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

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Abstract

This paper proposes the distributed data-driven 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, utilizing the neighboring agents process informations, the novel sliding surface is employed, which ensures the boundedness of distributed 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 motors.

KEYWORDS

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

I. INTRODUCTION

Motivated by the coordinated behaviors observed in nature, such as bird flocking or herd migration, the distributed control multi-agent systems(MASs) has been studied with interest in recent years. [1] Because of the distributed and flexible structure, the MASs based approaches have significant potential in addressing coordination challenges for complex systems [2]. The control of DC motors is essential in numerious technological applications, with single DC motor serving as the foundation for the systems in various fields, including vehicle coorporation [3], multi-robot systems and industrial machinery [4].

It is challenging to establish an accurate mathematical model for the speed regulation of multi-DC motor systems due to their nonlinear, time-varying, and multi-variable conditions [7]. Even if a relatively accurate mathematical models are developed, the associated control algorithms can become highly complex, so the model-based control approach is difficult to apply or extend to such systems. Nowdays, data-driven methods have been used to control, decision making, planing, fault diagnosis, predicting, etc. In [15]- [16], a compact form dynamic linarization (CFDL) data-driven modeling method is proposed for nonlinear systems. So far, the CFDL data-driven modeling method has proven to be highly useful in various domains [17]- [20] with different characteristics such as simplicity and particularly, a small amount of calculation, ease of implementation, and strong robustness, making it highly effective for addressing unknown nonlinear time-varying systems.

In [21], a model free adaptive control (MFAC) approach is presented for MASs, which uses input and output data to achieve consensus tracking trajectory.

Alternatively, the sliding mode control (SMC) adapts dynamically the system operation based on the current state of the system such as the error and its derivative, ensuring the system follows a predetermined sliding surface [22]. Because the sliding surface can be designed and has the purpose to deal with the object parameters and disturbances, the SMC provides the fast response, insensitivity to parameter changes and disturbances, and simplicity in implementation. The above advantages make SMC widely used in control systems and one of main topic to focus in the ongoing research. [28]- [30]

Inspired by the abovementioned considerations, this paper studies a novel model free adaptive sliding mode control for speed regulation of multi-DC motors. The proposed control method consists to eliminates the need for precise system models by dynamically adjusting the control law [21], where is particularly useful in systems where obtaining a detailed model is impractical or complex such as the tradition PID control method. Compared with other existing literature on multi-DC motors systems, the results of this paper have following distinct features.

1) The proposed method integrates encoder counts based on the well known constant elapsed time (CET) method [31] for accurate speed control in nonlinear, time-varying multi-DC motor systems. This innovation greatly enhances resolution and reliability, setting it apart from traditional methods.
2) The implementation of a fixed communication topology for agents interconnections, which makes the controller more applicable and flexible in real implementation.
3) Utilizes the pseudo partial derivative (PPD) estimation mechanism within the MFASMC scheme, which provides strong robustness

The following sections will outline the remaining content of this paper: section II provides preliminaries and problem formulation, Section III The main results, Section IV presents simulation results and performance analysis, demonstrating the efficacy of the proposed method under various operating conditions. At the end, Section V concludes the paper, summarizing the key findings potential points for future research.

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 $\mathcal{G}$ forms a strongly connected graph, ensuring 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

