t_0}^t \delta_1(\tau, k) d\tau - (\mathbf{K}H_v \otimes I_n) \delta_1(t, k) \end{aligned}$$

Hence, we get

$$\delta_1(t, k+1) = (I - \mathbf{K}H_v \otimes I_n) \delta_1(t, k) - \Gamma H_p \otimes I_n \int_{t_0}^t \delta_1(\tau, k) d\tau \quad (9)$$

From (8) and (9), we can obtain that

$$\begin{aligned} \delta(t, k+1) &= \begin{bmatrix} \delta_1(t, k+1) \\ \delta_2(t, k+1) \end{bmatrix} \\ &= \begin{bmatrix} I - (\mathbf{K}H_v) \otimes I_n & 0 \\ -(\Gamma H_p) \otimes I_n & I - (\mathbf{K}H_v) \otimes I_n \end{bmatrix} \begin{bmatrix} \delta_1(t, k) \\ \delta_2(t, k) \end{bmatrix} \\ &\quad - \begin{bmatrix} ((\Gamma H_p) \otimes I_n) \int_{t_0}^t \delta_1(\tau, k) d\tau \\ 0 \end{bmatrix} \end{aligned} \quad (10)$$

For the further derivation, we use the following notations:

$$\begin{aligned} \Lambda &= \begin{bmatrix} I - (\mathbf{K}H_v) \otimes I_n & 0 \\ -(\Gamma H_p) \otimes I_n & I - (\mathbf{K}H_v) \otimes I_n \end{bmatrix} \\ c &= \left\| (\Gamma H_p) \otimes I_n \right\| \end{aligned}$$

Then, taking norms to two sides of (10), we can yield that

$$\begin{aligned} \|\delta(t, k+1)\| &= \left\| \begin{bmatrix} \delta_1(t, k+1) \\ \delta_2(t, k+1) \end{bmatrix} \right\| \leq \|\Lambda\| \left\| \begin{bmatrix} \delta_1(t, k) \\ \delta_2(t, k) \end{bmatrix} \right\| \\ &\quad + c \int_{t_0}^t \|\delta_1(\tau, k)\| d\tau \\ &\leq \|\Lambda\| \|\delta(t, k)\| + c \int_{t_0}^t \|\delta(\tau, k)\| d\tau \end{aligned} \quad (11)$$

With both side of the equation (10) multiplied by  $e^{-\lambda t}$ ,  $\lambda > 0$ , we have

$$\|\delta(t, k+1)\|_{\lambda} \leq \bar{\rho} \|\delta(t, k)\|_{\lambda} \quad (12)$$

Where  $\bar{\rho} = \|\Lambda\| + c \frac{1 - e^{-\lambda T}}{\lambda}$ , the Theorem 1 note

that  $\|\Lambda\| \leq \bar{\rho} < 1$  can guarantee  $\bar{\rho} < 1$  by selecting  $\lambda$  sufficiently large, which completes the proof.

**Corollary 1:** Consider the multi-agent system (1) under Assumptions 1–2 and let the ILC control law (6) be applied. If there exist control gain matrices  $\mathbf{K}, \Gamma$  satisfying the linear matrix inequality (LMI)

$$\begin{bmatrix} -I & \Lambda \\ \Lambda^T & -I \end{bmatrix} < 0 \quad (13)$$

, then the follower agents can track the leader perfectly.

**Remark 3:**

Theorem 1 and Lemma 1 could ensure the existence of the control gain matrices  $\mathbf{K}, \Gamma$ , which are difficult to get. According to Corollary 1 we can obtain them easily via LMI toolbox.

### 4 Formation control scheme for multi-agent systems

In this section, we address formation control for multi-agent systems. Specifically, we say that multi-agent

system (1) achieves leader-following formation control if and only if the follower agents reach the desired formation. We show that if the consensus problems are solved, the formation problems can be obtained by simple transformation. We define the position error for agent  $i$  in the  $k$ -th iteration as

$$\tilde{x}_i(t, k) = x_i(t, k) - \Delta_i \quad (14)$$

where  $\Delta_i$  is the desired position state for agent  $i$  relative to the leader.

