2018 European Control Conference (ECC)
June 12-15, 2018. Limassol, Cyprus

Adaptive control of Upper Limb Exoskeleton Robot Based on a New Modified Function Approximation Technique (FAT)

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Abstract— **To improve the performance of passive-assistive rehabilitation motion with the help of an exoskeleton robot, an adaptive tracking controller based on Function Approximation Technique combined with disturbance observer, taking into consideration the actuators dynamics is presented. The control scheme aims to approximate the dynamic model of the robot and provides an accurate compensation of non-smooth nonlinear constraints that are excited by backlash, hysteresis, deadzone, and saturation of the robot's actuators. Unlike a conventional Function Approximation Technique approach, the required use of basis functions in estimation's law of the dynamic model is eliminated and the acceleration feedback is also eliminated. The output of the disturbance observer is linked directly to the current loop, which permits to the control system to be strong and active to eliminate the nonlinear constraints effects. Thanks to the proposed strategy, the designed control approach requires no knowledge of dynamic parameters of the exoskeleton robot, including the dynamics of its actuators to achieve the desired performance. Simulation results and a comparative study are presented to validate the proposed approach.**

I. INTRODUCTION

Rehabilitation robots have attracted great interest from the scientific community. This importance comes from its medical benefit to people with neurologic impairments [1]. These robots are still an open field of research because of its complex mechanical structure (designed to be comfortable for human use), the variety of assistance strategies, and the sensitivity of the interaction with different human conditions [4]. Human safety and reliable performance are among the major required criteria in robotic rehabilitation training. For instance, a force controller was proposed in [2] for an exoskeleton which permits to the human-robot system to achieve motor tasks based on muscle activity data. A computer torque controller was presented in [3] for tracking the trajectory of an upper-limb exoskeleton robot based on its model dynamics. The sliding mode approach combined exponential reaching law is introduced in [4] to reduce the chattering dilemma. Nevertheless, in previously cited papers, the control scheme is model-based, in which the control loop requires the full dynamic model of the exoskeleton.

*Research supported by ABC Foundation.

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Adaptive control design for the dynamic parameters is one of the challenging problems in robotics exoskeletons, particularly, when the number of degrees of freedom (DOFs) is high. Several approaches have been proposed to approximate the dynamic parameters. Some of the strategies use the linear parameterization of the dynamic equation of motion in order to obtain the regressor matrix required in the design of the updated control law [5, 6]. However, when the number of DOFs of the robot increases, it is not straightforward to find the parameters of the exoskeleton robot [7]. There are new methods designed to approximate the dynamic model without the computation of the regressor matrix, such as a Function Approximation Technique (FAT) [8, 9]. FAT strategy employs a finite linear combination of orthonormal basis functions to approximate the dynamic parameters of the robot, providing good performance [11]. Although this approach does not need the measure of the joint acceleration, nor the inversion of the estimated inertia matrix, it nevertheless suffers from the need of the basis functions in parameters estimation. The choice and the number of these basis functions influence directly the accurate estimation of the parameters and the online computation time. Recently, the approximation by fuzzy logic and neural networks presented a meaningful solution due to their attractive characteristics of the estimation of the unknown nonlinear dynamics of the robot with a minimum feedback from the robotic system [10, 11]. However, these strategies use heavy computation, which makes their implementation very hard. Time Delay Estimation approach is able to estimate the unknown uncertain parameters of the exoskeleton's dynamic [12, 13]. It uses time-delayed knowledge about the previous state response of the system and its control input to provide an accurate estimation of unknown dynamics. However, due to noisy measurements and nonlinearity of signals along the sampling time, a Time Delay Error exists, which would deteriorate the robustness and the accuracy of the exoskeleton robot.

The preceding adaptive controllers do not take into consideration the non-smooth nonlinear characteristics of the actuators such as backlash, hysteresis, deadzone, and saturation. In reality, the actuator dynamics participate significantly to the complete manipulator dynamics [14]. These constraints degrade the performance of conventional control and cause tracking errors. Therefore, it is necessary that the control input applied to the joint actuator of the exoskeleton robot to exceed its limits in order to guarantee both safety and the performance of the rehabilitation session. The elimination of these constraints in the exoskeleton implementation makes the robot system unsafe for the users. It is consequently imperative for us to design an adaptive controller that approximates the dynamic model of the robot and minimizes the non-smooth nonlinear constraints effects of joint actuators, while maintaining the stability of the exoskeleton robot at the same time.

The control proposed in this paper is an adaptive tracking control based on Function Approximation Technique (FAT) taking into consideration the actuators' dynamics. Unlike a conventional FAT approach, the need to use basis functions in the estimation law of the dynamic model is eliminated; the acceleration feedback is also eliminated. The non-smooth nonlinear constraints of the actuators are compensated by incorporating a disturbance observer. Unlike conventional approaches [15], the designed disturbance observer is added directly to the current loop, which makes the control system more powerful and faster to compensate for them. The stability analysis is formulated and proved based on Lyapunov theory. Furthermore, to study and discuss the superior performance achieved by incorporating the FAT approach and the disturbance observer theoretically and practically, it is used to control an exoskeleton robot. The validation of the control scheme is done by a basic passive rehabilitation. The comparative study is provided in this research with the conventional approach to show the advantages of the proposed approach.

