Data-Driven Model-Free Adaptive Sliding Mode Control for Multi DC Motor Speed Regulation

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Abstract

This paper proposes the distributed data-driven model-free adaptive sliding mode control approach to address the consensus problem of nonlinear multi-agent systems. Firstly, the equivalent data model for each agent is constructed using the compact-form dynamic linearization (CFDL) technique. Secondly, by utilizing process information from neighboring agents, the novel sliding surface is employed to ensure the boundedness of distributed measurement error. Subsequently, a distributed model-free adaptive sliding mode controller is developed for accurate consensus tracking. Finally, the effectiveness of the proposed control approach is verified through experiments on multi DC motor system.

KEYWORDS

Data-driven control, model-free adaptive sliding mode control, nonlinear multi-agent systems, multi DC motor speed control.

I. INTRODUCTION

Due to the capabilities and coordination efficiency, distributed multi-agent systems (MASs) excel in applications such as sensor networks, transportation, agriculture monitoring, and industrial process. This has attracted significant attention to MASs [1]–[3]. Over the past few years, one of the main challenges for collaborative control [4]–[6] is to handle consensus problem. In particular, it enables all agents to converge on the same reference trajectory despite varying initial values, which improves the performance and reliability of the system. However, traditional model-based control strategies are not suitable for complex systems that are difficult to model accurately.

Despite their effectiveness in certain scenarios, traditional control strategies [10]–[13] heavily depend on precise system models, and the modeling process becomes increasingly challenging as technology grows rapidly. Under such circumstances, it becomes difficult to solve practical problems using the above schemes. In modern industrial environments, vast amounts of process information often containing implicit and complex dynamic behaviors of the system are continuously generated and stored during operation. As a result, there has been a growing interest in alternative control methods that rely on data modeling.

Therefore, how to use this data to achieve system consensus control has become a powerful new topic. The data-driven control [17]–[20] refers to control systems utilizing system I/O data solely. Various data-based approaches have been developed, including model-free adaptive control, iterative learning control, virtual reference feedback tuning [21], PID control [22] and others. Among these, the model-free adaptive control approach [23]–[25] has been proposed, and has a great significance in addressing the aforementioned challenges. The design process relies solely on I/O data of the system, significantly avoiding the reliance on mathematical models. The algorithm has proven effective in practical domains such as motor systems, chemical industries, and machinery, demonstrating the adaptability and usefulness of the algorithm.

Alternatively, sliding mode control [26] has emerged as a highly attractive approach for the control researchers due to the robustness to parameter uncertainties and the capability to ensure fast responses. Currently, the novel sliding mode control method based on I/O data is presented in [27], which eliminates the need for explicit system models. Although considerable progress has been made in controlling nonlinear MASs, the dynamic couplings and complex nonlinear behaviors among agents [14] can be challenging practical implementation.

However, the effectiveness of existing approaches [31]–[34] is limited in highly uncertain environments because they typically rely on input-affine structures with known or partially known dynamics. How to achieve consensus tracking problem utilizing the model-free adaptive sliding mode controller approach for nonlinear MASs remains an open question.

Inspired by the above discussions, this paper proposes a data-driven model-free adaptive sliding mode control scheme. The contributions of this paper are structured as follows:

1) This paper establishes the model-free adaptive sliding mode control approach, which enables consensus tracking in nonlinear MASs, even under system uncertainties and unknown dynamics.
2) The method utilizes CFDL to construct equivalent data models based purely on input-output data. This allows for the systematic design of controllers for each agent without requiring internal system knowledge, making it highly practical for real-time applications.
3) A novel distributed sliding surface is developed using neighboring agent process data. This structure ensures the boundedness of measurement errors and enhances the robustness and convergence of the system through a designed stability mechanism.

The following sections will outline the remaining content of this paper: Section II provides preliminaries and problem formulation, Section III presents The main results, Section IV shows simulation results and performance analysis, demonstrating the effectiveness of the proposed method under distinct operating conditions. At the end, conclusions are summarized in Section V.

II. Preliminaries and problem formulation

A. Directed Graph Theory

The directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$ is employed to describe the information exchange between agents. Here, $\mathcal{A} = [a_{ij}] \in \mathbb{R}^{N\times N}$ represents the adjacency matrix, $\mathcal{V} = \{v_1, v_2, \ldots, v_N\}$ is the set of vertices, and $\mathcal{E} = [(v_j, v_i)|v_i \in \mathcal{V}] \subseteq \mathcal{V} \times \mathcal{V}$ is the set of edges. Moreover, $\mathcal{N}(i) = \{j \in \mathcal{V}|(i,j) \in \mathcal{E}\}$ denotes the neighbor set of agent i, where $a_{ij} \neq 0$. No self-loop is allowed in this article, which means $(i,i) \notin \mathcal{E}$ for any $i \in \mathcal{V}$, $a_{ii} = 0$. Furthermore, the degree matrix $K = diag(k_1, \ldots, k_N)$. If $k_i > 0$, agent i can directly obtain the information from the leader. The Laplacian matrix L is defined as $L = (\mathcal{D} - \mathcal{A})$, here $\mathcal{D} = diag(d_1, \ldots, d_N)$ and $d_i = \sum_{j=1}^{N} a_{ij}$ denotes the in-degree matrix. Moreover, the graph is strongly connected if the path exists between every pair of vertices.

B. Problem Formulation

Consider the nonlinear multi-agent systems composed of N agents:

$$y_i(k+1) = f_i(y_i(k), u_i(k)), \quad i = 1, 2, \ldots, N \tag{1}$$

where $u_i(k) \in \mathbb{R}$ and $y_i(k) \in \mathbb{R}$ represent the system input and output signals of agent i, respectively. $f_i(\cdot)$ signifies an unknown nonlinear function.

