An Enhanced Model Free Adaptive Control Approach for Functional Electrical Stimulation Assisted Knee Joint Regulation and Control

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***Abstract*— Functional electrical stimulation has been widely used in the neurologically disabled population as a rehabilitation method because of its intrinsic and higher ability to activate paralyzed muscles. However, the nonlinear and time-varying nature of the muscle against exogenous electrical stimulus makes it very challenging to achieve optimal control solutions in real-time, that results in difficulty in achieving functional electrical stimulus-assisted limb movement control in the real-time rehabilitation process. Model-based control methods have been suggested in many functional electrical stimulations elicited limb movement applications. However, in the presence of uncertainties and dynamic variations during the process the model-based control methods are unable to give a robust performance. In this work, a model-free adaptable control approach is designed to regulate knee joint movement with electrical stimulus assistance without prior knowledge of the dynamics of the subjects. The model free adaptive control with a data-driven approach is provided with recursive feasibility, compliance with input constraints, and exponential stability. The experimental results obtained from both non-disabled participants and a participant with spinal cord injury validate the ability of the proposed controller to allocate electrical stimulus for regulating seated knee joint movement in the pre-defined trajectory.**

***Index Terms*— Functional electrical stimulation, data-driven control, model-free adaptive control, neuroprosthesis, spinal cord injury.**

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I. Introduction

FUNCTIONAL electrical stimulation (FES) is one of the most accepted technologies used to elicit skeletal muscle contraction artificially. It creates a potential electric field across the applied area and generates muscle contraction by energizing the alpha motor neurons present in the applied area. It restores the limb function in the population suffering from different neurological disorders conditions such as Parkinson's disease (PD) [1], stroke [2], spinal cord injury (SCI) [3] and multiple sclerosis. However, unlike the conventional rehabilitation methods, for example physiotherapist, robotic system assisted or combination of both, the nonlinear and time-varying nature of the muscle subjected to exogenous electrical stimulus causes many difficulties in the controller modelling [4], [5]. As a result, maintaining high control efficiency while lowering the trajectory tracking error of FES-assisted limb movement and control is difficult.

There are several works available on model-based control strategies for FES-assisted limb movement and control in the past. For instance, Schauer et al. [6] proposed a novel empirical model of the human lower extremity and designed an optimized nonlinear controller for regulating the knee angle with FES assistance. Ferrarin et al. [7] developed a modified knee joint model by including a motor-assisted hybrid system to increase the trajectory tracking accuracy with the backstepping approach. In [1], Bellman et al. proposed a simple but novel model for the FES-assisted cycling model. They developed a robust controller to ensure cadence tracking efficiency by adjusting the parameter variation in the model. These models, however, only approximate the dynamics of the limb and do not account for the dynamic response of the muscle to the exogenous electrical stimulus, necessitating the implementation of a compensator [8] in the FES controller network.

The nonlinear and time-varying components of the skeletal muscle models add to the difficulty of the construction and analysis of the model-based control. Model-based control approaches have been developed, but their precision and usefulness may be constrained in various interactive scenarios or when multiple muscles are chosen for electrical stimulation to drive a single joint movement. In addition, model-based control creates a significant burden on the designers/clinicians for conducting rigorous experimental procedure to determine the dynamics of the specified body parts of the patients [9]. Also, the repetitive experimental methods create mental and physical anguish in both the designers and the patients. It demotivates the patients to attend further rehabilitative sessions. As a result, FES-assisted rehabilitation demands two significant steps. (i) from a control point of view, it requires intelligent strategies to prevent the reduction in susceptibility of the system, which leads to dynamic uncertainty, (ii) from a clinical point of view, the rehabilitation procedure should avoid the experimental burden in practice. Recent research [10], [11] has shown that model-independent control based on data-driven and dynamic linearization techniques has potential, and this approach is more versatile than model-based control because it avoids the complexity of dynamics modelling. Generally, the data-driven techniques incorporates the pseudo partial derivative (PPD), and the controller replaces the original nonlinear model with a commensurate data model [12]. Because of the model-independent nature of the data-driven-based model-free adaptable control (DD-MFAC), it is suitable for several practical nonlinear control applications [12], [13]. First, the controller does not have to represent the system in data-driven schemes; instead, it only depends on the real-time measurement data of the plant [14]. Second, DD-MFAC is a lower computation cost controller since it does not require external testing signals and training processes like neural networks-based nonlinear adaptive control [15]. Third, DD-MFAC is uncomplicated, simple to implement, computationally light, and very resilient [16]. Fourth, the DD-MFAC approach's monotonic convergence and bounded-input bounded-output stability can be ensured under some plausible practical assumptions [17]. While accounting for the benefits of DD-MFAC, we recognized that the strategy may also direct us in developing a productive control system for the FES assisted neuro-prosthesis sector. Also, the study provides the feasibility of whether the DD-MFAC is an effective solution to FES-assisted rehabilitation.

Control mechanism to regulate the limb movement with the use of minimal amount of electrical stimulation is an essential factor in FES-assisted applications [5]. However, the use of an existing DD-MFAC [12] may reduce the tracking performance in FES-assisted applications because the initial PPD value significantly impacts the convergence speed of an MFAC. Without suitable initial PPD selection, numerous efforts are required to find the optimal value [18], implying that incorrect PPD would result in slow convergence during control iterations [16]. Using such a control mechanism in FES-assisted rehabilitation may cause a considerable burden on clinicians and patients by adding rigorous experimental sessions to find better PPD value in addition to the rehabilitation training. To deal with this, the present work proposes a control scheme which is least affected by the initial PPD value compared to the existing DD-MFAC [11], [12], [19] to deliver a minimal amount of controlled electrical stimulation that can provide desired lower extremity movement in an FES-assisted neuro-prosthesis domain.