Then the equation (1) can be rewritten as (15)

$$\begin{aligned} \dot{\tilde{x}}_i(t, k) &= v_i(t, k) \\ \dot{v}_i(t, k) &= u_i(t, k) \end{aligned} \quad (15)$$

The formation control objective is to find the control input sequence  $\{u_i(t, k), t_0 \leq t \leq T, i = 1, 2, \dots, N; k \in \mathbb{Z}_+\}$  such that the follower agents keep a desired distance from the leader uniformly on  $[t_0, T]$  when the iteration number  $k$  approaches infinity.

As defined in Section 3, the formation disagreement error for agent  $i$  is

$$\begin{aligned} \delta_{1i}(t, k) &= \tilde{x}_i(t, k) - x_0(t), \\ \delta_{2i}(t, k) &= v_i(t, k) - v_0(t) \end{aligned} \quad (16)$$

Then the equation (3) can be rewritten as (17)

$$\delta(t, k) = \begin{pmatrix} \delta_{1i}(t, k) \\ \delta_{2i}(t, k) \end{pmatrix} = \begin{pmatrix} \tilde{x}(t, k) - 1_N x_0(t) \\ v(t, k) - 1_N v_0(t) \end{pmatrix} \quad (17)$$

In this way, formation control is reformulated as a consensus problem  $\lim_{k \rightarrow \infty} \delta(t, k) = 0$ .

The general formation errors for agent  $i$  are defined as

$$\begin{cases} e_{1i}(t, k) = \sum a_{ij} (\tilde{x}_j(t, k) - \tilde{x}_i(t, k)) \\ \quad + c_i (x_0(t) - \tilde{x}_i(t, k)) \\ e_{2i}(t, k) = \sum b_{ij} (v_j(t, k) - v_i(t, k)) \\ \quad + d_i (v_0(t) - v_i(t, k)) \end{cases} \quad (18)$$

Then, as discussed in the previous section, we can obtain the following theorem.

**Theorem 2:** Consider the multi-agent system given by (15) under Assumption 1-2 using the distributed learning control protocol (6) with the general consensus errors defined in (18). Then the follower agents reach the desired formation uniformly if there exist control gain matrices  $K, \Gamma$  such that  $\|\Lambda\| \leq \bar{\rho} < 1$  hold.

## 5 Simulation results

This section aims to present two simulation examples to demonstrate the effectiveness of the obtained theoretical results.

We consider a system consisting of three agents in directed graphs and the communication graphs of the three agents and the leader are shown in Fig.1. It is easy to verify

the leader nodes 0 are globally reachable in  $\bar{G}_p$  and  $\bar{G}_v$ , respectively.

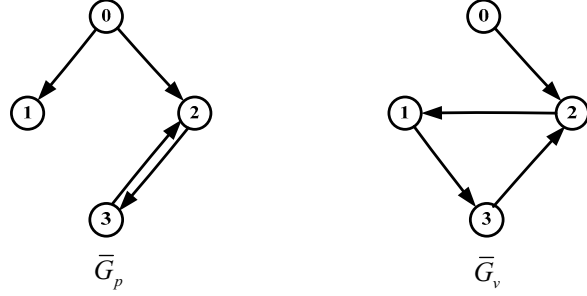


Fig.1 The leader-follower communication graph

The weighted adjacency matrix of  $G_p$  and  $G_v$  are

$$A_p = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0.5 \\ 0 & 0.3 & 0 \end{bmatrix} \text{ and}$$

$$A_v = \begin{bmatrix} 0 & 0.2 & 0 \\ 0 & 0 & 0.4 \\ 0.7 & 0 & 0 \end{bmatrix};$$

$$D_p = \text{diag}\{0.6, 0.8, 0\}, D_v = \text{diag}\{0, 0.9, 0\}.$$

**Example 1:** The trajectory of the leader node is assumed as  $x_0(t) = \sin t, v_0(t) = \cos t$  and  $t \in [0, 3\pi]$ . According to Corollary 1 we obtain the matrices:

$$K = \text{diag}\{2.6220, 0.7057, 0.6789\},$$

$$\Gamma = \text{diag}\{0.5492, 0.3061, 0.7035\}.$$

It is easily verified that  $\|\Lambda\| = 0.9939 < 1$ .