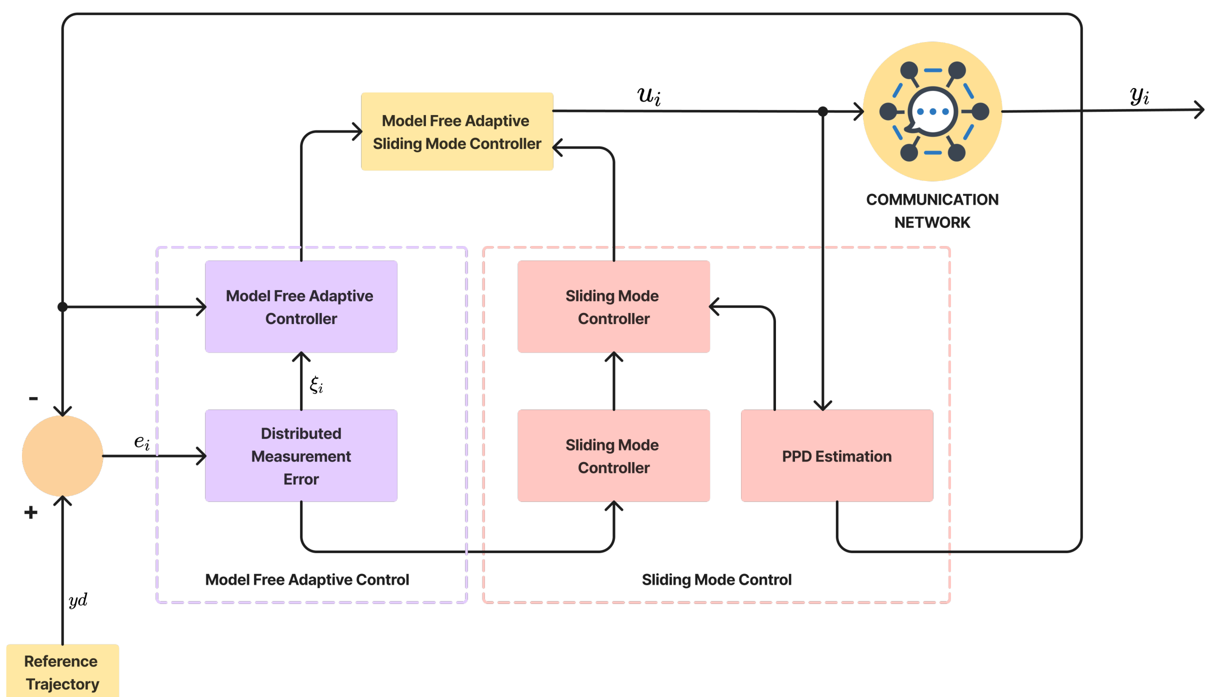

Fig. 1: Block diagram.

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 can be derived as

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

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

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:

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

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 is designed:

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

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 equivalent control law is designed as

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

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 as

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

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 designed:

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

where the parameter Γ_i is a gain factor.

C. Stability Analysis

Theorem 1: For the system (1) satisfying assumptions 1 and 2, utilizing 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 presented bellow:

$0 < h_0 < h_i(k) < \frac{\omega C_0}{2\sqrt{\sigma}} < 1$

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:

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

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

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

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

Part ii: In this part, mathematical induction will be utilized to prove that $\xi_i(k)$ remains bounded.

Substituting (5) into (9), then the expression for $\xi_i(k+1)$ is formulated as follows:

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

By applying the fundamentals of mathematical induction, then assuming $0 < h_0 < h_i(k) < \frac{\omega C_0}{2\sqrt{\sigma}} < 1$, 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).

$$|\xi_i(k+1)| \leq |1 - h_i(k)(1-\frac{1}{2})||\xi_i(k)| + |g_i(k)|$$

$$\leq \ |1 - h_i(k)(1 - \frac{1}{2})||\xi_i(k)| + g_0(k)$$
$$\vdots$$
$$\leq \ 1 - h_0(1 - \frac{1}{2})^k|\xi_i(k)| + \frac{g_0(1 - (1 - h_0(1 - \frac{1}{2}))^2)}{h_0(1 - \frac{1}{2})} \tag{19}$$

Therefore, the following result will be given as

$$\lim_{k\to\infty} \xi_i(k+1) = \frac{g_0}{h_0(1 - \frac{1}{2})} = \frac{\alpha g_0}{(\alpha - 1)h_0} \tag{20}$$

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 error remains bounded within a predifined region, achieving precise speed regulation.

Consider the network comprising:

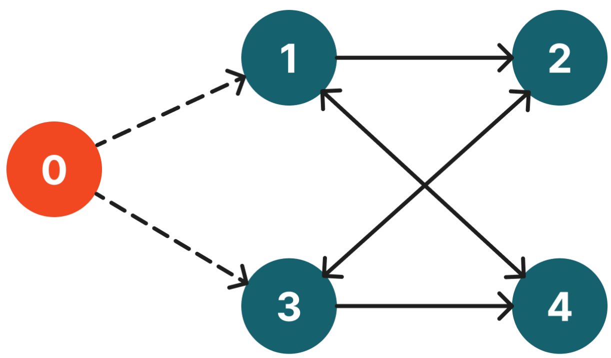

Fig. 2: Communication topology among agents.

