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 through stability mechanism. Subsequently, a distributed model-free adaptive sliding mode controller is developed for precise reference trajectory 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 excellent capabilities and coordination efficiency of distributed multi-agent systems (MASs) in various applications such as sensor network, transportation systems, agriculture monitoring and industrial process systems [1]–[3], MASs have attracted significant attention. As the fundamental structure for collaborative control [4], [5], one of the main challenges is to handle consensus problem. It means that all agents can follow the same trajectory from different initial values. However, traditional model-based control strategies are not suitable for complex systems that are difficult to model accurately. In modern industrial environments, vast amounts of process information often reflecting nonlinear system behaviors are continuously generated and stored during the system operation.

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. Therefore, how to use data to achieve system consensus control has become a powerful new topic. 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 learing control, virtual reference feedback tuning [21], PID control [22] and others. The model-free adaptive control approach [23]–[25] is proposed, which has a great significance in addressing the aforementioned challenges. In its design process, only I/O data of the system are utilized, significantly avoiding the reliance on mathematical models. The algorithm has thus 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 its robustness to parameter uncertainties and its ability to ensure fast responses. Currently, the novel sliding mode control method based on I/O data is presented in [27]. Although considerable progress has been made in controlling nonlinear MASs, the controller design remains highly challenging due to the dynamic couplings and nonlinear behaviors among agents [14]. This challenge becomes even more critical in practical situations where the exact mathematical models of the agents are unavailable.

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 precise 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. Moreover, the dynamic behavior of time-varying PPD may be highly complex and difficult to verify. Therefore, a data-driven method for studying numerical characteristics is the preferred solution.

III. Main Results

A. Model-Free Adaptive Controller Design

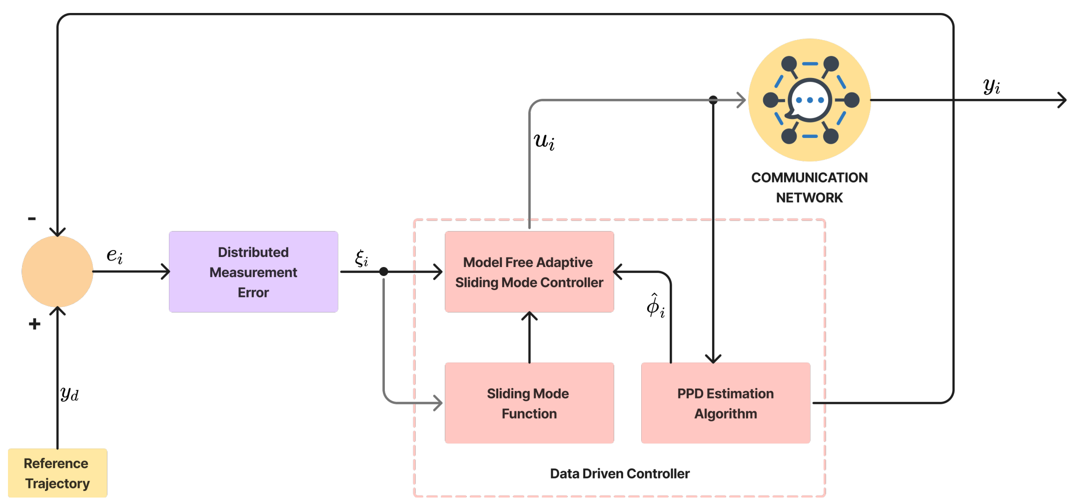

Fig. 1: Block diagram.

Consider the following PPD criterion function, for the above consensus tracking objective $\phi_i(k)$:

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

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

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

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

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.

B. Sliding Mode Controller Design

To design the sliding mode controller for the system, 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.

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

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

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

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

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

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

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

Subsequently, the final MFASMC input is:

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

where the parameter Γ_i is a gain factor.

C. 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. The functions used therein are given by:

$$\begin{cases} 0 < h_0 < h_i(k) < \frac{\omega C_0}{2\sqrt{\sigma}} < 1 \\ h_i(k) = \frac{\omega \phi_i(k)\hat{\phi}_i(k)}{\sigma + \hat{\phi}_i(k)^2} \\ g_i(k) = (1-h_i(k))(\sum_{j\in N_i} a_{ij} + d_i \Delta y_d(k+1)) - h_i(k)(\sum_{j\in N_i} a_{ij} + d_i)\tau_s sign(s_i(k)) \\ |g_i(k)| < g_0 \end{cases}$$

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:

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

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:

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

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:

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

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).