The results of using iterative consensus protocol (6) with the iteration  $k = 40$  are shown in Fig.2.

Clearly, from Fig.2 we can infer that the perfect consensus will be achieved with the evolution of the sup norm of position errors  $\delta_1$  and velocity errors  $\delta_2$ . Moreover, from Fig.3, the controls of the three agents are bounded at each iteration.

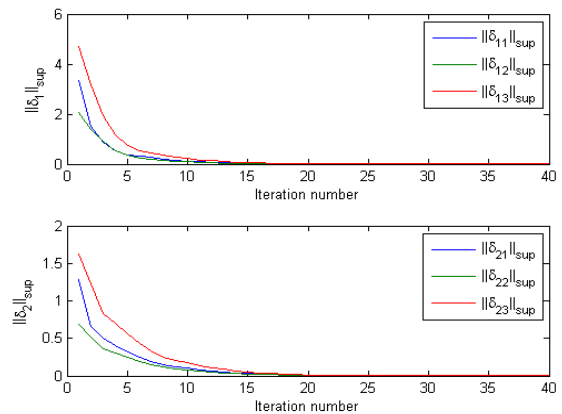


Fig.2 The sup norm of position and velocity errors with iteration  $k = 40$  for Example 1.

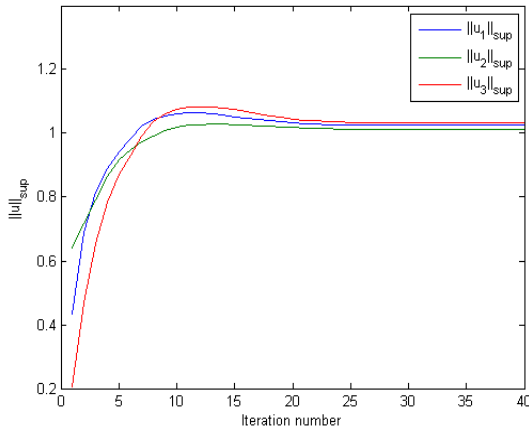


Fig.3 The sup norm of controls  $u$  with iteration  $k=40$  for Example 1.

**Example 2:** Formation problem for a multi-agent system on the interval  $t \in [0, 2\pi]$ .

Select the desired relative states  $\Delta_1=0.5$ ,  $\Delta_2=1$  and  $\Delta_3=1.5$ , and other conditions the same as example 1.

The results for formation control in each iteration are presented in Fig. 4 and 5. Fig.4 shows that not all agents can obtain the information of the leader, but the desired formation is well achieved for all the three followers. Fig.5 indicates that under the designed scheme, the formation error converges to zero as learning iteration increases. Moreover, the boundedness of the controls of the three agents is evident.

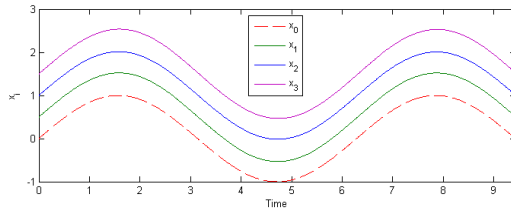


Fig. 4 Position states of the agents at the 40th iteration for Example 2.

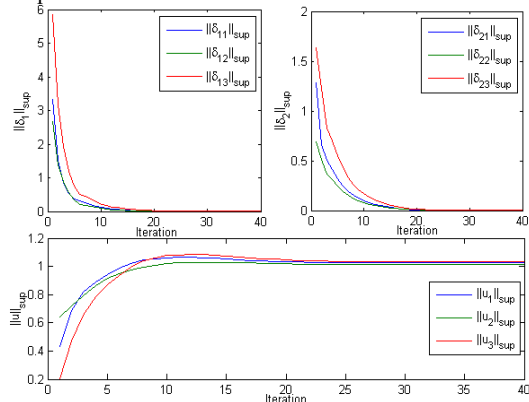


Fig.5 The sup norm of errors and controls with iteration  $k=40$  for Example 2.