Assumption 1: The partial derivative of $f_i(\cdot)$ with respect to $u_i(k)$ is continuous.

Assumption 2: The system (1) satisfies the generalized Lipschitz condition, meaning that if $\Delta u_i(k) = u_i(k) - u_i(k-1) \neq 0$ then $|\Delta y_i(k+1)| \leq b|\Delta u_i(k)|$ holds for any k, where $\Delta y_i(k+1) = y_i(k+1) - y_i(k)$.

Remark 1: The assumptions above are general. Assumption 1 is a general condition for controller design. Assumption 2 implies that the system input rate constrains the system output rate, which is satisfied in many practical systems.

Assumption 3: The communication graph $\mathcal{G}$ is strongly connected, ensuring that each follower can directly receive information from at least one leader.

Lemma 1 [8]: Consider the nonlinear multi-agent system (1) satisfying above three assumptions. If $|\Delta u_i(k)| \neq 0$ holds, then the system can be transformed into the CFDL data model as follows:

$$\Delta y_i(k+1) = \phi_i(k)\Delta u_i(k) \tag{2}$$

wherein $\phi_i(k)$ is called pseudo partial derivative (PPD), satisfying $|\phi_i(k)| \leq b$.

The distributed measurement error of $\xi_i(k)$ for N agents is established as:

$$\xi_i(k) = \sum_{j \in N_i} a_{ij}(y_j(k) - y_i(k)) + d_i(y_d(k) - y_i(k)) \tag{3}$$

if the agent i can receive data from the leader, then $d_i = 1$; otherwise, $d_i = 0$. Additionally, $y_d(k)$ represents the reference trajectory.

Remark 2: The CFDL technique requires no prior knowledge about the system dynamic model, making it highly suitable for distributed multi-agent systems. In addition, such methods are effective in handling complex systems where modeling is impractical. Moreover, the dynamic behavior of time-varying PPD may be highly complex, which is challenging to verify. Thus, a data-driven control method is employed to adaptively study the dynamic behavior, thereby ensuring effective control performance.

III. Main Results

This section is devided in two parts. The first part introduces the model-free adaptive controller design, which is based on the CFDL technique. The second part introduces the sliding mode controller design, which is formulated based on the distributed measurement error. The overall block diagram of the proposed control scheme is shown in Fig. 1, which is illustrates the system control process.

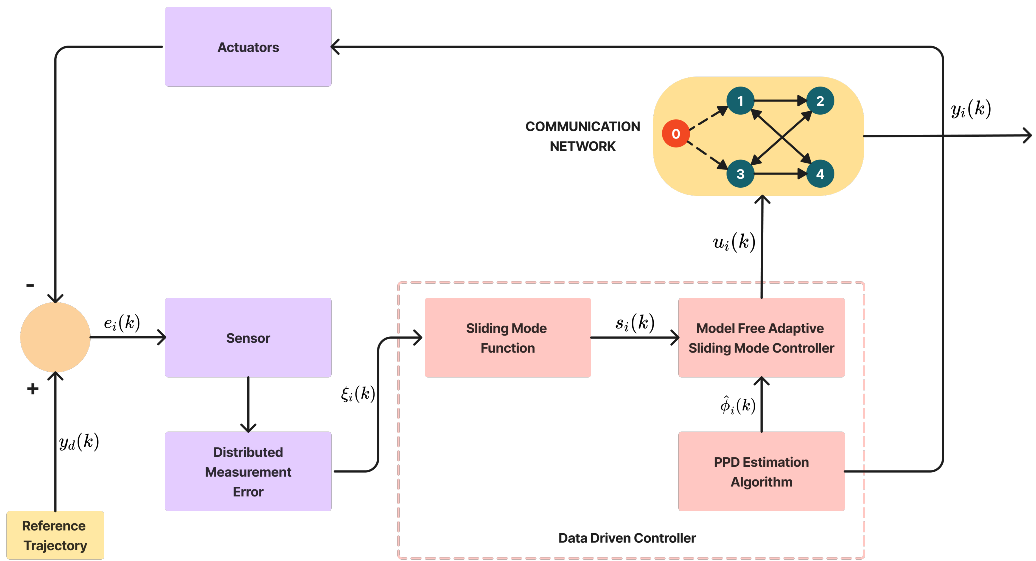

Fig. 1: Block diagram.

A. *Model-Free Adaptive Sliding Mode Controller Design*

Consider the following PPD criterion function for the parameter with unknown dynamics in (2):

$$J(\phi_i(k)) = |\Delta y_i(k) - \phi_i(k)\Delta u_i(k-1)|^2 + \mu|\phi_i(k) - \hat{\phi}_i(k-1)|^2 \tag{4}$$

By utilizing the optimal condition $\frac{\partial J(\phi_i(k))}{\partial \phi_i(k)} = 0$, the updating law with reset algorithm is derived:

$$\hat{\phi}_i(k) = \hat{\phi}_i(k-1) + \frac{\eta \Delta u_i(k-1)}{\mu + \Delta u_i(k-1)^2}(\Delta y_i(k) - \hat{\phi}_i(k-1)\Delta u_i(k-1)) \tag{5}$$

$$\hat{\phi}_i(k) = \hat{\phi}_i(1), \text{ if } |\hat{\phi}_i(k)| \leq \epsilon \ or \ sign(\hat{\phi}_i(k)) \neq sign(\hat{\phi}_i(1)) \tag{6}$$

herein, $\eta \in (0, 1)$, $\mu > 0$ represents a positive weight factor. Additionally, ϵ is a small positive number. Finally, $\hat{\phi}_i(k)$ signifies the estimated value of $\phi_i(k)$.

