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 input-output data of agents, the novel sliding surface is employed, which ensures the boundedness of distributed error through stability-guaranteeing mechanism. Subsequently, a distributed model-free adaptive sliding mode controller is developed to ensure the reference trajectory tracking. Finally, the effectiveness of the proposed control approach is verified through experiments on multi-DC motors.

KEYWORDS

Model-free adaptive sliding mode control, compact form dynamic linearization, nonlinear multi-agent system, data-driven 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 numerous 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. As the common condition for model-free control methods, Assumption 1 is crucial in ensuring effective system performance. Assumption 2 implies that the system input rate constrains the system output rate, which is satisfied in many practical systems.

Assumption 3: The network of followers 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 two assumptions. If $|\Delta u_i(k)| \neq 0$ holds, then the system can be transformed into the CFDL data model as follows:

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

where $\phi_i(k)$ 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 can be highly complex and more challenging to verify. Therefore a data-driven method for studying numerical characteristics is the preferred solution.

III. MAIN RESULTS
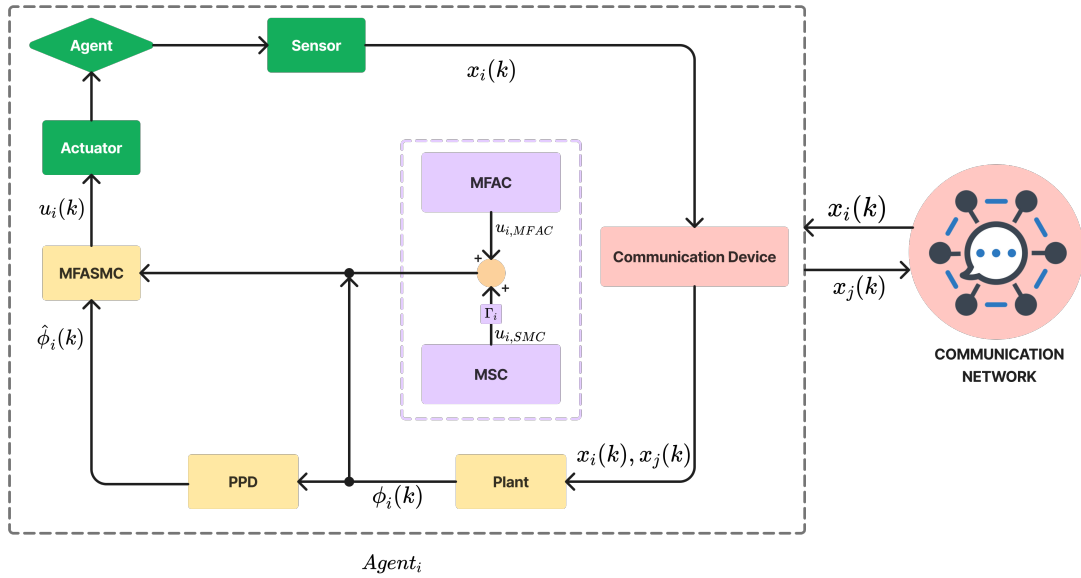
A. Model Free Adaptive Controller Design

Fig. 1: Block diagram.

Consider the following PPD criterion function, which is used to evaluate the performance of the parameter $\phi_i(k)$:

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

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

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

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

Herein, $\eta \in (0,1)$, $\mu > 0$ the weight factor, ϵ is a small positive number and $\hat{\phi}_i(k)$ represents the estimated value of $\phi_i(k)$. The following distributed MFAC algorithm is then 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 SMC for system, the sliding mode surface is first defined as

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

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

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

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

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

Considering (8), with the assistance of reaching law $S_i(k+1) = 0$, the equivalent control law is then designed as

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

The controller contains equivalent control law and switching control law, which is set as

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

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

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

Taking in considaration both(10), (11) and (12) , the controller is summarized as follows:

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

$$- \frac{\xi_i(k)}{\alpha(\sum\limits_{j \in N_i} a_{ij} + d_i)} + \tau_s sign(S_i(k)) \bigg) \tag{13}$$

Subsequently, the final MFASMC input is designed:

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

where the parameter Γ is a gain factor.