## 6 Conclusions

We studied the ILC for multiple double-integrator agents with the position and velocity interactions among agents being modeled by totally independent graphs. ILC consensus algorithm has been constructed as distributed consensus protocol. And we have derived a sufficient condition to guarantee the multi-agent consensus in the given finite interval  $[t_0, T]$  under independent position and velocity topologies. Moreover, the proposed scheme is also extended to achieve the formation control for the multi-agent systems. The simulation results verify the effectiveness and practicality of the proposed consensus algorithms in this paper.

Future developments could involve the choice of the optimal learning gain matrices to improve the convergence performance and the robustness problem of the resetting errors.

### References:

- R.O. Saber, R.M. Murray. (2003). Consensus protocols for networks of dynamic agents. *Proc. Amer. Contr. Conf.*, 23, 951–956.
- R.O. Saber, R.M. Murray. (2004). Consensus problems in networks of agents with switching topology and time-delays. *IEEE Trans. Automat. Control*, 49, 1520–1533.
- W. Ren, R.W. Beard. (2005). Consensus seeking in multi-agent systems under dynamically changing interaction topologies. *IEEE Trans. Automat. Control*, 50, 655–661.
- W. Ren. (2008). On consensus algorithms for double-integrator dynamics. *IEEE Trans. Automat. Control*, 53, 1503–1509.
- R.O. Saber, J.A. Fax, R.M. Murray. (2007). Consensus and cooperation in networked multi-agent systems. *Proceedings of the IEEE*, 95, 215-233.
- J. Qin and H. Gao. (2012). A sufficient condition for convergence of sampled data consensus for double-integrator dynamics with nonuniform and time-varying communication delays. *IEEE Trans. Automat. Control*, 57, 2417-2422.
- Z.K. Li, X.D. Liu, W. Ren, L.H. Xie. (2013a). Distributed tracking control for linear multiagent systems with a leader of bounded unknown input. *IEEE Transactions on Automatic Control*, 58, 518-523.
- Z.K. Li, W. Ren, X.D. Liu, M.Y. Fu. (2013b). Consensus of multi-agent systems with general linear and Lipschitz nonlinear dynamics using distributed adaptive protocols. *IEEE Transactions on Automatic Control*, 58, 1786-1791.
- H.S. Ahn, Y. Chen, K.L. Moore. (2007). Iterative learning control: brief survey and categorization. *IEEE Transactions on System, Man and Cybernetics, Part C*, 37, 1099 – 1121.
- D.Y. Meng, Y.M. Jia. (2012). Iterative learning approaches to design finite-time consensus protocols for

- multi-agent systems. *Systems and Control Letters*, 61 ,187-194.
- D.Y. Meng, Y.M. Jia, J.P. Du, F.S Yu. (2012). Tracking control over a finite interval for multi-agent systems with a time-varying reference trajectory. *Systems and Control Letters*, 61, 807-818 .
- D.Y. Meng, Y.M. Jia, J.P. Du, J. Z. Zhang. (2014). On iterative learning algorithms for the formation control of nonlinear multi-agent systems. *Automatica*, 50, 291-295.
- D.Y. Meng, Y.M. Jia. (2014). Formation control for multi-agent systems through an iterative learning design approach. *International Journal of Robust and Nonlinear Control*, 24, 340-361.
- Y. Liu, Y.M. Jia. (2012). An iterative learning approach to formation control of multi-agent systems. *Systems & Control Letters*, 61 ,148-154.
- Y.F. Su, and J. Huang. (2012). Two consensus problems for discrete-time multi-agent systems with switching network topology. *Automatic*, 48 , 1988-1997.
- J.S. Li, J.M. Li. (2012). Consensus seeking in multi-agent systems by the iterative learning control. *Control Theory and Applications*, 29 ,1073-1077.
- J.S. Li, J.M. Li. (2013). Adaptive iterative learning control for consensus of multi-agent systems. *IET Control Theory Appl.*, 7 ,136-142.
- J. Qin, C. Yu. (2013). Coordination of multi-agents interacting under position and velocity topologies. *IEEE Transactions on Neural Networks and Learning Systems*, 24 ,1588-1597.
- J.P. Hu, Y.G. Hong. (2007). Leader-following coordination of multi-agent systems with coupling time delays. *Physica A-Statistical Mechanics and Its Applications* , 374 , 853 – 863.