The following distributed MFAC algorithm is presented:

$$u_{i,\text{MFA}}(k) = u_{i,\text{MFA}}(k-1) + \frac{\rho\hat{\phi}_i(k)}{\lambda + \hat{\phi}_i(k)^2}\xi_i(k) \tag{7}$$

where $\rho \in$ (0,1) is a step-size constant, which is added to make (7) general.

To design the sliding mode controller, the sliding surface function is given by:

$$s_i(k) = \alpha\xi_i(k) - \xi_i(k-1) \tag{8}$$

herein $\alpha > 1$ represents a positive constant.

Furthermore, from (2) and (3), the formula (3) is updated as

$$\xi_i(k+1) = \xi_i(k) - (\sum_{j\in N_i} a_{ij} + d_i)\phi_i(k)\Delta u_i(k) + \sum_{j\in N_i} a_{ij}\Delta y_j(k) + d_i \Delta y_d(k+1) \tag{9}$$

wherein $\Delta y_j(k+1)$ is replaced with $\Delta y_j(k)$ because the data at the next moment cannot be obtained.

Therefore, considering (8), with the assistance of reaching law $s_i(k+1)=0$, the following equivalent control law can be derived.

$$\Delta u_{i,\mathrm{SM}}^{eq}=\frac{\omega\hat{\phi}_i(k)}{\sigma+\hat{\phi}_i(k)^2}\left(\frac{\xi_i(k)+\sum_{j\in N_i}a_{ij}\Delta y_j(k)+d_i\Delta y_d(k+1)}{\sum\limits_{j\in N_i}a_{ij}+d_i}-\frac{\xi_i(k)}{\alpha(\sum\limits_{j\in N_i}a_{ij}+d_i)}\right) \tag{10}$$

The controller consists of an equivalent control law and switching control law, which means:

$$u_{i,\mathrm{SM}}(k)=u_{i,\mathrm{SM}}(k-1)+\Delta u_{i,\mathrm{SM}}^{M}(k)+\Delta u_{i,\mathrm{SM}}^{s}(k) \tag{11}$$

Additionally, the switching control law $\Delta u_{i,\mathrm{SM}}^{s}(k)$ is presented:

$$\Delta u_{i,\mathrm{SM}}^{s}(k)=\frac{\omega\hat{\phi}_i(k)}{\sigma+\hat{\phi}_i(k)^2}\tau_s sign(s_i(k)) \tag{12}$$

As a consequence, taking into consideration (10), (11) and (12), the controller is summarized as follows:

$$\begin{aligned}u_{i,\mathrm{SM}}(k)=u_{i,\mathrm{SM}}(k-1)+\frac{\omega\hat{\phi}_i(k)}{\sigma+\hat{\phi}_i(k)^2}\Bigg(&\frac{\xi_i(k)+\sum_{j\in N_i}a_{ij}\Delta y_j(k)+d_i\Delta y_d(k+1)}{\sum_{j\in N_i}a_{ij}+d_i}\\ &-\frac{\xi_i(k)}{\alpha(\sum\limits_{j\in N_i}a_{ij}+d_i)}+\tau_s sign(s_i(k))\Bigg)\end{aligned} \tag{13}$$

Subsequently, the final MFASMC input is:

$$u_i(k)=u_{i,\mathrm{MFA}}(k)+\Gamma_i u_{i,\mathrm{SM}}(k) \tag{14}$$

where the parameter Γ_i is a gain factor.

B. Stability Analysis

Theorem 1: For the system (1) satisfying assumptions 1 and 2, using the designed algorithms (5) along with the reset law (6), the sliding surface (8) and controller (13) can ensure the boundedness of $\hat{\phi}_i(k)$. Simultaneously, the distributed measurement error remains bounded. This result holds under the condition $0<h_0<h_i(k)<\frac{\omega C_0}{2\sqrt{\sigma}}<1$, which guarantees the proper behavior of the function hi(k). The functions used therein are given by:

$$\begin{cases}h_i(k)=\frac{\omega\phi_i(k)\hat{\phi}_i(k)}{\sigma+\hat{\phi}_i(k)^2}\\ g_i(k)=(1-h_i(k))\left(\sum_{j\in N_i}a_{ij}+d_i\right)\Delta y_d(k+1)-h_i(k)\left(\sum_{j\in N_i}a_{ij}+d_i\right)\tau_s\,\mathrm{sign}(s_i(k))\\ |g_i(k)|<g_0\end{cases}$$

Proof: The proof is devided into two parts.

Part i: Define $\tilde{\phi}_i(k)=\hat{\phi}_i(k)-\phi_i(k)$. Using the PPD estimation algorithm (5), the following result is derived:

$$\begin{aligned}\tilde{\phi}_i(k)&=\big(\hat{\phi}_i(k-1)-\phi_i(k-1)\big)+\frac{\eta\Delta u_i(k-1)}{\mu+\Delta u_i(k-1)^2}\big(\phi_i(k-1)\Delta u_i(k-1)\\&-\hat{\phi}_i(k-1)\Delta u_i(k-1)\big)-\phi_i(k)+\phi_i(k-1)\\&=\tilde{\phi}_i(k-1)+\frac{\eta\Delta u_i(k-1)}{\mu+\Delta u_i(k-1)^2}\big(\phi_i(k-1)\Delta u_i(k-1)\\&-\hat{\phi}_i(k-1)\Delta u_i(k-1)\big)-\phi_i(k)+\phi_i(k-1)\\&=\tilde{\phi}_i(k-1)+\frac{\eta\Delta u_i(k-1)}{\mu+\Delta u_i(k-1)^2}\Delta u_i(k-1)\big(\phi_i(k-1)-\hat{\phi}_i(k-1)\big)-\phi_i(k)+\phi_i(k-1)\\&=\left(1-\frac{\eta\Delta u_i(k-1)^2}{\mu+\Delta u_i(k-1)^2}\right)\tilde{\phi}_i(k-1)-\Delta\phi_i(k)\end{aligned} \tag{15}$$