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

Therefore, the following result will be given as

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

The proof is completed.

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. For the purpose of improving the reference trajectory tracking, the CFDL technique is employed alongside a novel sliding surface. 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.

Consider the network comprising:

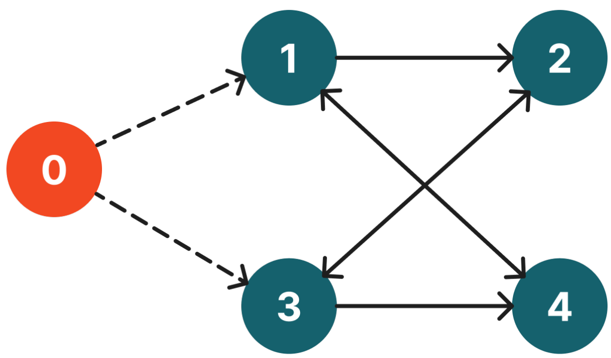

Fig. 2: Communication topology among agents.

IV. Simulation Example

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

The output data model of each agents is governed by:

$$
y_i(k+1) = 0.5y_i(k)u_i(k) + \frac{6m}{rT} - a_iy_i(k)^{p_i} + 0.45, \quad i = 1,2,3,4,
$$

where the agent-specific parameters are:

$$
a_i = \begin{cases} 0.03 & \text{if } i = 1, \\ 0.01 & \text{if } i = 2, \\ 0.02 & \text{if } i = 3, \\ 0.01 & \text{if } i = 4, \end{cases} \qquad p_i = \begin{cases} 3 & \text{if } i = 1,3, \\ 2 & \text{if } i = 2,4. \end{cases}
$$

in this scenario, the dynamics are assumed to be unknown and are only used to generate the I/O data for the MASs.

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 $D = \text{diag}(1, 0, 1, 0)$, the following two different reference trajectories are introduced to demonstrate the effectiveness of the proposed method.

Example 1: Consider the following reference trajectory:

$y_d(k) = 0.6, k \in [0, 200]$

The initial parameters are chosen as $u_i(1) = 0.01$, $y_i(1) = 0.6$ and $\phi_i(0) = 4$ for all agents in this simulation, $\Gamma_1 = \Gamma_3 = 0.45$ and $\Gamma_2 = \Gamma_4 = 0.15$, with $\tau_s = 10^{-5}$, $m = 200$, sampling rate $rT = 1024$, $\eta = 1$, $\mu = 0.005$, other parameters are given as $\rho = 7.5$, $\lambda = 350$, $\omega = 10$, $\sigma = 95$, $\alpha = 15$ with $\epsilon = 10^{-5}$.

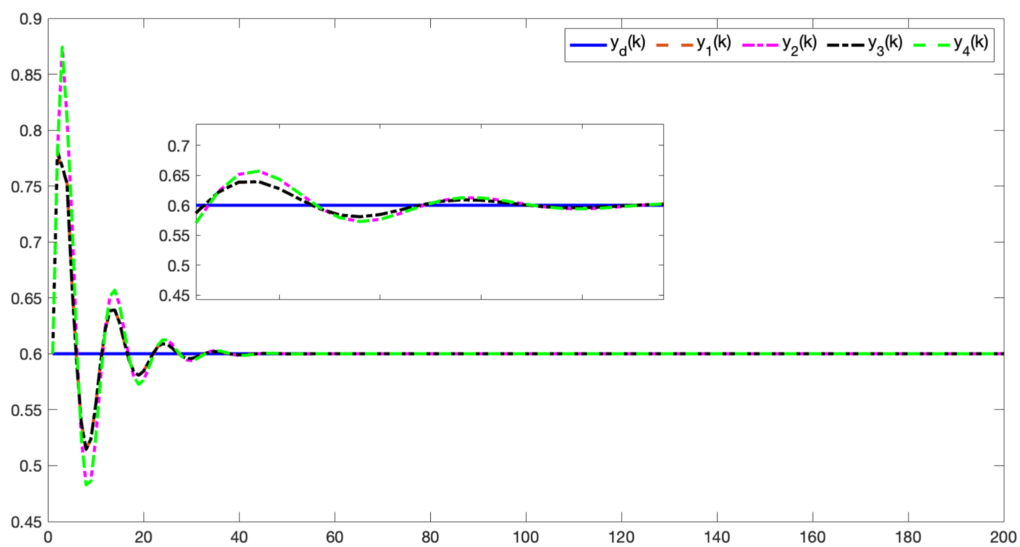

Fig. 3: Tracking performance of all agents under the time-invariant reference trajectory.