Motivated by the above-addressed issues, to increase the effectiveness of the DD-MFAC in the rehabilitation domain, this study introduces a new PPD estimator that reduces the amount of electrical stimulation in the FES neuro-prosthesis environment as a model-independent control. The important leverage of the suggested approach is that the parameters can be simply adjusted without being influenced by the initial PPD, improving convergence performance. Thus, it assists clinicians in avoiding lengthy experimental sessions in search of a more effective PPD. Also, it reduces the existing pre-experimental burden to identify the dynamics of the limb which is going to control in FES-assisted rehabilitation, especially in the SCI domain. In addition, we are investigating the stability and tracking error monotonic convergence to verify the effectiveness and merits of the proposed DD-MFAC as a tool for controlling the electrical stimulation intensity through comparison experiments with existing and proposed DD-MFAC on FES-induced knee joint regulation during a seated leg extension. The experiments were performed on healthy participants and a participant with SCI.

The main contributions of this work include: 1) The DD-MFAC approach is developed with a new PPD estimation method, which only depends on past input and output data, to control the nonlinear time-varying systems such as FES-triggered neuro-prosthesis. The convergence attribute of the proposed control scheme is unaffected by the initially chosen PPD. On the other hand, existing DD-MFAC approaches significantly impacts on initial PPD. 2) The best that we can tell, this is the first result on dynamic linearization-based DD-MFAC for FES-assisted limb movement and control. 3) The proposed method reduces the experimental burden which is usually seen in the FES-assisted neuro-prosthesis domain.

II. Control Strategy

This article aims to develop a DD-MFAC-based neuromuscular electrical stimulation (NMES) controller that will allow a human shank to track the desired trajectory. Considering the following nonaffine nonlinear discrete-time single-input single-output (SISO) system with unknown order as the representation of the human lower extremity driven by FES.

$$\begin{aligned}\theta(t+1) = g(&\theta(t), \theta(t-1), \ldots, \theta\left(t-n_y\right), \\ &u(t), u(t-1), \ldots, u(t-n_u))\end{aligned} \tag{1}$$

where $\theta(t) \in \mathbb{R}$ and $u(t) \in \mathbb{R}$ are the angular position of the human shank and FES control input at time instant t, respectively. $\theta(t) = 0$ and $u(t) = 0$ for all $t < 0$. $g(\ldots)$ is an unknown continuously differentiable nonlinear function representing the dynamics of the human lower extremity and $g(0, \ldots, 0) = 0$. n_y and n_u are the two unknown positive integers which represent the system orders. $t \in \{0, 1, \ldots, T-1\}$, with T being the endpoint of the finite interval. For the system shown in Eq.1, the controller aim is to find a suitable bounded controlled FES input $u(t)$ such that the human shank $\theta(t)$ can track the pre-defined trajectory $\theta_d(t)$.

To restrict the discussion, the following assumptions are made about the system (1).

Assumption 1: The partial derivative of $g(\ldots)$ with respect to control inputs $u(t)$ are continuous.

Assumption 2: The system represented in Eq. 1 is generalized Lipschitz, that is, $|\Delta\theta(t+1)| \leq c_1 |\Delta u(t)|$ for any t and $|\Delta u(t)| \neq 0$, where $\Delta\theta(t+1) = \theta(t+1) - \theta(t)$, $\Delta u(t) = u(t) - u(t-1)$ and c_1 is a positive constant.

From a practical standpoint, the assumptions put on the controlled system are rational and acceptable. Assumption 1 is a typical condition of control system design for general nonlinear systems. At any point along the continuous-time axis, Assumption 2 shows the relationship between incremental FES input and leg movement output. Trials for qualitative analysis determine the constant c_1. It implies that a change in a finite input will lead to a change in a finite output, which is plausible for the general system.

Theorem 1: Nonlinear behaviour of the muscle against electrical stimulation satisfying the Assumptions 1 and 2 when $|\Delta u(t)| \neq 0$ for all t, can be transformed into the following compact form of dynamic linearization (CFDL):

$$\theta(t+1) = \theta(t) + \psi(t)\,\Delta u(t) \tag{2}$$

where $\psi(t) \in \mathbb{R}$ is called pseudo partial derivative (PPD) [20], and it satisfies $|\psi(t)| \leq c_1$. The detailed proof can be found in [14].

Remark 1: The derived linear model (Eq. 2) is a virtual dynamic linearization of the nonlinear system (Eq. 1) that is rebuilt when I/O data changes, and it is independent of the mechanism of the real system.

Define the following cost function:

$$J(u(t)) = |\theta_d(t+1) - \theta(t+1)|^2 + \tau\,|\Delta u(t)|^2 \tag{3}$$

where $\tau \in \mathbb{R}^+$ is a scaling factor used to limit the rate at which the control input changes. Substituting Eq. 2 into Eq. 3 and for getting the optimal FES control signal, we solve the resultant equation for getting optimal value [14], [21], [22] i.e., $\partial J(u(t)) \big/ \partial u(t) = 0$, and it gives

$$u(t) = u(t-1) + \frac{\sigma\hat{\psi}(t)}{\tau + \left|\hat{\psi}(t)\right|^2} e(t) \tag{4}$$

where $\sigma \in (0, 2]$ is the step size factor, which is added to make Eq. 4 more general and $e(t) = \theta_d(t) - \theta(t)$ is the tracking error. Since $\psi(t)$ is unknown, the following estimation function is used to find the unknown PPD.

$$\hat{\psi}(t) = \hat{\psi}(t-1) + \frac{\zeta\,\Delta u(t-1)}{\nu + |\Delta u(t-1)|^2} \times \left(\Delta\theta(t) - \hat{\psi}(t-1)\,\Delta u(t-1)\right) \tag{5}$$

where $\zeta \in \mathbb{R}^+$ is step factor, and $\nu \in \mathbb{R}^+$ is the weighting coefficient, and detailed proof of Eq. 5, can be found in [12].