C. Stability Analysis

Theorem 1: For the MASs (1) that satifies Assumptions 1 and 2, assuming $|\xi_{i,0}| < \min\{a_{i,0}, b_{i,0}\}\rho_{i,0}$ are satisfied, the controller parameters establish $0 < h_0 < h_i(k) < \frac{\omega C_0}{2\sqrt{\sigma}} < 1$, then using the PPD update law (5) can ensure the boundedness of $\hat{\phi}_i(k)$.

Proof: The proof is devided in two parts.

Part i: Set $\tilde{\phi}_i(k) = \hat{\phi}_i(k) - \phi_i(k)$, based on PPD estimation algorithm (5), we can obtain:

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

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 minimun value is $\frac{\eta \epsilon^2}{\mu + \epsilon^2}$, therefore there must be a constant q_1 to satisfy inequality $0 < \eta \leq 1$ and $u > 0$

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

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

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

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 $\xi_i(k)$ is remain bounded.

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

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

$$-\frac{\omega\phi_i(k)\hat{\phi}_i(k)}{\sigma+\hat{\phi}_i(k)^2}\left(\sum_{j\in N_i}a_{ij}+d_i\right)\tau_s sign(S_i(k)) \tag{18}$$

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).

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

Therefore, the following result will be given as

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

The proof is completed.

Remark 3: Theorem 1 guarantees the boundedness of $\hat{\phi}_i$ and the distributed measurement error for the MASs described by (1) under assumptions 1 and 2. The proof employs the PPD update law (5) to ensure that $\tilde{\phi}_i(k)$ remains bounded, as demonstrated through the application of the factor $q_1 < 1$. Then, mathematical induction confirms that $\xi_i(k)$ is bounded. Therefore, this result shows the effectiveness of the proposed controller in achieving stable performance for the MASs.
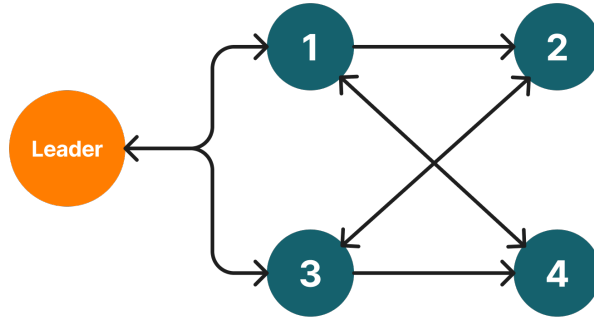
Consider the network comprising:

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:

$$\text{Agent 1}: \quad y_1(k+1) = \frac{mu_1(k)}{0.1T}$$
$$\text{Agent 2}: \quad y_2(k+1) = \frac{mu_2(k)}{0.1T}$$
$$\text{Agent 3}: \quad y_3(k+1) = \frac{mu_3(k)}{0.3T}$$
$$\text{Agent 4}: \quad y_4(k+1) = \frac{mu_4(k)}{0.3T}$$

It is evident that the agents considered are heterogeneous, as the dynamics differ from one another. 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. Assume that the information exchange among agents is directed and fixed. 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 $D = \text{diag}(1, 0, 1, 0)$, we consider the following two different desired trajectories.

Exemple 1: The expression for $y_d(k)$ is:

$y_d(k) = 6$

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 $\tau_s = 10^{-5}$, $m = 200$, sample rate $rT = 1024$, $\eta = 1$, $\mu = 0.005$, other parameters are given as $\rho = 7.5$, $\lambda = 350$, $\omega = 10$, $\sigma = 95$ and $\alpha = 15$ with $\epsilon = 10^{-5}$.
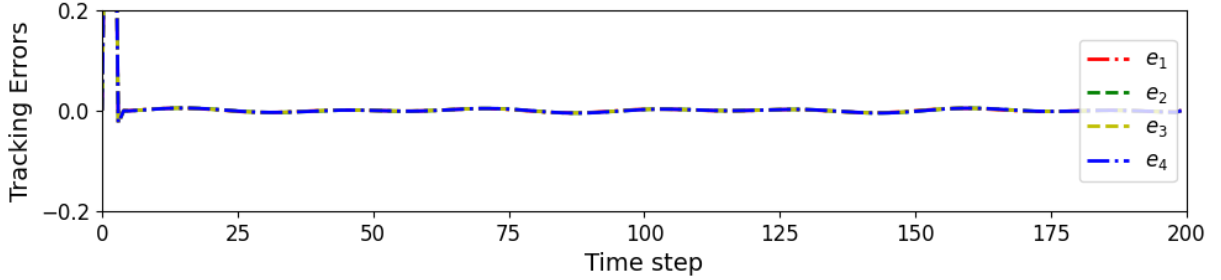

Fig. 3: Tracking errors for time varying desired trajectory.