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:

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

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 $D = \mathrm{diag}(1, 0, 1, 0)$, we consider the following two different desired trajectories.

Example 1: Consider the following reference trajectory:

$y_d(k) = 0.6$

as k in the range $0 \leq k \leq 200$.

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 $\epsilon = 10^{-5}$.

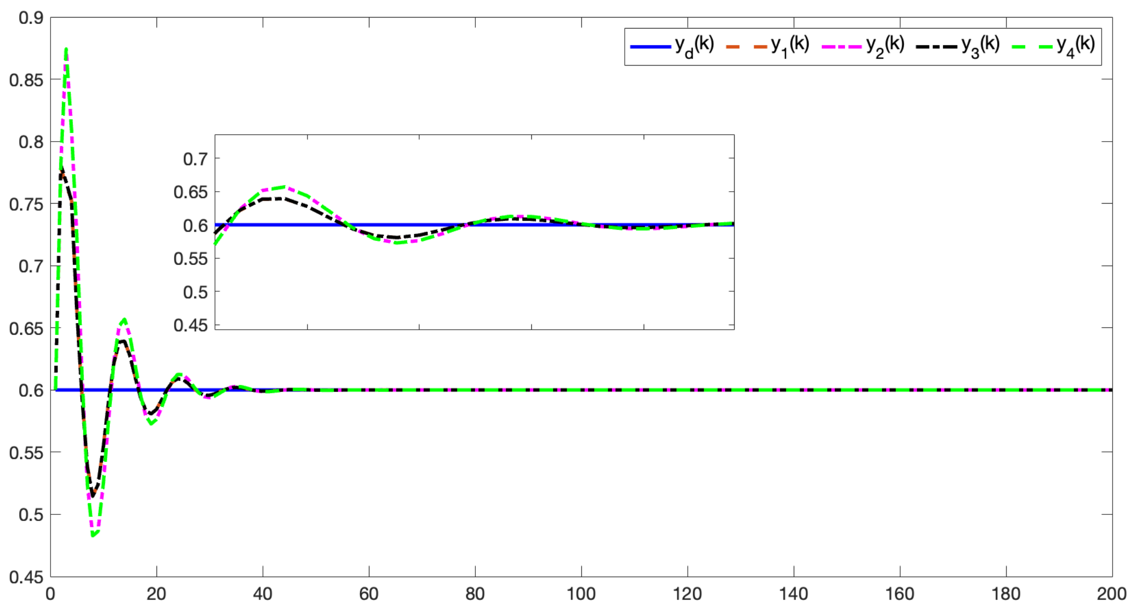

Fig. 3: Tracking performance of all agents under the time-invarying reference trajectory.

Fig. 3 demonstrates the tracking performance for the time-invariant signal. Moreover, Fig. 4 shows that the distributed measurement error remains bounded and constrained within the range.