The convergence performance of the conventional data-driven control is limited because it highly depends on the initial PPD value. Since finding a good initial PPD requires multiple attempts, and choosing the wrong PPD will cause a sluggish convergence [18]. In [11], a high-order PPD estimator is suggested to increase the performance. Since the PPD estimator function was iteration and manual tuning dependent, the performance of the controller is limited in non-iteration applications. In addition, the study [11] used constant weight factors for PPD estimation. Because it is a manually tuned parameter, multiple attempts may be required to find a good estimate. The main disadvantage of manual tuning is that it does not rely on the performance variance of the system needed to control. So, it is important to reduce/avoiding the use of such parameters is an important task while considering the design of an FES-assisted automated rehabilitation system. In addition, developing an adaptive control mechanism to adjust the stimulus intensity in such application is also an essential factor. The design parameters used to predict the control signal should vary based on the limb movement and it varies from subject to subject. The control signal and weighted error of the previous trial (Eq. 4) are two significant elements used to update the control signal of the present trial. Most existing results in the literature are expressed in this way. While considering this, the following is a natural question: generally, a controller takes action based on a past, present, prediction of the future or combination of those control errors [16]. Can we also update the PPD with this information? Because in data-driven control, PPD is also a parameter for predicting the control signal and depends on the system response. Intuitively, this could lead to better system performance as the PPD can now look into the performance of the system and compensate in advance.

Motivated from the above issues, this article proposes an enhanced PPD-based DD-MFAC, which can quickly tune the parameters without significant effects from the initial PPD. The proposed criterion function is as follows:

$$J\left(\hat{\psi}(t)\right) = \left|\Delta\theta(t) - \hat{\psi}(t)\,\Delta u(t-1)\right|^2 + \nu\left|\hat{\psi}(t) - e(t)\,\hat{\psi}(t-m)\right|^2 \tag{6}$$

Therefore, using the derivation of Eq. 6 as a foundation, Eq. 7 expresses the enhanced PPD modeling approach as follows and $\partial J\left(\hat{\psi}(t)\right) \big/ \partial\hat{\psi}(t) = 0$:

$$\frac{\partial J\left(\hat{\psi}(t)\right)}{\partial\hat{\psi}(t)} = 2\left(-\Delta u(t-1)\right)\left(\Delta\theta(t) - \hat{\psi}(t)\,\Delta u(t-1)\right) + 2\nu\left(\hat{\psi}(t) - e(t)\,\hat{\psi}(t-m)\right)$$

$$\hat{\psi}(t) = \frac{\Delta u(t-1)\,\Delta\theta(t)}{\nu + |\Delta u(t-1)|^2} + \frac{\nu e(t)\,\hat{\psi}(t-m)}{\nu + |\Delta u(t-1)|^2} \tag{7}$$

The reset mechanism utilized is as follows to ensure that the dynamic linearization model is always accurate and to compensate for the time-varying parameter:

$$\hat{\psi}(t) = \hat{\psi}(0), \quad \text{if } \hat{\psi}(t) \leq e \text{ or } |\Delta u(t)| \leq \text{e} \tag{8}$$

where e is the tracking error. We assume that $|e(0)|$ and $\left|\hat{\psi}(0)\right|$ are bounded. As a result, Eq. 4,5,7 and 8 describes the overall control strategy of the proposed DD-MFAC. The proposed method will select the control mechanism of Eq. 5 when $1 \leq t < m$, and Eq. 7 will determine when $t \geq m$,

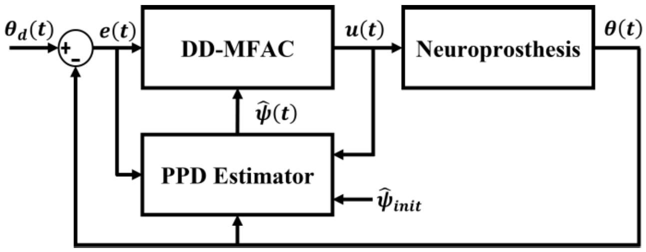

Fig. 1. Overview of the proposed control system.

where m is the PPD estimation switching time. The controller diagram is shown in Fig. 1.

Remark 2: Different from the previous DD-MFALC [11], [23], [24], the proposed algorithm does not require any iterations to improve the performance.

III. Stability Analysis

There are two parts to this section. To establish the boundedness of the PPD estimated values is the first stage. The second phase is to prove the MFAC system's convergence and bounded input bounded output stability.

Assumption 3: For all $t = 0, 1, 2, \ldots, T-1$, $\psi(t)$ satisfies $\psi(t) \geq 0$ or $\psi(t) < 0$ or $\psi(t) = 0$. Without loss of generality, we assume $\psi(t) \geq 0$.

Remark 3: Assumption 3 is comparable to the control input direction limitation in [21]. i.e., in our system, with the increase of FES intensity, the quadriceps muscle will contract, and angular displacement of the shank will increase. The positive correlation described in Assumption 3 is satisfied by such a change in displacement and control input. So, the following theorem can therefore be deduced:

Theorem 2: For the nonlinear behaviour of the muscle against electrical stimulus described by Eq. 1, provided the Assumptions (1)-(3) hold, then:

1) $\forall t = 0, 1, 2, \ldots, T-1$, $\hat{\psi}(t)$ is bounded.
2) $(\theta_d(t+1) - \theta(t+1)) = 0$.
3) For all $t = 0, 1, 2, \ldots, T-1$, $u(t)$ is bounded.

Proof: See Appendix A.

Remark 4: From proof of theorem 2 (Appendix A), it is clear that the PPD parameter is dynamic in nature. In addition to that, as per Eq. 8, the magnitude of the controller is always limited.

Remark 5: As compared to the previous works [11], [23] the proposed algorithm is independent of the higher-order scaling factor (Eq. 7), and shows better performance, as seen from the subsequent results.