Fig. 3 demonstrates the tracking output of the proposed control scheme for the case of a time-invariant reference signal. It can be clearly observed that the agents effectively follow the reference trajectory, which is set to a constant value of 0.6, and the tracking performance closely aligns with this target.

Moreover, Fig. 4 illustrates the corresponding distributed measurement error, which remains bounded within the range of [-0.01, 0.01], indicating accuracy of the control strategy. These results confirm that the controller maintains stability.

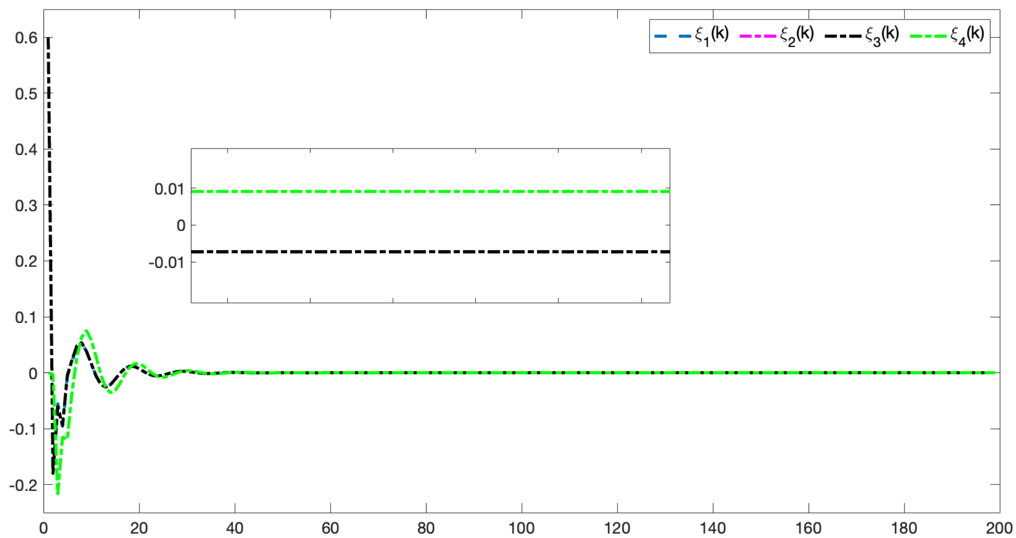

Fig. 4: Distributed measurement error of all agents under the time-invarying reference trajectory.

Example 2: The expression for the reference trajectory is:

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

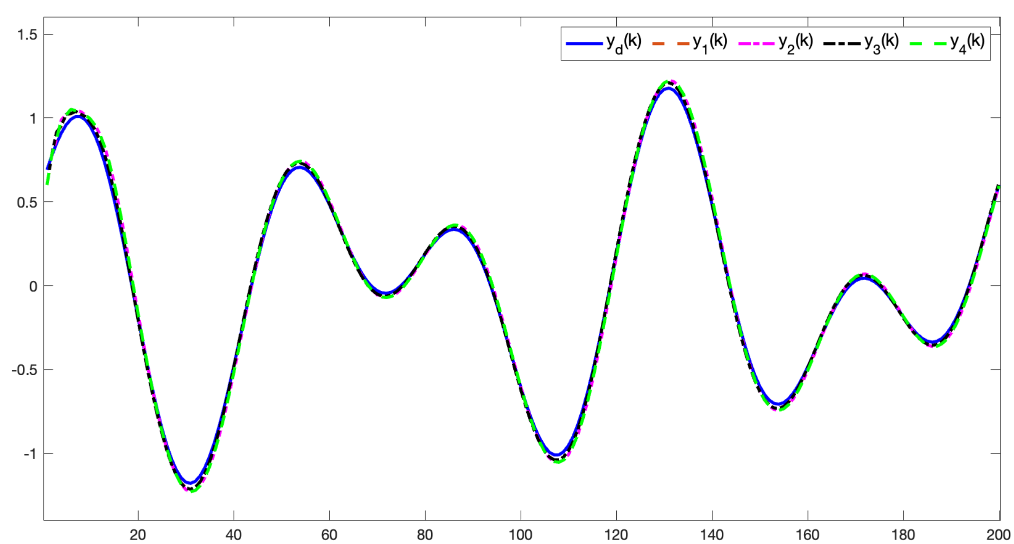

Fig. 5: Tracking performance of all agents under the time-varying reference trajectory.