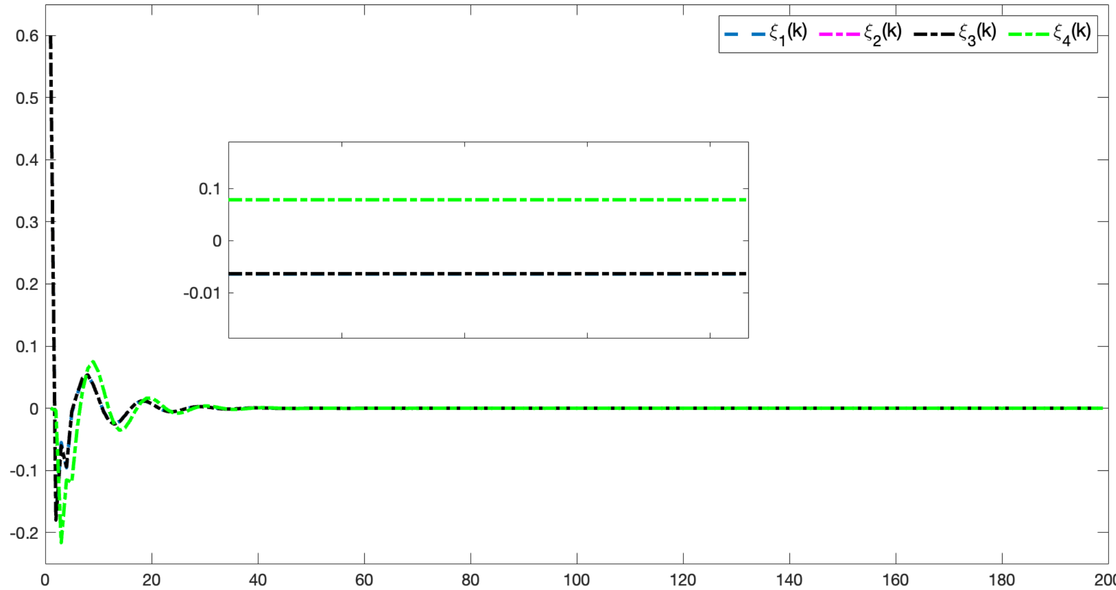

Fig. 4: Distributed error of all agents under the time-invarying reference trajectory.

Example 2: The expression for $y_d(k)$ is:

$$y_d(k) = 0.5 \sin\left(\frac{k\pi}{30}\right) + 0.3 \cos\left(\frac{k\pi}{10}\right)$$

as k in the range $0 \leq k \leq 200$.

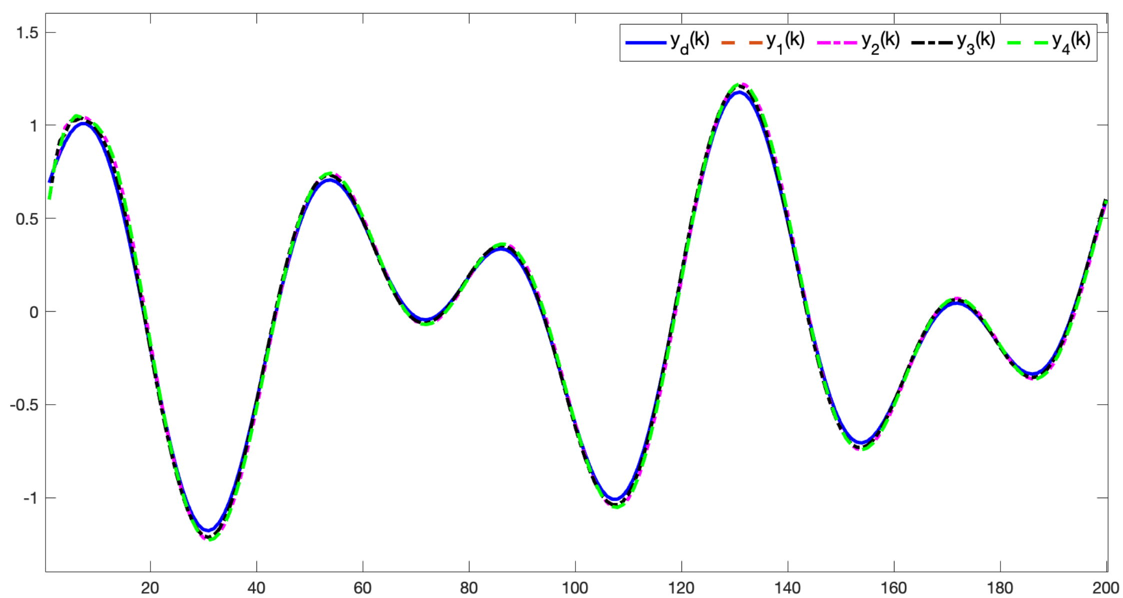

Fig. 5: Tracking performance of all agents under the time-varying reference trajectory.