IV. Experimental Procedures and Results

A. Experimental Setup

The experiments were carried out on the modified leg extension machine (Fig. 2), as shown. An encoder measures the knee joint angle with a resolution of 1024 pulses per revolution on the modified leg extension machine. A RehaStim eight-channel stimulator (Hasomed Inc., GmbH) was utilized to generate a biphasic pulse train with a 35-Hz frequency and 40-mA current amplitude to stimulate the muscles. The stimulation was given to the participants through self-adhesive, reusable neuromuscular stimulation electrodes placed on the distal–medial section and proximal–lateral region of the quadriceps femoris muscle groups. Safety measures were used, involving the utilization of an emergency stop button held by a researcher to turn off the instrument and an auxiliary emergency button on the modified leg extension chair which the participant can access. The operations could be stopped or put on hold at any time if the participants felt uncomfortable. The shank frame was made in such a way that the length can be adjusted based on the needs of the different participants. The participants can also alter the stabilizing belt's width at the waist and shoulder to fit them.

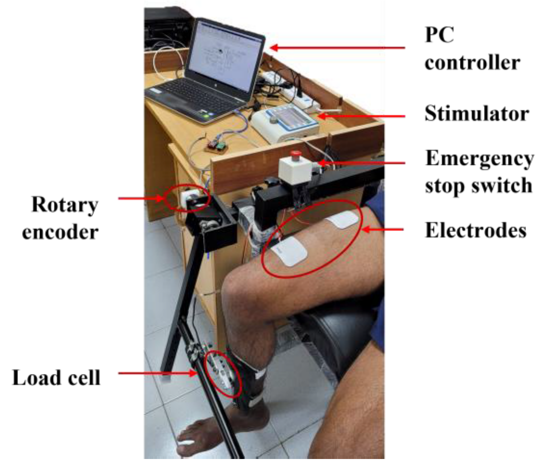

Fig. 2. The experimental setup included a customized hybrid leg extension system and an FES stimulator.

Three participants without disability and a participant with Level T5 compression SCI participated in the study. The time interval between trauma and participation in study was 2.2 months. The institutional review board of AIIMS, New Delhi and the AIIMS Ethical Committee, New Delhi, gave their approval for the study (approval reference number: IEC-674/01.10.2021, RP-38/2021). In addition to that, the proposed trial was registered in the clinical trials registry - India (ICMR-NIMS) with a registration number CTRI/2021/11/037818. Before beginning the experiments, all subjects gave their informed consent, who also passed the preliminary screening experiments for physical and mental demands. The screening experiments are used to confirm the participants' muscle responses to FES as well as their perception of pain. Participants would not continue to subsequent trials if there were no muscle responses to FES (as in some cases of SCI) or if they did not feel comfortable using FES. Those who pass the screening process are able to take part in controller validation experiments.

The participants were given instructions before the experiment to relax and evade any voluntary interference with the modified leg extension system. Further reducing the voluntary interference with the leg extension control, the participants were not permitted to view the control performance or the necessary virtual limits on the computer screen. To evaluate the efficacy of the suggested control approach, two sets of tests were performed on each participant. The operation was