Denote that the term $\frac{\eta\Delta u_i(k-1)^2}{\mu+\Delta u_i(k-1)^2}$ is monotonically increasing with respect to $\Delta u_i(k)^2$, and its minimum value is $\frac{\eta\epsilon^2}{\mu+\epsilon^2}$. Therefore, there must be a constant q_1 satisfying the inequalities $0<\eta\leq 1$ and $u_i>0$

$$0<\left|1-\frac{\eta\Delta u_i(k-1)^2}{\mu+\Delta u_i(k-1)^2}\right|\leq 1-\frac{\eta\epsilon^2}{\mu+\epsilon^2}=q_1<1 \tag{16}$$

Because of $|\phi_i(k)|<\bar{d}$, and $|\Delta\phi_i(k)|<2\bar{d}$, the following equation (15) is written as:

$$\begin{aligned}|\tilde{\phi}_i(k)| &\leq q_1|\tilde{\phi}_i(k-1)|+2\bar{d}\\ &\leq q_1^2|\tilde{\phi}_i(k-2)|+2q_1\bar{d}+2\bar{d}\\ &\quad\vdots\\ &\leq q_1^{k-1}|\tilde{\phi}_i(1)|+\frac{2\bar{d}}{1-q_1}(1-q_1^{k-1})\end{aligned} \tag{17}$$

which implies $\tilde{\phi}_i(k)$ is bounded. Since the boundedness of $\phi_i(k)$ is guaranteed by Lemma 1.

Part ii: The boundedness of $\xi_i(k)$.

By combining (5) with (9), the expression for $\xi_i(k+1)$ is updated:

$$\begin{aligned}\xi_i(k+1) &= \xi_i(k)+\sum_{j\in N_i}a_{ij}\Delta y_j(k)+d_i\Delta y_d(k+1)-\frac{\omega\phi_i(k)\hat{\phi}_i(k)}{\sigma+\hat{\phi}_i(k)^2}(1-\frac{1}{\alpha})\xi_i(k)\\ &\quad-\frac{\omega\phi_i(k)\hat{\phi}_i(k)}{\sigma+\hat{\phi}_i(k)^2}\sum_{j\in N_i}a_{ij}\Delta y_j(k)-\frac{\omega\phi_i(k)\hat{\phi}_i(k)}{\sigma+\hat{\phi}_i(k)^2}d_i\Delta y_d(k+1)+\Bigg(\sum_{j\in N_i}a_{ij}+d_i\Bigg)\tau_s\,\mathrm{sign}(s_i(k))\\ &= \Bigg(1-\frac{\omega\phi_i(k)\hat{\phi}_i(k)}{\sigma+\hat{\phi}_i(k)^2}(1-\frac{1}{\alpha})\Bigg)\xi_i(k)+\Bigg(\sum_{j\in N_i}a_{ij}\Delta y_j(k)-\frac{\omega\phi_i(k)\hat{\phi}_i(k)}{\sigma+\hat{\phi}_i(k)^2}\sum_{j\in N_i}a_{ij}\Delta y_j(k)\Bigg)\\ &\quad+\Bigg(d_i\Delta y_d(k+1)-\frac{\omega\phi_i(k)\hat{\phi}_i(k)}{\sigma+\hat{\phi}_i(k)^2}d_i\Delta y_d(k+1)\Bigg)+\Bigg(\sum_{j\in N_i}a_{ij}+d_i\Bigg)\tau_s\,\mathrm{sign}(s_i(k))\\ &= \Bigg(1-\frac{\omega\phi_i(k)\hat{\phi}_i(k)}{\sigma+\hat{\phi}_i(k)^2}(1-\frac{1}{\alpha})\Bigg)\xi_i(k)+\Bigg(1-\frac{\omega\phi_i(k)\hat{\phi}_i(k)}{\sigma+\hat{\phi}_i(k)^2}\Bigg)\Bigg(\sum_{j\in N_i}a_{ij}\Delta y_j(k)\\ &\quad+d_i\Delta y_d(k+1)\Bigg)-\frac{\omega\phi_i(k)\hat{\phi}_i(k)}{\sigma+\hat{\phi}_i(k)^2}\Bigg(\sum_{j\in N_i}a_{ij}+d_i\Bigg)\tau_s\,\mathrm{sign}(s_i(k))\end{aligned} \tag{18}$$

Subsequently, take $0<h_0<h_i(k)<\frac{\omega C_0}{2\sqrt{\sigma}}<1$ into consideration, where $\phi_i(k)<C_0$ and $|g_i(k)|<g_0$, the inequality is obtained by taking the absolute value of each term of (18).

$$\begin{aligned}|\xi_i(k+1)| &\leq |1-h_i(k)(1-\frac{1}{\alpha})||\xi_i(k)|+|g_i(k)|\\ &\leq |1-h_i(k)(1-\frac{1}{\alpha})||\xi_i(k)|+g_0(k)\\ &\quad\vdots\\ &\leq 1-h_0(1-\frac{1}{\alpha})^k|\xi_i(k)|+\frac{g_0(1-(1-h_0(1-\frac{1}{\alpha}))^2)}{h_0(1-\frac{1}{\alpha})}\end{aligned} \tag{19}$$

Therefore, the following result will be given as

$$\lim_{k\to\infty}\xi_i(k+1)=\frac{g_0}{h_0(1-\frac{1}{\alpha})}=\frac{\alpha g_0}{(\alpha-1)h_0} \tag{20}$$

In summary, both the parameter estimation $\hat{\phi}_i(k)$ and the measurement error $\xi_i(k)$ remain bounded under the proposed adaptive sliding mode control scheme. The condition $0<h_0<h_i(k)<\frac{\omega C_0}{2\sqrt{\sigma}}<1$ ensures that the adaptive parameters are stable, thereby enabling stability and effectiveness of the distributed controller. This completes the proof.