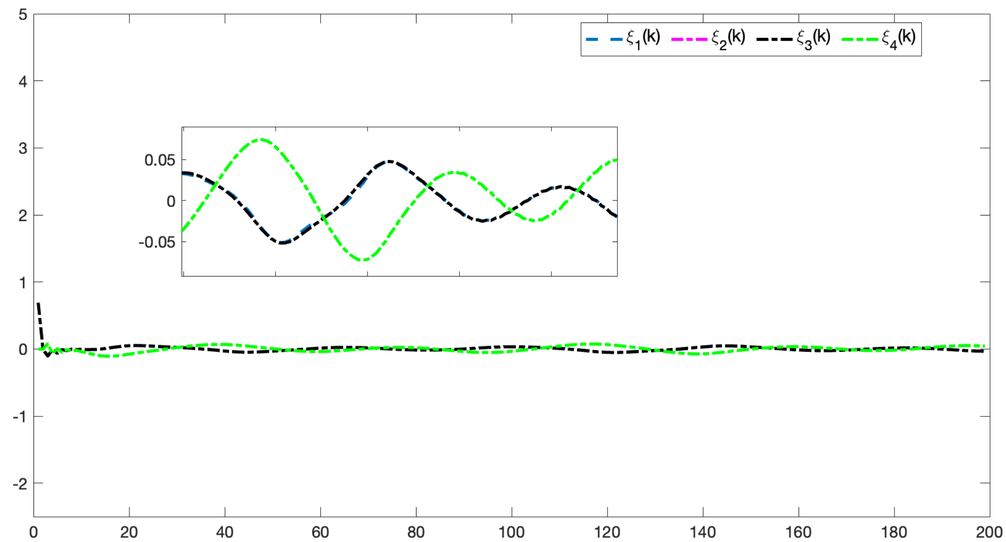

Fig. 6: Distributed measurement error of all agents under the time-varying reference trajectory.

Fig. 5 presents the tracking performance for all agents for the time-varying trajectory. All agents successfully track the time-varying reference trajectory. Additionally, as shown in Fig. 6, the distributed measurement errors of all agents are bounded within a specified range

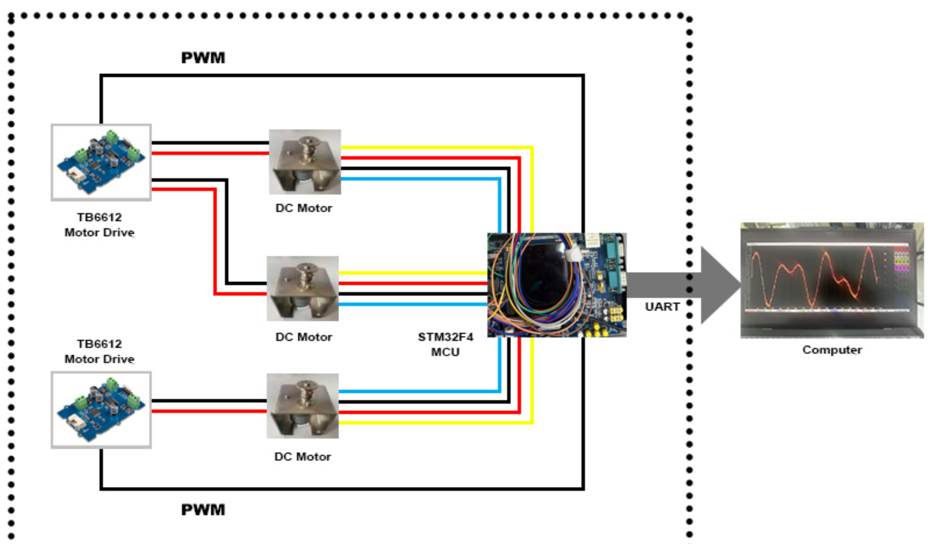

Fig. 7: System connection diagram of multi DC motor consensus tracking control.