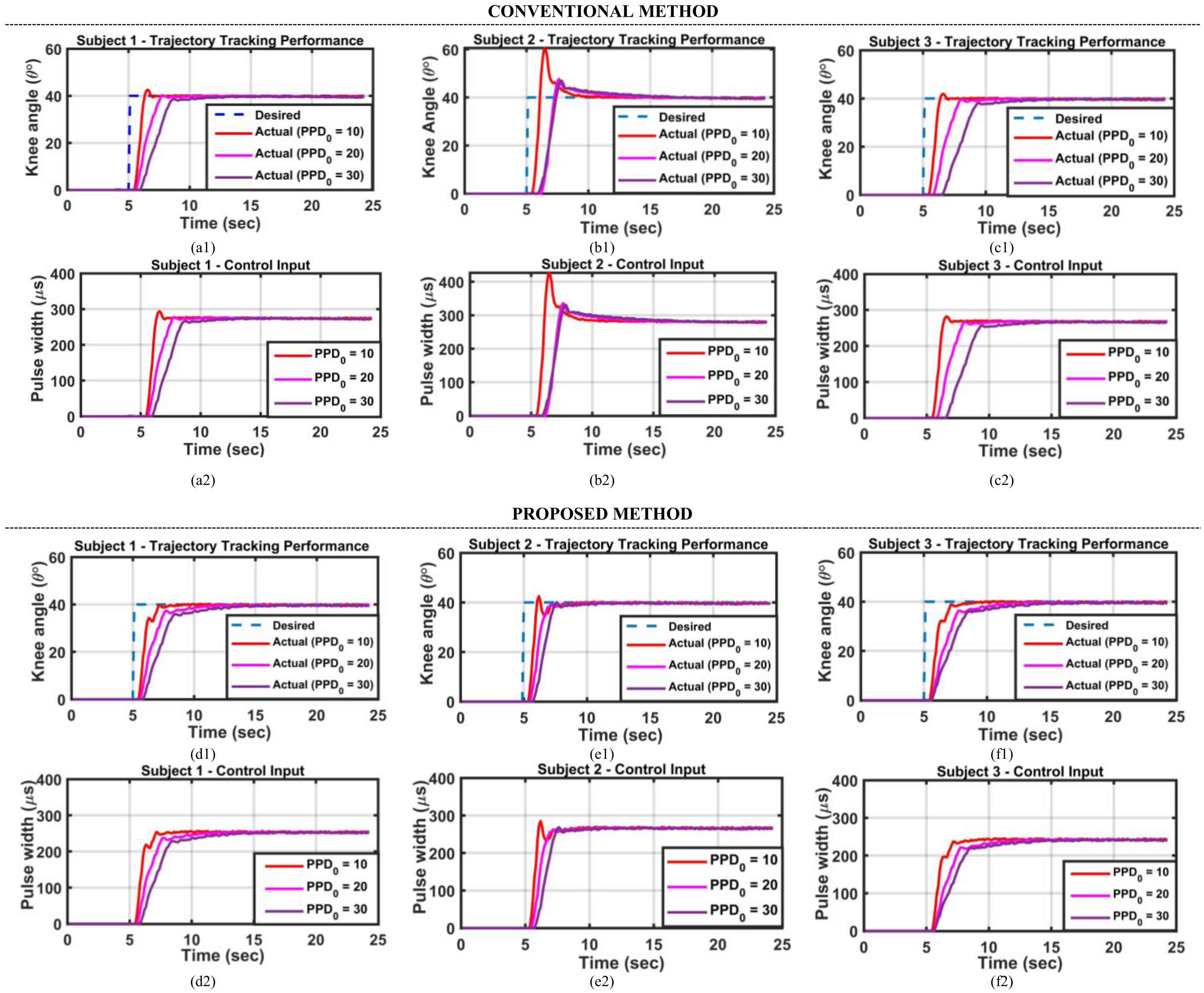

Fig. 3. Control performance of conventional DD-MFAC and proposed DD-MFAC. (a1) - (c1) Performance of the conventional DD-MFAC on three non-disabled participants with three different values of initial PPD, i.e., $\hat{\psi}_{init} = 10, 20, 30$ respectively. (a2) - (c2) Control inputs of the non-disabled participants (for the case (a1) - (c1)). (d1) - (f1) Performance of the proposed DD-MFAC on non-disabled participants with three different values of initial PPD, i.e., $\hat{\psi}_{init} = 10, 20, 30$ respectively. (d2) - (f2) Control inputs of the non-disabled participants (for the case (d1) - (f1)).

carried out in 24-sec sessions. This time frame was chosen for the convenience of the participant and to ensure consistency in the outcomes. The total experiment duration for each subject is taken around 60 to 90 minutes. Because of the test preparation, retesting, parameter adjusting, 5 minutes rest between each test and other unplanned events, this time changed slightly in several circumstances.

B. Control Performance

Two sets of experiments were performed: 1) regulation of knee angle to 40° by conventional DD-MFAC [11] and with the proposed controller. 2) regulation of knee angle to 40° with the proposed controller with different PPD values. In both sets of tests, the scaling factors τ, σ, ζ, ν remained constant. Fig. 3 and 4 depict the result of the closed-loop tracking performance of the shank movement with the assistance of functional electrical stimulus in healthy and spinal cord-injured subjects, respectively. In addition, it demonstrates the performance of the trajectory tracking rehabilitative task of the conventional and proposed data-driven model free adaptive controller with different values of initial pseudo partial derivative in healthy and spinal cord injured subjects. As evident from Fig. 3 and 4, the exogenous electrical stimulation used by the proposed controller for healthy (Fig. 3 (d2 – f2)) and spinal cord injured subjects (Fig. 4(c2 – d2)) is less as compared to the conventional (healthy Fig. 3(a2 – c2) and spinal cord injured patient Fig. 4(a2 – b2)) data-driven controller. The depicted Table. I shows the RMSE values of the shank movement in tracking performance with conventional and proposed control methods on healthy and spinal cord-injured subjects with different initial pseudo-partial derivatives. From Table.I and Fig. 3 and 4, it is evident that the proposed controller can provide good assistance in FES-assisted limb movement and