Remark 3: Unlike the consensus tracking control schemes used in the existing literature, this paper proposes a model-free adaptive sliding mode control strategy for MASs. In this approach, the CFDL technique is employed alongside a novel sliding surface, relying solely on data for the purpose of attaining the reference trajectory tracking. Specifically, regardless of the nonlinear and time-varying dynamics of agents, the proposed methodology ensures that distributed measurement error remains bounded, thereby achieving precise speed regulation.

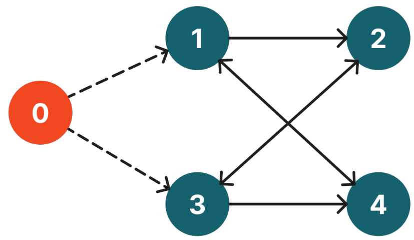

Fig. 2: Communication topology among agents.

IV. Simulation Example

This section describes the usefulness of the provided control approach, which is validated by both numerical simulations and physical experiments results.

The DC brushed motors operate at 12V with a no-load speed of 293±21RPM and a gear ratio of 20, providing increased torque. Hall encoders with 13 pulses per revolution are used to capture rotor motion. The motor speed is measured in revolutions per second (r/s) based on encoder measurements and the sampling interval t. The total number of encoder counts per revolution is calculated as $rT = 4N_eRr$, where N_e is the encoder line count equal to 13, R_r is the reduction ratio equal to 20 and the factor of 4 accounts for quadrature encoding. The number of rotations, N_r is determined using $N_r = \frac{m}{rT}$, with m representing the total encoder count. The output data model of each agent is governed by:

$$y_i(k+1) = 0.5y_i(k) + b_iu_i(k) - 0.02y_i(k)^{p_i} + 0.45, \quad i = 1, 2, 3, 4,$$

where the parameters corresponding to each agent are:

$$b_i = \begin{cases} \frac{6m}{rT} & \text{if } i = 1, 3 \\ \frac{5.75m}{rT} & \text{if } i = 2, 4 \end{cases} \qquad p_i = \begin{cases} 3 & \text{if } i = 1, 3 \\ 2 & \text{if } i = 2, 4 \end{cases}$$

Noting that the multi-agent systems are heterogeneous, with four agents having different dynamic models. In addition, these models are not used in the control design but only serve to generate the I/O data required for the MAS simulations; further details of the models are not disclosed.

As illustrated in Fig. 2, the virtual leader is designated as vertex 0. It can be observed that only agents 1 and 3 can receive information from the leader, forming a strongly connected communication graph. The Laplacian matrix of the graph is given as follows:

$$L = \begin{bmatrix} 1 & 0 & 0 & -1 \\ -1 & 2 & -1 & 0 \\ 0 & -1 & 1 & 0 \\ -1 & 0 & -1 & 2 \end{bmatrix}$$

with $D = \text{diag}(1, 0, 1, 0)$.

Example 1: In this example, the reference trajectory is time-invariant value signal $y_d(k) = 0.6$.

The initial parameters are chosen as $u_i(1) = 0$, $y_i(1) = 0$ and $\hat{\phi}_i(0) = 1$ for all agents in this simulation, $\Gamma_1 = \Gamma_3 = 0.45$ and $\Gamma_2 = \Gamma_4 = 0.15$, with $\tau_s = 10^{-5}$, $m = 600$, $rT = 1024$, $\eta = 1$, $\mu = 0.005$, other parameters are given as $\rho = 7.5$, $\lambda = 350$, $\omega = 10$, $\sigma = 95$, $\alpha = 15$ with $\epsilon = 10^{-5}$.

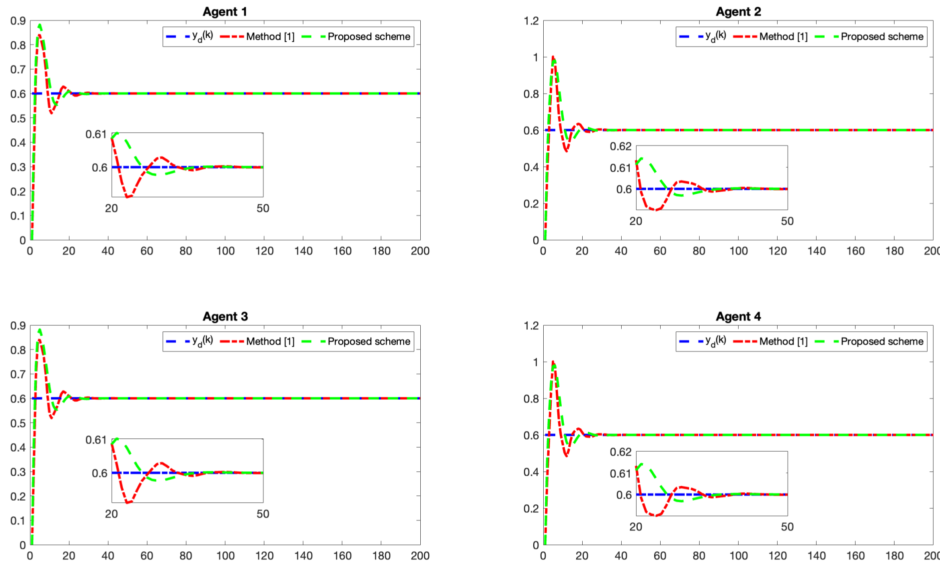

Fig. 3: Tracking performance of all agents under the time-invarying reference trajectory.