The remainder of the paper is organized as follows. The kinematics and dynamics of the robot are presented in the next section. The control scheme is described in section III. Simulation and comparison results are shown in section IV. Finally, the conclusion is presented in section V.

II. Characterization of the Rehabilitation System

A. *Exoskeleton robot development*

The developed exoskeleton robot ETS-MARSE (*École de technologie supérieure - Motion Assistive Robotic-exoskeleton for Superior Extremity*) is a redundant robot consisted of 7DOFs, as shown in Fig. 1. It was created to provide assistive physiotherapy motion to the injured upper-limbs. The idea of the designed exoskeleton is extrapolated from the anatomy of the upper limb of the human, to be ergonomic for its wearer. The shoulder part consists of three joints, the elbow part comprises by one joint, and the wrist part consists of three joints. The design of the ETS-MARSE has special features compared with the existing exoskeleton robots. All special characteristics of the ETS-MARSE and comparison with similar existing exoskeleton robots are summarized in [16].

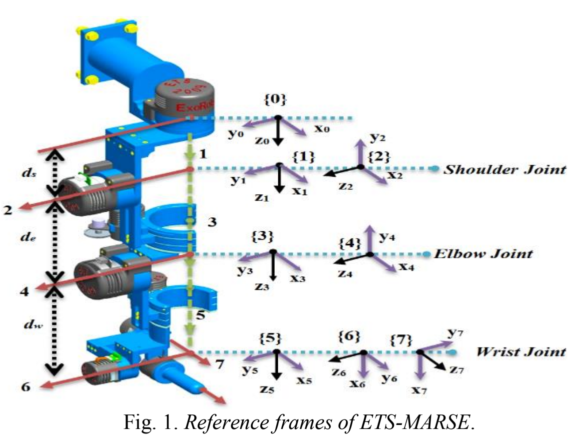

Fig. 1. *Reference frames of ETS-MARSE.*

B. *Dynamics of ETS-MARSE robot*

Consider the dynamics of the ETS-MARSE, driven by DC motors under saturation constraints, and expressed as follows :

$$M(\theta)\ddot{\theta} + C(\theta,\dot{\theta})\dot{\theta} + G(\theta) = K_n I \tag{1}$$

and

$$L\dot{I} + R_e I + K_e\dot{\theta} = \beta(u) \tag{2}$$

where θ, $\dot{\theta}$, and $\ddot{\theta} \in R^7$ are respectively the joints position, velocity, and acceleration vectors, $M(\theta) \in R^{7\times 7}$, $C(\theta,\dot{\theta})\dot{\theta} \in R^7$ and $G(\theta) \in R^7$ are respectively the symmetric positive definite inertia matrix, the Coriolis and centrifugal vector, and the gravitational vector (including the user's arm and the exoskeleton arm). $K_n \in R^{7\times 7}$ is a constant diagonal matrix for the invertible motor torque transmission, which defines the electromechanical conversion between current and torque. $I \in R^7$ is the armature currents vector, and $u \in R^7$ is the control input voltage. $L \in R^{7\times 7}$ is the actuator inductance diagonal matrix. $R_e \in R^{7\times 7}$ is the actuator resistance diagonal matrix, and $K_e \in R^7$ is the diagonal matrix that defines the effect of back-emf of the actuator. The input saturation constraints can be given such that:

$$\beta(u) = \begin{cases} \beta_{max} sign(u), & |u| \geq \beta_{max} \\ u, & |u| < \beta_{max} \end{cases} \tag{3}$$

where β_{max} is the upper bound of the motor voltage, for the continuous control input $u \in R^7$, with $\beta(u) = [\beta(u_1) \cdots \beta(u_7)]^T$. To facilitate the handling of the control scheme let us note $M = M(\theta)$, $C = C(\theta,\dot{\theta})$ and $G = G(\theta)$.

C. *Problem Statement*

We assume that the matrices M, C, G, K_e, R_e and L, in the (1) and (2) are not available, and the acceleration is not easily measured. Consequently, in this paper, the dilemma can be solved obtaining the voltage control input u able to force the measured trajectory $\theta \in R^7$ to track the desired trajectory θ_d and the desired current I_d to converge to the perfect current of (1). Even if the dynamic model of the robot and the parameters of its actuators are not perfectly known. The passive rehabilitation is investigated with model-based control and adaptive control. Before describing the control methodology, the properties and assumptions used in this paper are given as follows:

Property 1: [6] The known part of inertia matrix M is symmetric and positive definite for all $\theta \in R^n$ and satisfying: $\gamma_{min}(M)I_{7\times 7} \leq M \leq \gamma_{max}(M)I_{7\times 7}$, where γ_{min} and γ_{max} are minimum and maximum eigenvalues of the inertia matrix and $I_{7\times 7}$ is the identity matrix.