As shown in Fig. 3, the tracking errors between the actual and desired trajectories for agents e_1, e_2, e_3, and e_4 are relatively small and converge to zero over time. However, the individual agents exhibit varying levels of tracking error, suggesting that their unique dynamics or initial conditions may influence the performance.
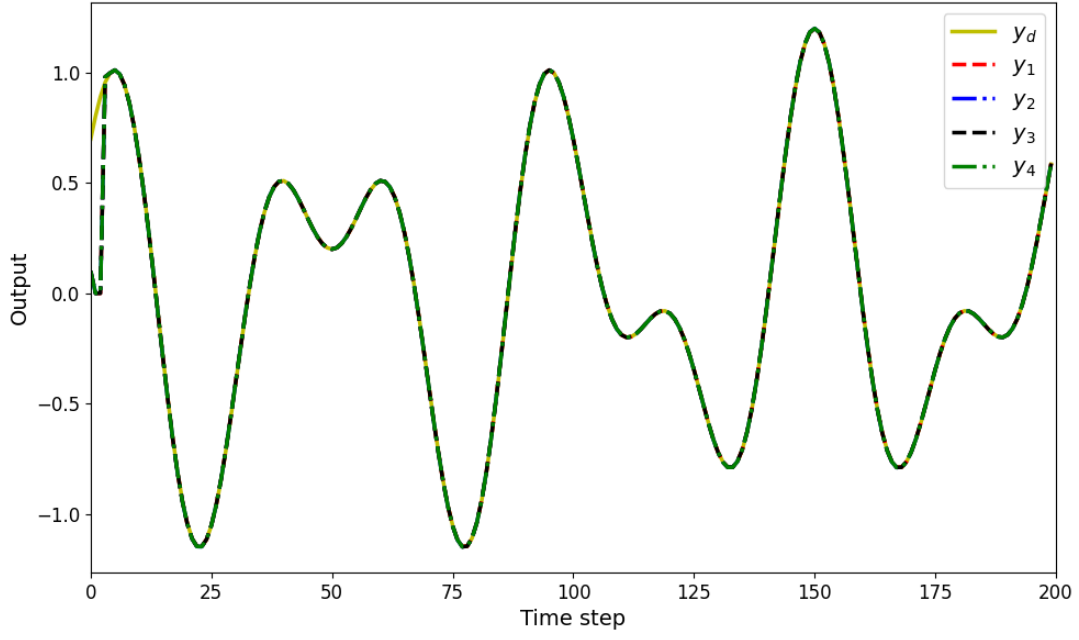
Fig. 4: Tracking performance of all agents for time-varying desired trajectory.

Fig. 4 presents a detailed analysis of the tracking performance for all agents. All agents successfully track the time-varying desired trajectory, confirming the effectiveness of the proposed control system. While minor variations in individual trajectories are evident, each agent generally adheres to the desired path. Factors such as agent dynamics, communication delays, and environmental disturbances could potentially influence the tracking performance.
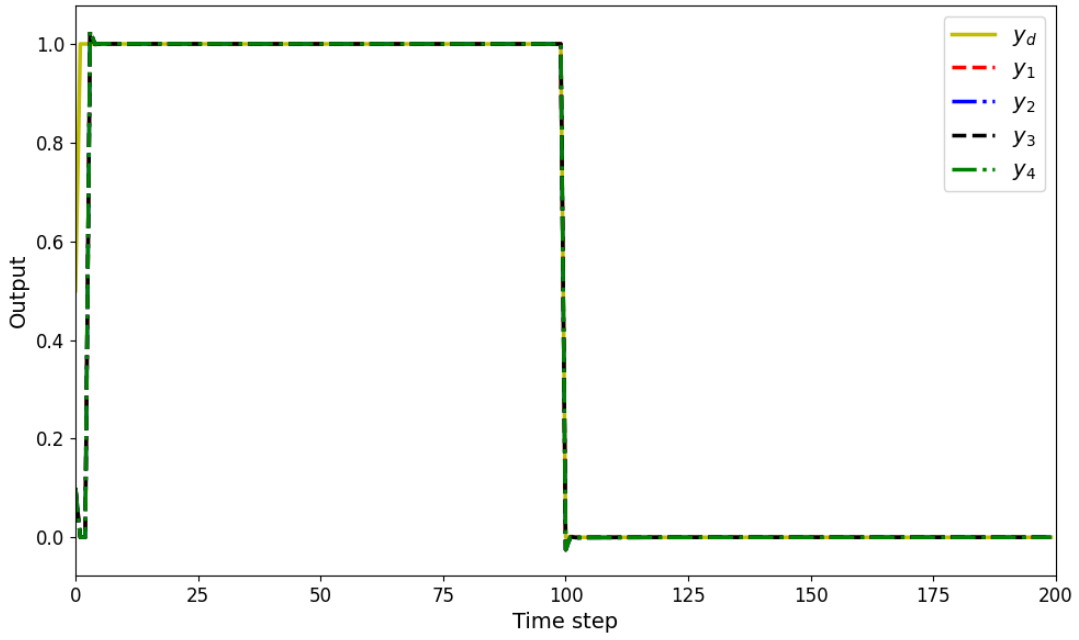