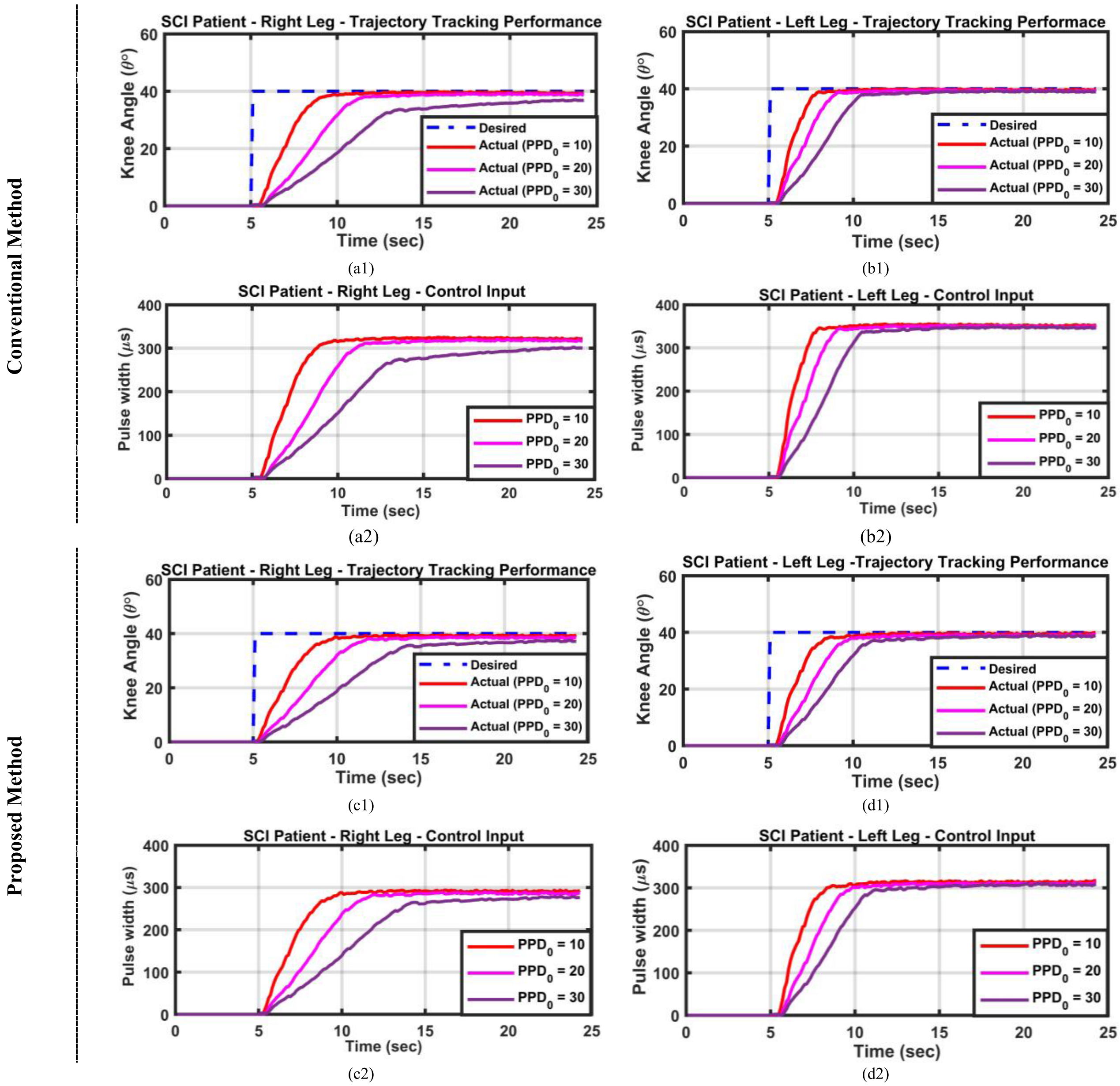

Fig. 4. Control performance of conventional DD-MFAC and proposed DD-MFAC on SCI patient. (a1) - (b1) Performance of the conventional DD-MFAC with three different values of initial PPD, i.e., $\hat{\psi}_{init} = 10, 20, 30$ on right and left leg of the patient respectively. (a2) - (b2) Control inputs (for the case (a1) - (b1)). (c1) - (d1) Performance of the proposed DD-MFAC with three different values of initial PPD, i.e., $\hat{\psi}_{init} = 10, 20, 30$ on left leg of the patient respectively. (c2) - (d2) Control inputs (for the case (c1) - (d1)).

trajectory tracking rehabilitative tasks without the knowledge of the model parameters of the subject being rehabilitated.

Remark 6: Even with the promising result, the proposed control scheme does not ensure robustness towards the local minimum issue. But the higher order dynamics of the proposed scheme (Eq. 7) provide additional information on the shape of the objective function [20], which helps the controller unit to estimate pseudo partial derivative more precisely to maintain the system being controlled.

V. Discussion

Restoring mobility or providing physical rehabilitation to a person with neurological impairment, with the assistance of an electrical stimulus, is the most exciting and challenging task. The biggest obstacle in clinical trials is the identification of stimulus parameters based on the subject characteristics variation due to the presence of an electrical stimulus. So, finding the musculoskeletal model of each participant is considered a pre-experimental work associated with FES-assisted rehabilitation for this reason. Also, it is a time-consuming hectic process. So, this article proposes a dynamic linearization-based DD-MFAC for regulating the knee angle with the assistance of FES. The DD-MFAC approach is a model-free and adaptive method that relies solely on FES and knee angle data from the modified knee extension regulation setup. The dynamic linearization approach was used to establish the data model and the experiment, with the enhanced PPD estimation algorithm determining the PPD. The

TABLE I
QUANTITATIVE COMPARISON FOR EXPERIMENTAL RESULTS

RMSE (θ°)				
	PPD VALUE	Subject 1	Subject 2	Subject 3
Conventional DD-MFAC (Healthy)	10	4.42	4.06	4.53
	20	4.64	4.19	4.92
	30	5.38	4.74	5.23
Proposed DD-MFAC (Healthy)	10	4.61	4.84	5.71
	20	4.52	4.04	4.40
	30	4.98	4.21	4.56
SCI Subject 1				
		RL	LL	
Conventional DD-MFAC	10	5.45	4.14	-
	20	6.88	5.84	-
	30	8.08	6.39	-
Proposed DD-MFAC	10	5.19	3.48	-
	20	6.27	5.03	-
	30	7.74	6.17	-

*RL – Right Leg, LL – Left Leg

main advantage of DD-MFAC is its ability to leverage the data from prior events, accelerate the parameter estimation, and enhance the trajectory tracking convergence while ensuring control accuracy.

During the control decision process, we propose an enhanced PPD estimation approach for a DD-MFAC that completely utilizes the input and output data from present and prior events. Compared to the existing method [11], the use of error value as a scaling factor for PPD estimation was motivated by the need to obtain consistent performance for all the participants despite the variance in their physical attributes. By eliminating the rigorous pre-clinical experimental procedures, the proposed controller potentially reduces the experimental burden [9] associated with conventional FES-assisted automated physical rehabilitation. In addition, Fig. 3 and 4 illustrate that the proposed controller scheme optimizes (see Fig. 3(d2 – f2) and 4(c2 – d2)) the use of exogenous electrical stimulus to maintain the limb in a pre-defined trajectory as compared to the conventional data-driven control scheme (see Fig. 3 (a2 – c2) and 4 (a2 – b2)). Though the learning methods necessitated the use of memory to store data, the feedback setup can provide additional benefits such as a higher convergence rate [25], [26] and making control simple. Based on the readily available memory devices at a reasonable cost [27], [28], the proposed method can be implemented in real-time applications.

Although the FES-assisted limb movement and trajectory tracking performance of the proposed method is similar to the studies reported in [6], [9], [29], and [30]. However, the proposed method is more promising in the FES-assisted rehabilitative domain than the traditional one. Because the conventional approach demands accurate model information of the subject, it can be obtained only through hectic pre-clinical experimental procedures. In contrast, the proposed method does not require the subject's model information. It does away with the rigorous pre-clinical experimental procedures [9], [29] associated with the traditional, model-based FES-assisted rehabilitation process.