Fig. 3 demonstrates the tracking performance of all agents under the proposed control scheme for the case of a time-invariant reference signal. It can be observed that the agents effectively follow the reference trajectory, which is set to a constant value of 0.6, with negligible steady-state error and without overshoot. Moreover, Fig. 4 illustrates the distributed measurement error, which remains bounded within the range of [-0.02, 0.02], indicating accuracy of the control strategy. These results confirm that the controller maintains stability.

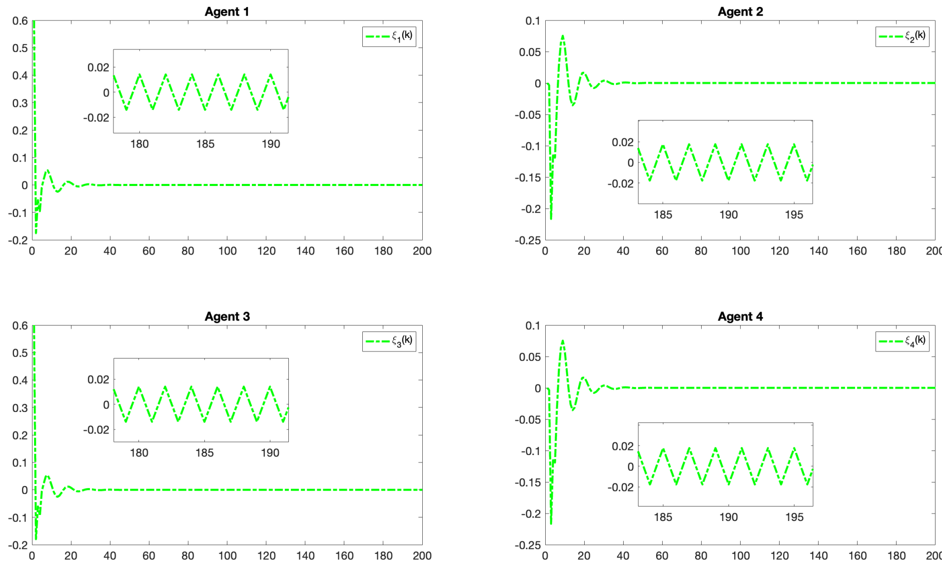

Fig. 4: Distributed measurement error of all agents under the time-invarying reference trajectory.

TABLE I: Mean square error comparison (Example 1)

$\mathrm{MSE}_i(k)$	Method [1]	Proposed scheme
Agent 1	4.9135×10^{-3}	4.0732×10^{-3}
Agent 2	3.2197×10^{-3}	2.2558×10^{-3}
Agent 3	4.9135×10^{-3}	4.0732×10^{-3}
Agent 4	3.2197×10^{-3}	2.2558×10^{-3}
Average	4.0666×10^{-3}	3.1649×10^{-3}

To quantitatively evaluate the advantages of the developed method, the mean square error(MSE) is calculated for each agent. The MSE values are presented in TABLE I. For each agent, the MSE is calculated according to the formula:

$$\mathrm{MSE}_i(k) = \frac{1}{m}\sum_{k=1}^{m} \xi_i^2(k)$$

where m denotes the total number of time steps. In comparison to the existing approach [1], the developed strategy demonstrates significant improvement in accuracy, reducing the average MSE across agents by a factor of approximately 1.29. This notable reduction confirms the effectiveness of the proposed technique.

Example 2: The expression for the reference trajectory is:

$$y_d(k) = 0.6\sin(0.07\pi(k)) + 0.6\cos(0.04\pi(k)), k \in [0, 200]$$

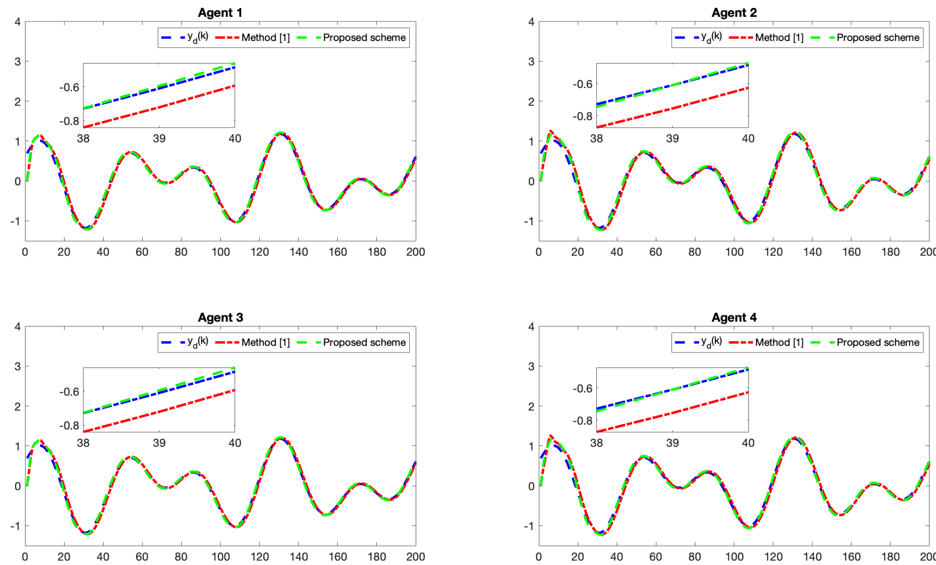

Fig. 5: Tracking performance of all agents under the time-varying reference trajectory.