Fig. 5: Tracking performance of all agents for time-invariable desired trajectory.
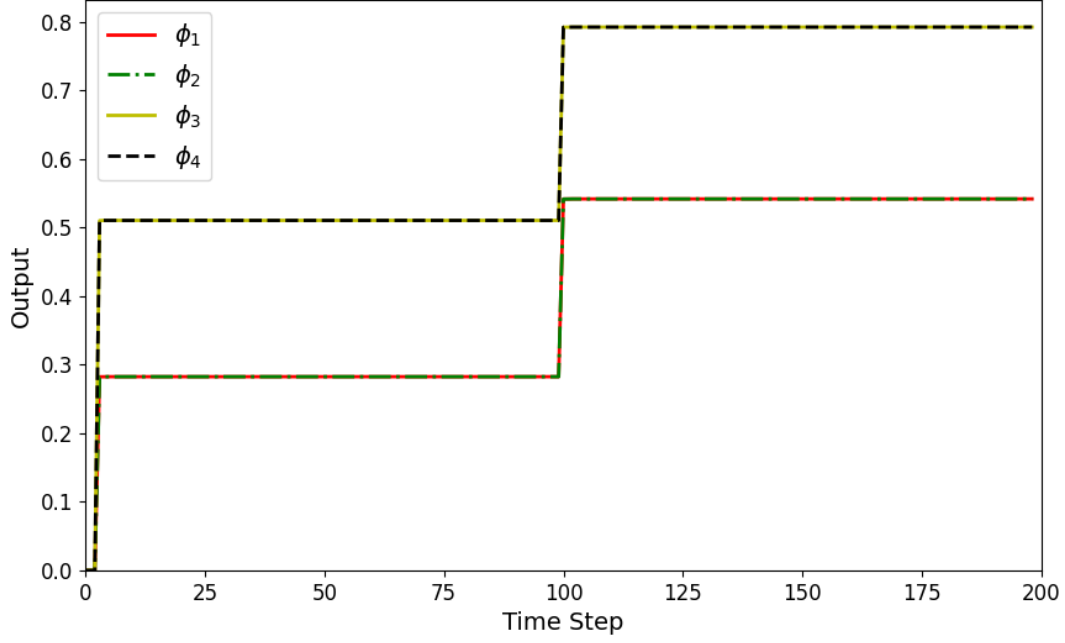
Fig. 6: PPD Estimation of all agents.

Fig. 5 demonstrates that all agents successfully track the time-invariable desired trajectory. Meanwhile, Fig. 6 shows the PPD estimation for all agents, highlighting the accuracy of the adaptive estimation process within the control framework.