The regulation control experiment results (see Fig. 3(a1-c1, and d1-f1) and 4(a1, b1, c1, and d1)) showed that the proposed controller has a faster convergence with less control action (i.e., minimal electrical stimulation use) and is less influenced by initial PPD than the traditional one. But the RMSE (Table. 1) of the proposed DD-MFAC does not result in much better performance in trajectory tracking than the conventional DD-MFAC [11], [12], [16]. These results were along expected lines because, for a better PPD estimation, the proposed algorithm uses tracking error data, and it helps the system to know about the controller performance one step prior to the conventional DD-MFAC methods [23], [20], [21]. This leads to better tracking performance with reduced control effort, whereas the traditional method demands more control effort (see Fig. 3(a2 – c2, and d2 – f2) and 4(a2, b2 and c2, d2)). From this, we can infer that performance and effort are conflicting objectives, i.e., reducing error requires more effort. The proposed approach finds the optimal control effort to balance tracking performance and control effort. Also, the results validate the research question we raised regarding the PPD estimation, i.e., tracking error information is a good factor that can account for the PPD estimation. Because, as compared to the conventional method [11], the proposed control scheme which includes the trajectory tracking error data for PPD estimation provides a better limb movement in the pre-defined trajectory by conserving the use of exogenous electrical stimulus.

In addition to the unilateral movement of the lower extremity of the subjects with electrical stimulus assistance, bilateral symmetrical and asymmetrical movements are also an important process in the physical rehabilitation for a neurologically impaired population, and its being the ultimate goal of our study, we deferred further investigation into this reflection in favor of comparing a few experimental plots (see Figs. 3 and 4), which serve as an example of the potential effects of our model-independent methodology. Even if the SCI patient knows the pre-defined trajectory, they cannot execute it by themselves. In such a situation, the exogenous electrical stimulus aids the limb movement completion in the patient, enhancing motor relearning to promote rehabilitation. The observed large delays in the trajectory tracking performance that have been noticed are related to the subjects' electromechanical delay [31], the interval between stimulation and quantifiable force output change (here, leg movement), and electrical stimulation threshold level. It is necessary to account for the usual FES occurrence of dead zones and delayed input for electromechanical delay.

Additionally, the model-independent nature of the controller is strongly motivated to possibly achieve physical rehabilitation in neurologically disabled populations by avoiding lengthy experiments to estimate the physical model of the musculoskeleton part of the patient, which are typically conducted before the rehabilitation process [9], [32]. We may deduce from experimental data that the suggested approach can be effective for FES-assisted mobility control and rehabilitation procedures. By removing the pre-session burden on conducting model identification experiments, both clinician and patient can save time and the patient will get more effective physical rehabilitation. It may give a better experience to both clinicians and SCI patients. Additionally, it may potentially lessen the side effects of SCI [33]; for example, a few weeks after SCI, the muscles may begin to atrophy and may be susceptible to disturbances like spasticity and clonus. Compared to conventional methods like model-based control, the proposed control scheme may allow the clinician to easily conduct an FES-assisted automated physical rehabilitation to recondition the muscles. However, to confirm this, more tests are needed to conduct with a larger population.

The stability of a controller is an important fact in closed-loop applications, especially when it comes to FES-assisted rehabilitative applications. Because an unsteady controller might cause safety issues by providing excess stimulations to the patient. The theoretical analysis (Appendix A) guarantees the proposed controller's stability, convergence, and input boundedness. Even though the controller gives a better trajectory tracking performance, more tests with a bigger population are required before the establishment. The result should not be extended to other neurologically disabled populations without conducting more clinical studies.

VI. Limitations and Future Scopes

A model (Eq. 1) was assumed as the representation of the human lower extremity driven by FES, requiring a controller with adaptable gain and control variables by its nature to achieve extensive system tracking and control. Even though it has been shown that adaptable gain parameters have an exceptional impact on nonlinear system control [11], [16] (and references within), it was assumed during this study that the cumulative effect of multiple gain parameters of the controller can be approximated at small events with fixed gain parameters to achieve a better system control.

Accounting for a nonlinear muscle fatigue parameter in FES-related applications is very difficult and it makes system control to be more difficult. But muscle fatigue estimation unit should be considered when the controller produces an unacceptable error, especially in long-duration FES trials. Because it may increase the controller effort to achieve a reduced trajectory tracking error. The FES recruits muscle fibres repeatedly in a non-selective nature, i.e., FES does not have any coordinated control over the motor units that are recruited [9]. This means that excessive stimulation drastically reduces the effect and causes rapid fatigue. Furthermore, an additional limitation of the current study is that the electromechanical delay was also not the prime focus of this work.

So, in future research, other adaptable data-driven algorithms and tuning methods [10] which can account FES elicited muscle fatigue [3], electromechanical delay [34] could be explored for PPD tuning and to improve control efficiency for FES-related assistive applications [35]. It encourages us towards a path in which data-driven control can perform better in FES assisted rehabilitation applications. In addition, a comparative analysis of the computation/execution time of the proposed model-independent control approach with existing model-based control schemes can be explored to find the merit of the proposed controller. It also provides insight into the applicability of the proposed controller where the information of the model is minimally available cases and not available cases.

VII. Conclusion

In order to operate a neuro-prosthesis system and complete a knee angle regulation task while dealing with model uncertainties brought on by the application of exogenous electrical stimulation, this research suggests a reliable dynamic linearization-based DD-MFAC technique. The tracking error and online I/O data of the plant are the only inputs used in the control construction. In this technique, the FES intensity is changed to obtain the desired knee angle trajectory while the CFDL solves the best control sequence that balances control performance and effort. To demonstrate the effectiveness of the suggested DD-MFAC scheme, theoretical analyses of the bounded-input bounded-output stability and monotonic convergence as well as experimental results have been used. Additionally, the suggested technique avoids the meticulous subject preparation before each experimental session due to its model-independent nature. This study demonstrates how the challenges typically encountered in the field of FES-assisted neuro-prostheses can be overcome by combining a CFDL-based control approach with a data-driven method.

Appendix A
Proof of Theorem 2

Proof: There are two steps to this proof. The first step is to establish that the estimated PPD value is bounded. The second step is proof of system convergence and the bounded-input bounded-output stability of the proposed MFAC.

Step 1: Based on the estimation parameter switching criteria, step 1 is subdivided into three cases.