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 (MCU) STM32F407ZGT6 is used for high-resolution pulse width modulation (PWM) 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:

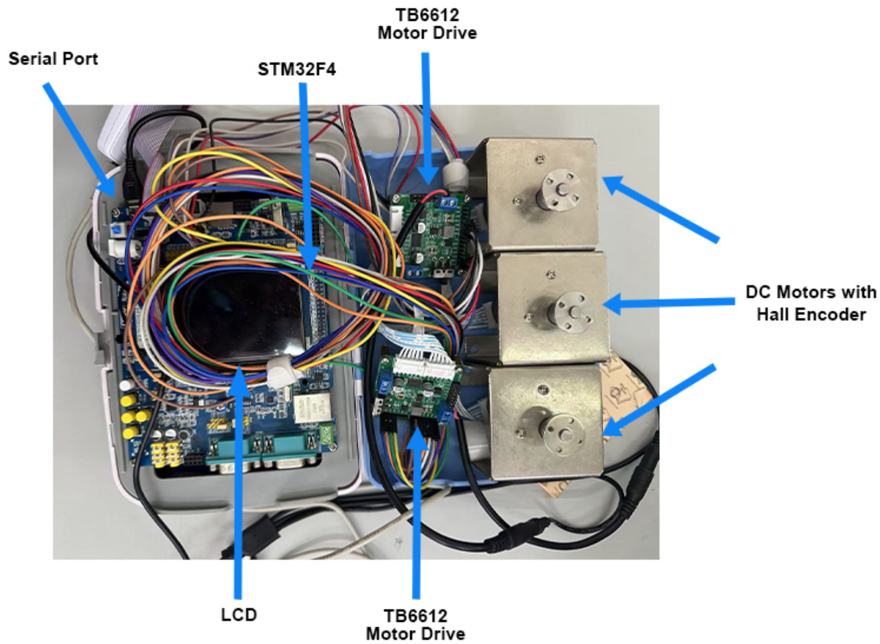

Fig. 8: Multi DC motor system.

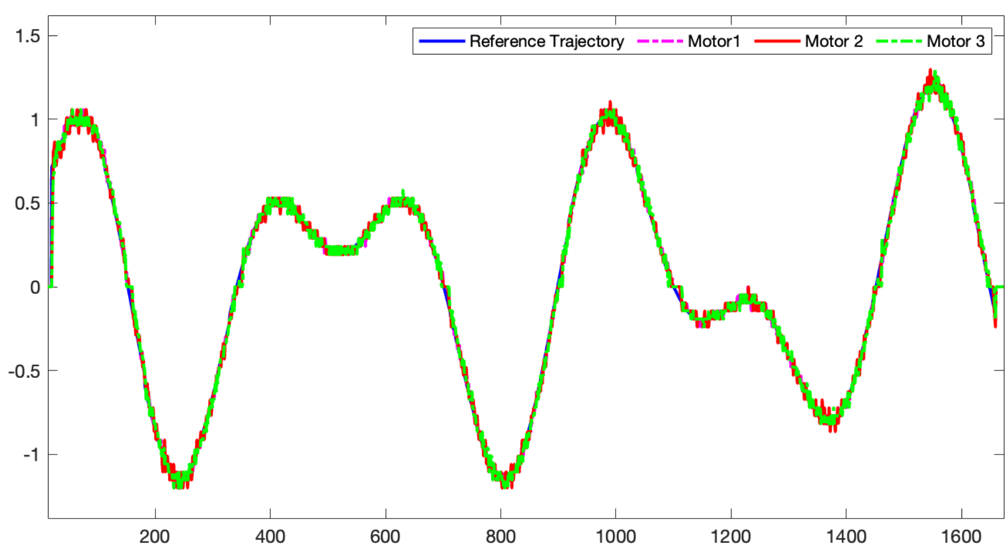

Fig. 9: Tracking performance of 3 DC motors for time-invariable desired trajectory.

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 accur, the system eventually reaches 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.

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. Finally, the effectiveness of the proposed control approach is verified through physical experiments on multi DC motor system.

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