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:

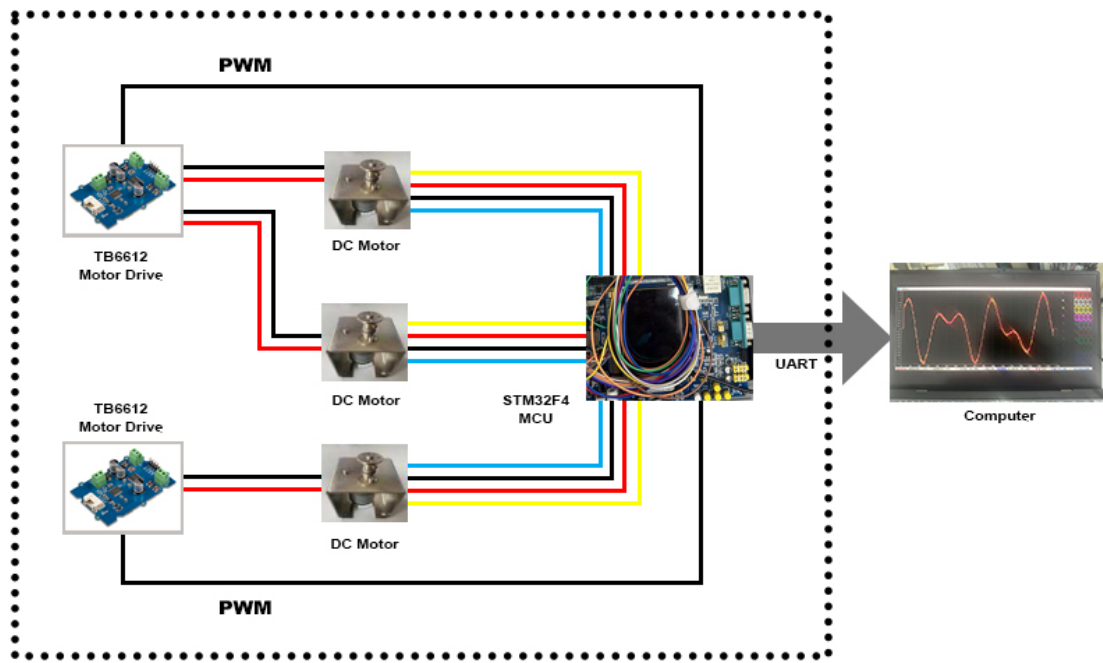$$y_d(k) = 0.5\sin(0.07\pi(k)) + 0.7\cos(0.04\pi(k))$$