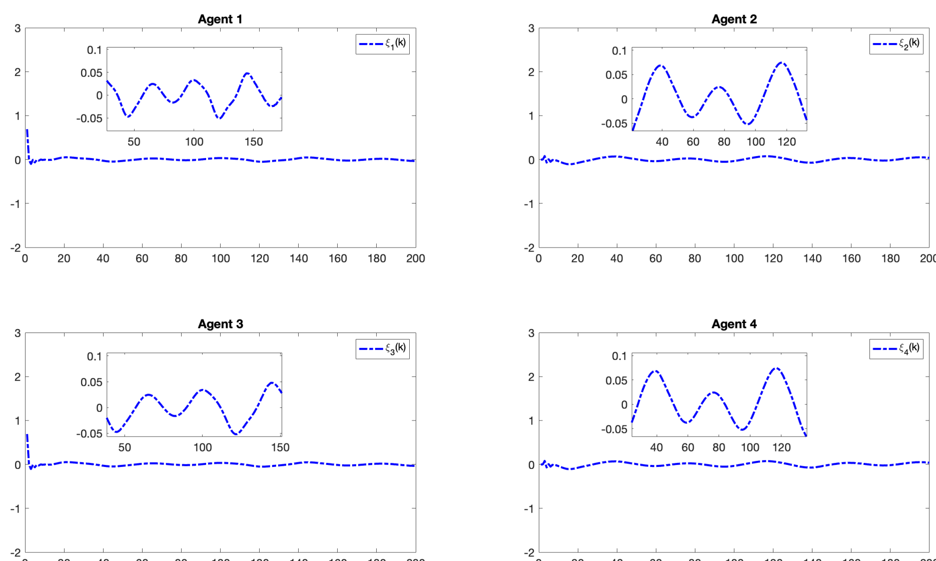

Fig. 6: Distributed measurement error of all agents under the time-varying reference trajectory.

Fig. 5 presents the tracking performance for all agents for the time-varying trajectory. All agents are able to accurately track the time-varying reference trajectory. Additionally, as shown in Fig. 6 the distributed measurement errors among agents are bounded.

For time-varying reference trajectories, the mean squared errors of distributed measurements for two control strategies are detailed in TABLE II. Relative to the conventional approach [1], the proposed scheme reduces in average MSE by approximately 1.16.

TABLE II: Mean square error comparison (Example 2)

$\text{MSE}_i(k)$	Method [1]	Proposed scheme
Agent 1	2.8319×10^{-3}	2.6984×10^{-3}
Agent 2	1.4561×10^{-3}	9.8907×10^{-4}
Agent 3	2.8319×10^{-3}	2.6984×10^{-3}
Agent 4	1.4561×10^{-3}	9.8907×10^{-4}
Average	2.1445×10^{-3}	1.8432×10^{-3}

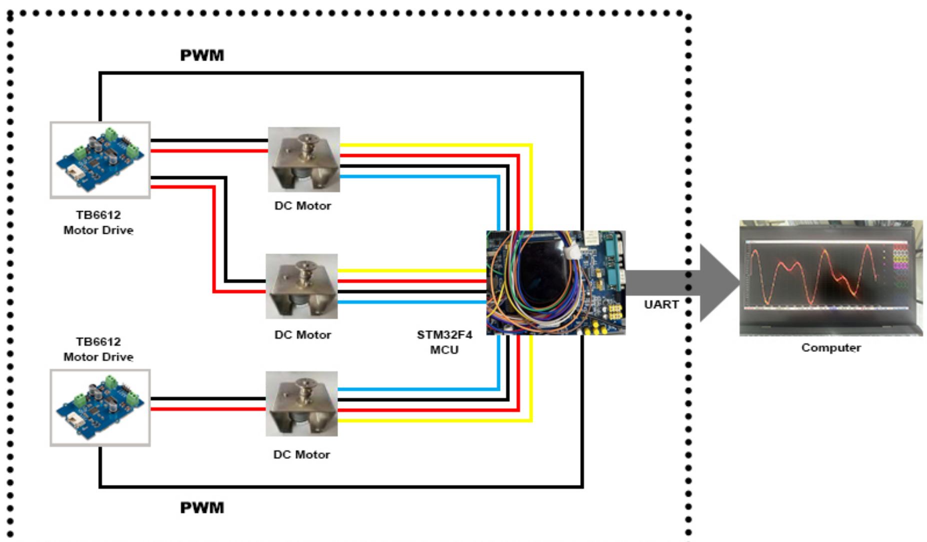

Fig. 7: System connection diagram of multi DC motor consensus tracking control.

To verify the proposed consensus tracking control methodology, the experimental validation is conducted using a multi DC motor system, as illustrated in Fig. 8. The system consists of three DC motors equipped with Hall encoders and reduction gears, an STM32F407 main control chip, two motor drive modules, and an LCD display module. The microcontroller unit STM32F407ZGT6 is used for high-resolution pulse width modulation output generation to achieve precise motor speed control. The timer module is utilized for this purpose.