Case 1: When $\hat{\psi}(t) \leq e$ or $|\Delta u(t)| \leq$ e, $\hat{\psi}(t) = \hat{\psi}(0)$. So, $\hat{\psi}(t)$ is bounded.

Case 2: When $1 \leq t < m$, subtract $\psi(t)$ from both sides of Eq. 5, and let $\tilde{\psi}(t) = \hat{\psi}(t) - \psi(t)$ and we have:

$$\tilde{\psi}(t) = \tilde{\psi}(t-1) - (\psi(t) - \psi(t-1)) + \frac{\zeta \Delta u(t-1)}{\nu + |\Delta u(t-1)|^2} \times \left(\Delta\theta(t) - \hat{\psi}(t-1)\Delta u(t-1)\right) \tag{A1}$$

Substituting Eq. 2 into (A1) and take the absolute value on both sides, we have

$$\left|\tilde{\psi}(t)\right| \leq c_2\left|\tilde{\psi}(t-1)\right| + 2c_1 \leq c_2^2\left|\tilde{\psi}(t-2)\right| + (1+c_2)\,2c_1 \leq \cdots \leq c_2^m\left|\tilde{\psi}(0)\right| + \frac{(1-c_2^{m-1})2c_1}{1-c_2} \tag{A2}$$

The value of m is set manually during the control process, it is considered as bounded. Since c_2 hold the value $(0, 1)$, $\tilde{\psi}(t)$ is bounded. With an appropriate value of ζ and ν, and holding the condition $|\Delta u(t)| \neq 0$, there exist a condition $0 < c_2 < 1$. As a result, $\tilde{\psi}(t)$ is bounded. As per Theorem 1,

$\psi(t)$ is bounded, and that $\hat{\psi}(t)$ is also bounded. (The detailed proof can be found in [12]).

Case 3: When $t \geq m$, substitute Eq. 2 into Eq. 7 and taking absolute value at both sides, we can have

$$\begin{aligned}\left|\hat{\psi}(t)\right| &= \left|\frac{\psi(t-1)\,\Delta u^2(t-1)}{\nu+|\Delta u(t-1)|^2}+\frac{\nu\zeta e(t)\,\hat{\psi}(t-m)}{\nu+|\Delta u(t-1)|^2}\right| \\ &\leq |\psi(t-1)|\left|1-\frac{\nu}{\nu+|\Delta u(t-1)|^2}\right| \\ &\quad + |\zeta|\left|e(t)\,\hat{\psi}(t-m)\right|\left|1-\frac{|\Delta u(t-1)|^2}{\nu+|\Delta u(t-1)|^2}\right| \\ &< \cdots < |\psi(t-1)|+|\zeta|\left|e(t)\,\hat{\psi}(t-m)\right|\end{aligned} \tag{A3}$$

As per Theorem 1, we can deduce that $\psi(t)$ is bounded. Since the boundedness of $\hat{\psi}(t-1)$ when $1 \leq t < m$ has been proved, and error is also bounded (see Eq. A6). Since $|e(0)|$ is bounded and considering Eq. (A6), $|e(t)|$ is bounded. So, $\left|e(t)\,\hat{\psi}(t-m)\right|$ is also bounded. Therefore $\hat{\psi}(t)$ is also bounded.

Step 2: This step proves the convergence of tracking error and control input boundedness. (As per step 1 of Appendix A, PPD is bounded in all cases. So the proof of convergence of tracking error and control input boundedness is having steps as same as [12]. In order to avoid repetition, here, we only mentioned some important equations and notes).

Define the tracking error as follows:

$$e(t+1) = \theta_d(t+1) - \theta(t+1) \tag{A4}$$

As per Theorem 1 and Eq. 4, (A4) can be expressed as follows:

$$e(t+1) = \left(1-\psi(t)\,\frac{\hat{\psi}(t)\,\sigma}{\tau+\left|\hat{\psi}(t)\right|^2}\right)e(t) \tag{A5}$$

In contrast to traditional DD-MFAC control techniques, the suggested control scheme can leverage error data as a PPD scaling factor. Which can be thought of as a parameter tuning element for improving the efficiency of the proposed control scheme [11], [12]. In order to show the tracking error convergence, taking norms on both sides of Eq. (A5) yields

$$\begin{aligned}|e(t+1)| &= \left|1-\psi(t)\,\frac{\sigma\hat{\psi}(t)}{\tau+\left|\hat{\psi}(t)\right|^2}\right||e(t)| \\ &\leq c_3\,|e(t)| \leq \cdots \leq c_3^t\,|e(1)|\end{aligned} \tag{A6}$$

The range $0 < c_3 < 1$, offers the tracking error convergence to zero when $t \to \infty$. Also, the exponential convergence of tracking error will guarantee faster convergence. Solving the above inequality gives

$$0 < \sigma < \frac{2\left(\tau+\hat{\psi}(t)^2\right)}{\psi(t)\,\hat{\psi}(t)} \tag{A7}$$

Since $\psi(t)$ and $\hat{\psi}(t)$ are bounded, and from the PPD estimation algorithm and PPD resetting scheme, we can say that $\psi(t)\,\hat{\psi}(t) > 0$. The parameters used in the above inequality are bounded and $\hat{\psi}(t)$ converges to $\psi(t)$. Since value of $\tau > 0$, an appropriate value of σ will hold the inequality always in $0 < c_3 < 1$. So, as a result, inequality A6 follows, and the closed-loop system stability may be assured. Resultantly the tracking error will converge to zero.

Considering the Eq. A6, Eq. 4 yields

$$|\Delta u(t)| \leq c_4\,|e(t)| \tag{A8}$$

$$\begin{aligned}|u(t)| &\leq c_4\,|e(t)| + c_4\,|e(t-1)| + \cdots + c_4\,|e(1)| + |u(1)| \\ &\leq c_4\frac{c_3}{1-c_3}\,|e(1)| + |u(1)|\end{aligned} \tag{A9}$$

which proves that $u(t)$ is bounded $\forall t$.

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