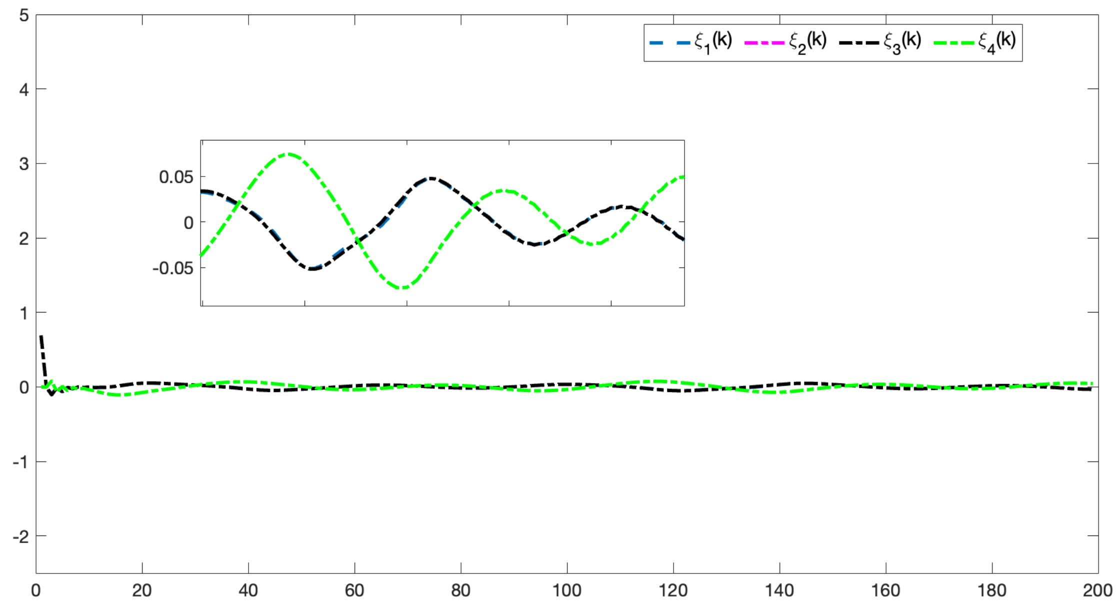

Fig. 6: Distributed error of all agents under the time-varying reference trajectory.

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

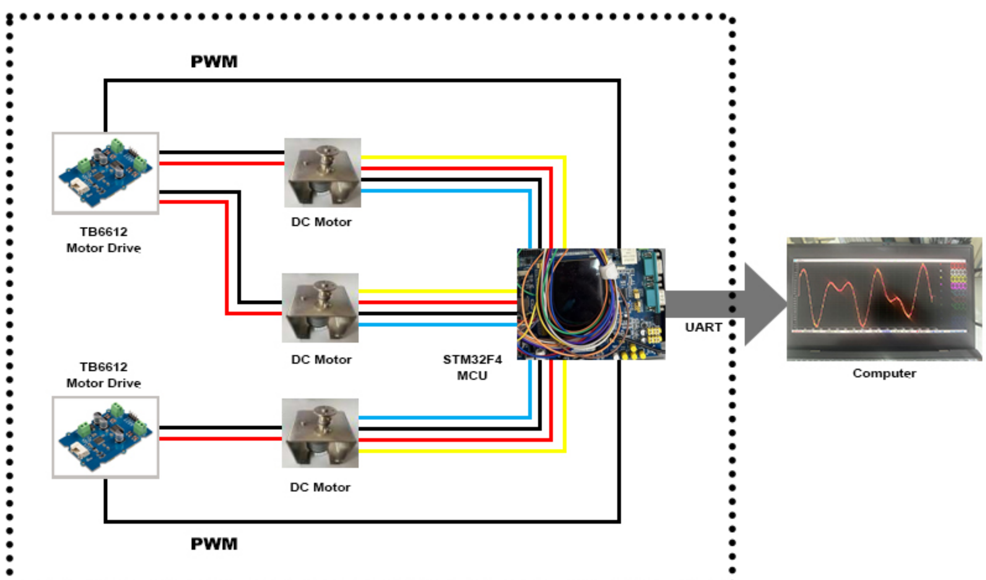

Fig. 7: System connection diagram of multi-DC motors consensus tracking control.

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:

$$y_d(k) = 0.5\sin(0.07\pi(k)) + 0.7\cos(0.04\pi(k))$$

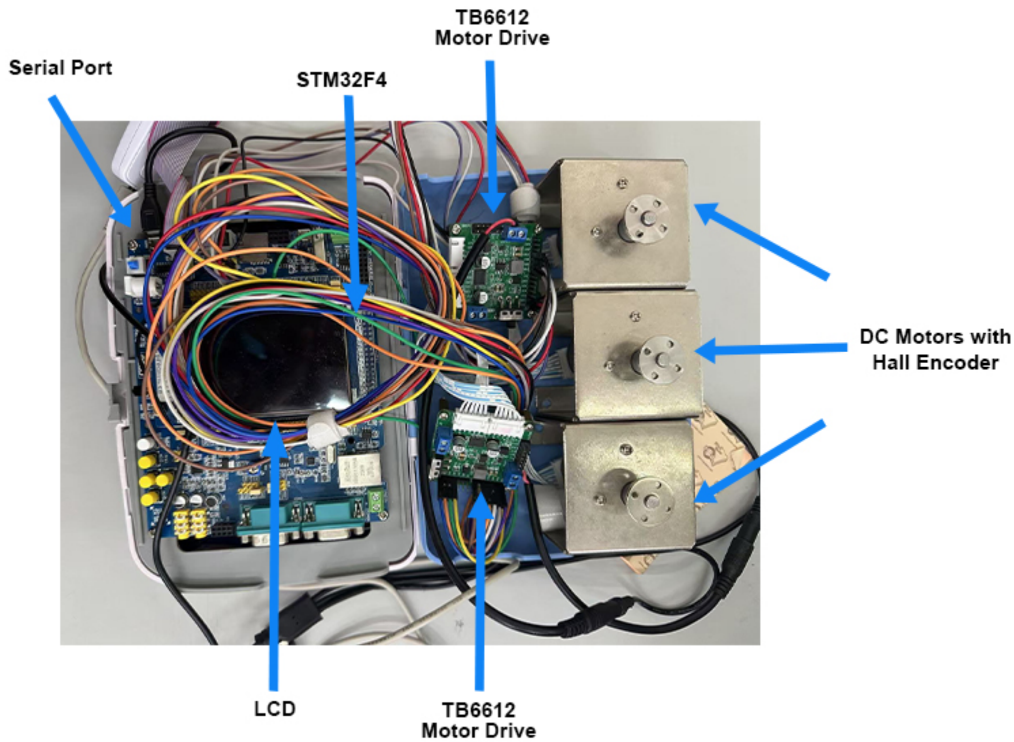

Fig. 8: Multi-DC motors system.

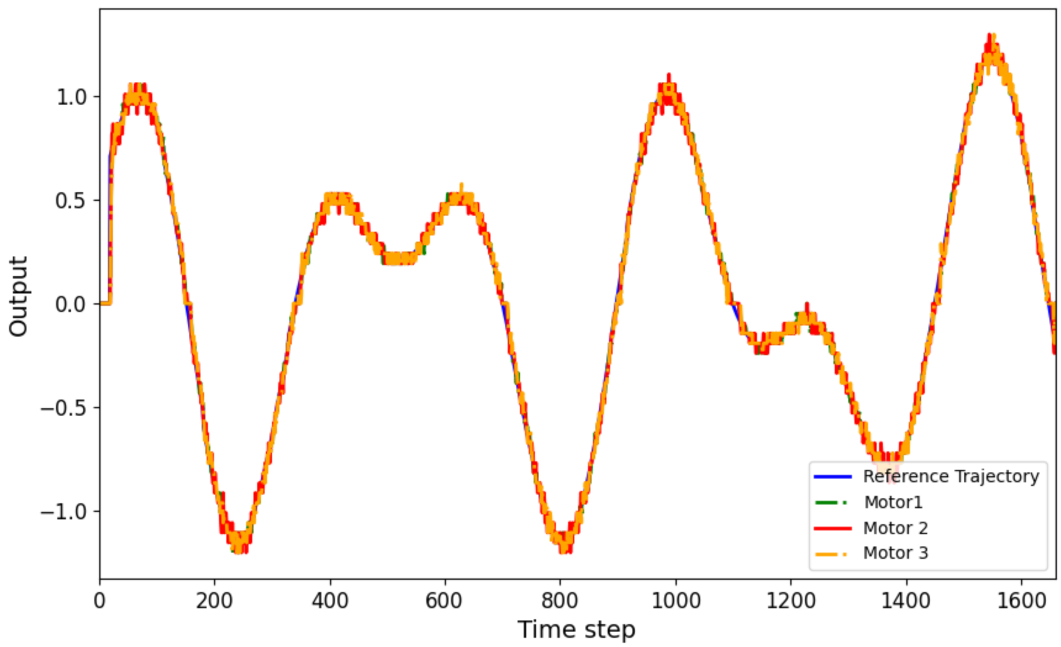

Fig. 9: Tracking performance of 3 DC motors for time-invariable desired trajectory.

Fig. 9 shows the tracking performance of multi-DC motors 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 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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