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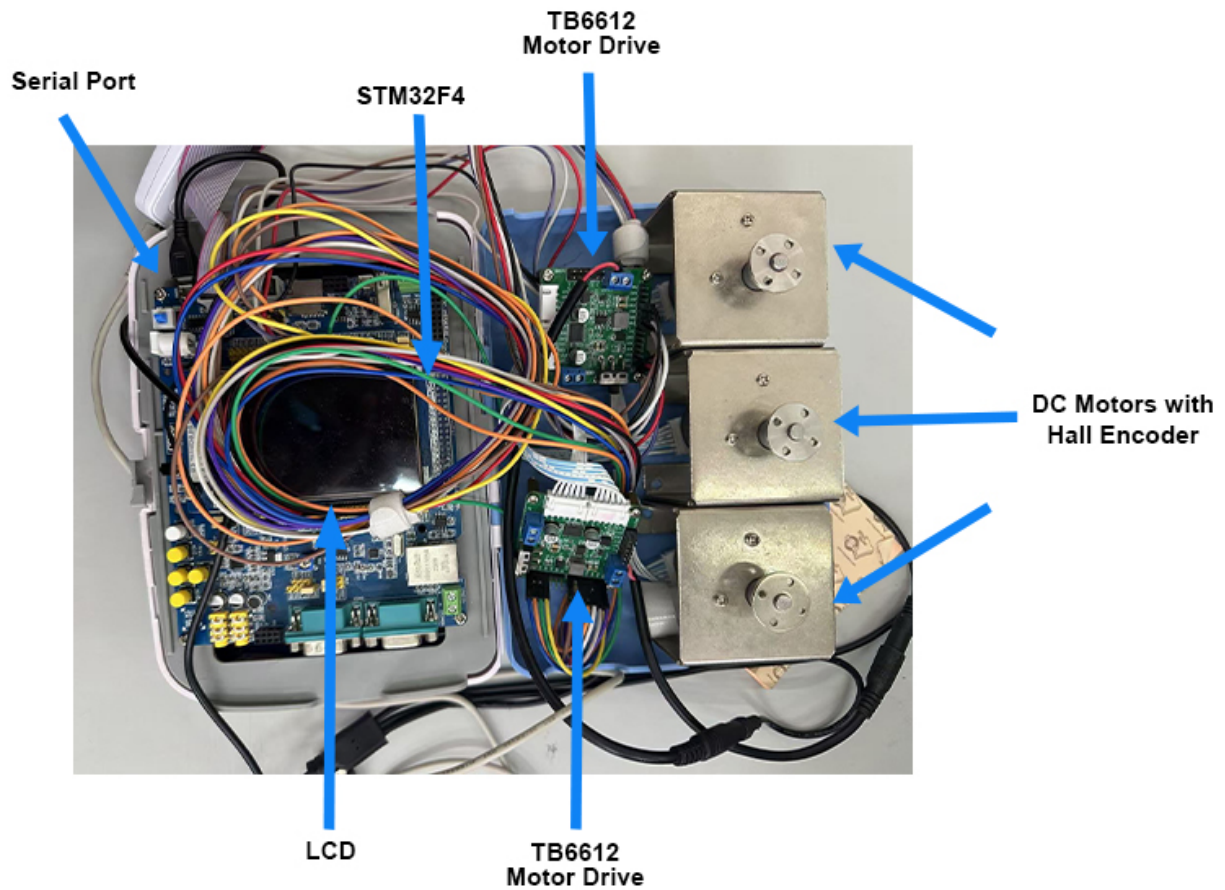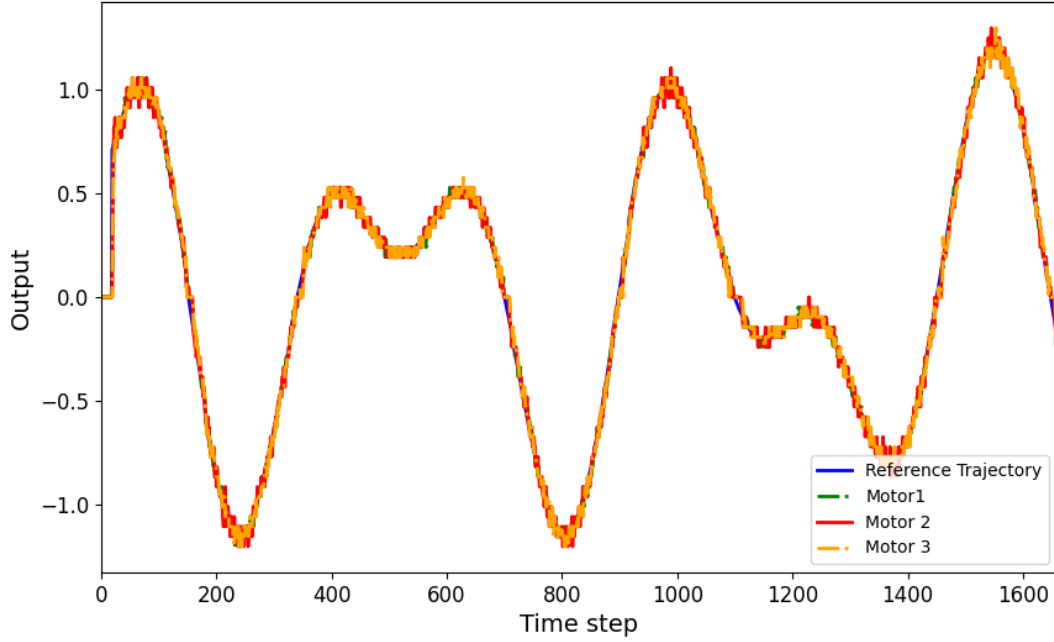

Fig. 8: Multi-DC motors system.

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

Fig.9 shows the tracking performance of multi-DC motors. As presented, all DC motors successfully track the desired trajectory, demonstrating the effectiveness of the proposed control method. Where the reference trajectory is presented by blue.

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 paper, a novel model-free adaptive sliding mode control was presented for multi-DC motors speed regulation. The proposed method achieves robust performance and adaptability in the presence of varying conditions. Utilizing a fixed topology represented by Laplacian matrice, the control strategy effectively manages the interconnections among multiple DC motors. The advantages and effectiveness of the proposed approach are demonstrated through detailed simulation results. Future work will focus on implementing the proposed approach in practical scenerios under hardware constraints.

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