In addition, the controller code is written in C language using STM32CubeIDE, while STM32CubeMX is used for pin configuration. The main purpose of the experiment is to ensure that the three motors accurately track the reference trajectory:

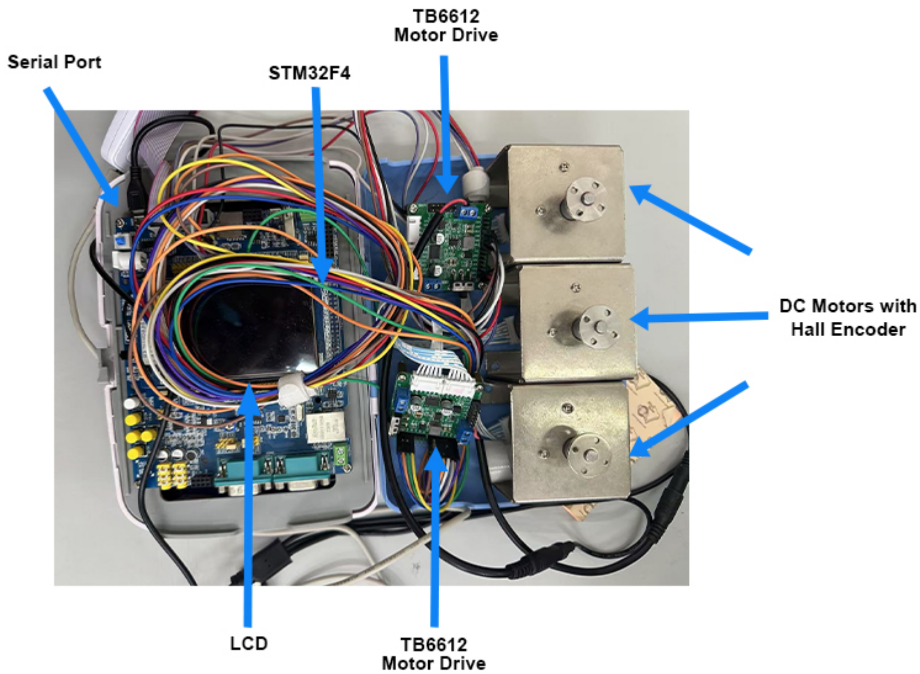

Fig. 8: Multi DC motor system.

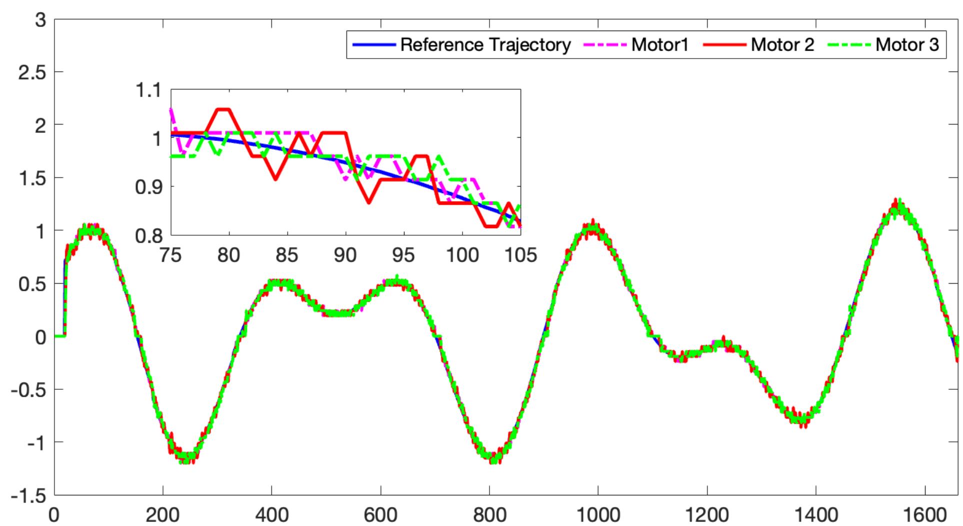

Fig. 9: Tracking performance of 3 DC motors for time-invariable desired trajectory.

Fig. 9 shows the tracking performance of multi DC motor demonstrating the effectiveness of the proposed control method. Overall, the simulation results suggest that the proposed control system is capable of tracking a constant desired trajectory for multiple agents. While initial transient errors may occur, the system ultimately achieves a steady-state condition with minimal tracking error. The variations in tracking performance among the agents highlight the potential influence of individual characteristics and external factors.

The distributed errors for three DC motors result in mean squared errors of 1.0840×10^{-3}, 1.5036×10^{-3}, and 1.4887×10^{-3}, respectively. The average of 1.3588×10^{-3} demonstrates the effectiveness of the proposed control method in practical applications. Meanwhile, the method consistently maintains mean squared error around 10^{-3}.

Remark 5: In summary, the proposed control approach is validated through both simulation and experimental results, which ensure accurate consensus tracking for MASs. The tracking performance is related to parameters such as ρ, ω, σ, α, and the sampling period. However, the algorithm ability to address system uncertainties can be enhanced by appropriately increasing ρ and ω. Furthermore, it is necessary to make precise adjustments to other parameters, such as Γ_i and τ_s, to maintain bounded distributed measurement errors and achieve accurate performance. The experimental results further confirm the practical applicability of the proposed control strategy in a real-world multi DC motor system.

V. Conclusion

In this study, the model-free adaptive sliding mode control approach is presented to address the consensus problem of MASs. Firstly, the equivalent data model for each agent is obtained using the CFDL method. Secondly, a novel sliding surface ireas presented to ensure that the distributed measurement error remains bounded. Moreover, the developped strategy effectively mitigates the impact of distributed measurement errors across agents. The simulation results, quantitatively demonstrate the superiority of the proposed technique. Specifically, the mean squared error for each agent is calculated, revealing an average mean squared error reduction of approximately 1.29 compared to the existing approach [1], and approximately 1.16 for time-varying signals. Finally, the effectiveness of the proposed control approach is verified through physical experiments on multi DC motor system.

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