

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

Tony Blaise Bimenyimana

Abstract

Here goes an Abstract

I. INTRODUCTION

IN short time ago, the field of control systems experienced significant advancements, particularly in the domain of multi-agent systems. Distributed coordination of multi-agent systems has been utilized in range of practical applications, including satellite formation, autonomous, underwater vehicules,automated highway systems, and mobile robots. These applications highlight the importance and adaptability of multi-agent systems in addressing complex real world challenges.

A critical aspect of multi-agent systems is robust speed regulation, effectively managing multi direct current (DC) motors is essential for acheiving complex machine movements. The complexity of such systems arises from the necessity to maintain synchronization and optimal performance despite parametric uncertainties and external disturbances. Conventional control methodologies, such us Proportional-Integral-Derivative (PID) control and Linear Quadratic Regulator (LQR), often fall short in these dynamic and unpredictable environments, highlighting the need for more adaptive and resilient approaches.

Firstly, this paper aims to address these challenges by representing an innovative control strategy. Moreover, the proposed method synergizes the strengths of Model Free Adaptive Control (MFAC) and Sliding Mode Control (SMC) to achieve robust and efficient speed regulation in multi-agents systems. Secondly, By leveraging the adaptability of MFAC and the robustness of SMC, this approach seeks to enhance the performance and realilbty of multi DC motors speed regulation in the presence of uncertainties and perturbations.

Model Free Adaptive Control (MFAC) is a technique that eschews the need for an explicit mathematical model of the system, making it highly adaptive to real time changes and disturbances. This adaptability ensures optimal control performance in varying conditions. On the other hand, Sliding Mode Control (SMC) is well known for its robustness and ability to handle Nonlinearities and uncertainties by enforcing high frequency switching control law. SMC ensures that the system states are driven to and maintained within a specified sliding surface.

Finally, the integration of these two methodologies facilitates a control strategy that is both adaptive and resilient. MFAC continously adjusts the control parameters based on real-time system feedback, while SMC provides a robust framework to manage system uncertainties and external disturbances. This combination is particularly well-suited for the complex dynamics and interactions inherent in multi-agent systems, offering a comprehensive solution to the challenges of robust speed control.

The following sections will outline the remaining content of this paper: section 2 provides——. Section 3 ————. Section 4 presents simulation results and performance analysis , demonstrating the efficacy of the proposed method under various operating conditions. At the end, Section 5 concludes the paper, summarizing the key findings potential points for future research, including the extension of the proposed approach to other types of multi-agent systems and exploring further enhancements to the control algorithms.

II. PRELIMINARIES AND PROBLEM FORMULATION

A. Preliminaries

The set of real numbers is denoted by \mathbb{R} . For a given matrix $A \in \mathbb{R}^{n \times n}$, $\|A\|$ represents its matrix norm. The notation $\text{diag}(\cdot)$ refers to a diagonal matrix, and I signifies an identity matrix of appropriate dimensions. In the context of multi-agent systems, graph theory serves as a powerful tool to model interaction topologies. We will now provide a brief introduction to directed graphs within algebraic graph theory. Let $G = (V, E, A)$ be a weighted directed graph, where $V = \{1, 2, \dots, N\}$ represents the set of vertices, $E \subseteq V \times V$ denotes the set of edges, and A is the adjacency matrix. Here, V also indexes the agents. If agent j can receive a message from agent i , then $(i, j) \in E$, making j the child of i and i the parent of j . The neighborhood of agent i is given by $N_i = \{j \in V \mid (j, i) \in E\}$.

The weighted adjacency matrix $A = (a_{i,j}) \in \mathbb{R}^{N \times N}$ is defined such that $a_{i,i} = 0$, $a_{i,j} = 1$ if $(j, i) \in E$; otherwise, $a_{i,j} = 0$. The Laplacian matrix of G is defined as $L = D - A$, where $D = \text{diag}(d_1^{\text{in}}, d_2^{\text{in}}, \dots, d_N^{\text{in}})$ and $d_i^{\text{in}} = \sum_{j=1}^N a_{i,j}$ is called the in-degree of vertex i . A graph is said to be strongly connected if there exists a path between any pair of vertices.

B. Problem Formulation

In this research, the speed regulation problem of DC motors is frequently examined under the assumption that all motors demonstrate identical dynamic characteristics. Nevertheless, heterogeneity is still a fundamental characteristic of systems comprising multi DC motors. Even if the motors are of the same type and have similar structural features, their parameters can never be exactly the same. This inherent variability makes achieving coordinated speed regulation across heterogeneous motors a more complex task. Let consider a multi DC motors system consisting of N motors where the interaction topology is represented by G . Assume that each motor i the following nonlinear dynamics is considered:

$$y_i(k+1) = f_i(y_i(k), u_i(k)), \quad i = 1, 2, \dots, N \quad (1)$$

Where $y_i(k) \in \mathbb{R}$ represents the output (speed of DC motor), $u_i(k) \in \mathbb{R}$ is the control input (the voltage) and $f_i(\cdot)$ is an unknown nonlinear function, respectively.

We consider a scenario where multiple agents aim to track a consensus trajectory $yd(k)$, which is exclusively accessible to a subset of agents. This trajectory is assumed to be generated by a virtual leader designated as vertex 0. To model this interaction, we construct a direct graph $G' = (V \cup \{0\}, E', A')$ where V denotes the set of agents, E' represents the edge set defining connections from agents to the virtual leader, and A' constitute a weighted adjacency matrix detailing these connections.

This analysis presupposes nonlinear dynamics governing each agent's evolution, encompassing dependencies on their respective states and inputs. These nonlinear dynamics accommodate various complexities, facilitating an investigation into how agents align with the desired trajectory $yd(k)$.

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

Assumption 2: The model $y_i(k+1) = f_i(y_i(k), u_i(k))$ is generalized Lipschitz, 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 $\Delta y_i(k+1) = y_i(k+1) - y_i(k)$ and b is a positive constant.

Remark 1: The practical applicability of the aforementioned assumptions to nonlinear systems has been extensively discussed in [?], affirming their suitability for practical multi-agent systems. **Assumption 1** establishes a foundational criterion for controller design, ensuring the continuity of the partial derivative of the nonlinear function $f_i(\cdot)$ with respect to $u_i(k)$. **Assumption 2** implies that the rate of change in an agent's output in response to changes in its control input is bounded. This constraint ensures that, from an energetic perspective, finite changes in control input energy correspond to bounded changes in output energy rates, a crucial consideration for system stability and performance.

C. Linearization Technique

This paper delves into the Compact Form Dynamic Linearization (CFDL) technique, this method simplifies the dynamic of nonlinear systems into a linear form that is easier to handle and control. The CFDL is particularly useful when the control input $u_i(k) = 0$ holds, enabling the system to be described through a compact dynamic linearization model. The system under consideration is governed by the following equation:

$$\Delta y_i(k+1) = \phi_i(k) \Delta u_i(k) \quad (2)$$

Where $|\phi_i(k)| \leq b$. b is a positive constant and the variable $\phi_i(k)$ named pseudo-partial-derivative.

We define the distributed measurement output of $x_i(k)$ for i -th agents as follow:

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