Property 2: [6] The matrix $\dot{M} - 2C$ is skew-symmetric for all $\theta, \dot{\theta} \in R^n$ and satisfying $\dot{\theta}^T\left(\frac{1}{2}\dot{M} - C\right)\dot{\theta} = 0$.

Assumption 1: The parameters of the actuators L, R_e and K_e are positive bounded and satisfying $\|L\| \leq \varphi_1, \|R_e\| \leq \varphi_2$ and $\|K_e\| \leq \varphi_3$ where φ_1, φ_2 and φ_3 are finite positive constants.

Assumption 2: The desired trajectory is bounded.

Lemma 1:[17] assume that Lyapunov function $V(y)$ is continuous and positive definite, realizing $\lambda_1(\|y\|) \leq V(y) \leq \lambda_2(\|y\|)$ and its derivative $\dot{V}(y) = dV(y)/dt$ and fulfills $\dot{V}(y) \leq -\alpha_1 V(y) + \alpha_2$, where α_1 and α_2 are positive constants, therefore the solution $y(t)$ is also bounded.

Lemma 2: A function $\omega(t)$ is considered continuous and differentiable bounded, $\forall t \in [t_0, t_1]$, if $\omega(t)$ fulfills $|\omega(t)| \leq \delta$, where δ is a positive constant, therefore $\dot{\omega}(t)$ is bounded.

Remark 1: The function $\omega(t)$ in **Lemma 2** should not be piecewise function. Conversely, **Remark 2** will present more details about the piecewise function given in function (3).

Notation 1 [8]**:** Given two vectors $x, y \in R^n$, and the matrix $A \in R^{n\times n}$ where $x^T y = Tr(xy^T) = Tr(yx^T) = y^T x$ and $\|B\|^2 = Tr(B^T B)$; $Tr(.)$ presents the trace operation of matrix.

III. CONTROL DESIGN

A. *Model-Based Control Algorithm*

The goal of this section aims to set up a model-based tracking control where the dynamic model of the exoskeleton robot and its actuators' parameters are known. Let us define the set of the position and velocity errors as follows:

$$\begin{aligned} s &= \dot{\theta} - \vartheta \\ \vartheta &= \dot{\theta}_d - \lambda\tilde{\theta} \\ \zeta &= \dot{\vartheta} \\ \tilde{\theta} &= \theta - \theta_d \end{aligned} \tag{4}$$

where, $\dot{\theta}_d \in R^7$ and $\dot{\theta} \in R^7$ are the desired trajectory and measured trajectory respectively and $\lambda = \mathrm{diag}(\lambda_{\mathrm{ii}})$ for $i = 1, \ldots, 7$, is a diagonal positive-definite matrix. Based on (4), we can rewrite (1) as follows:

$$M\dot{s} + Cs + M\zeta + C\vartheta + G = K_n I \tag{5}$$

If the matrices M, C, and G of (5) are known, it is easy to design a control law I to ensure the stability of the robot system (5). Therefore,

$$I_d = K_n^{-1}(M\zeta + C\vartheta + G - K_1 s) \tag{6}$$

where $K_1 \in R^{7\times 7}$ is a diagonal positive definite matrix. Substituting (6) into (5), the closed loop dynamics of the exoskeleton can be written such that:

$$M\dot{s} + Cs + K_1 s = 0 \tag{7}$$

Consider the Lyapunov function candidate as follows:

$$V_1 = \tfrac{1}{2} s^T M s \tag{8}$$

Taking the time derivative of V_1 and using the control input (6), we find:

$$\dot{V}_1 = -s^T K_1 s + \frac{1}{2} s^T (\dot{M} - 2C) s \tag{9}$$

According to **Property 2**, equation (9) becomes:

$$\dot{V}_1 = -s^T K_1 s \tag{10}$$

According to (10), $\dot{V}_1 \leq 0$ this means that the system is stable. However, to drive the actual current I converge to the ideal current (6), it is important to select a voltage control input in (2) as follow:

$$u = L\dot{I}_d + R_e I + K_e \dot{\theta} - \Delta u - K_2 e_I \tag{11}$$

where $\Delta u = \beta(u) - u$; where $\beta(u)$ is nominal input, and $e_I = I - I_d$ is the current error. $K_2 \in R^{7\times 7}$ is diagonal positive definite matrix. By replacing te (11) into (2), we find:

$$L\dot{e}_I + K_2 e_I = 0 \tag{12}$$

From the above equation, it is clear that with a suitable choice of K_2, it is simple to demonstrate that $I \longrightarrow I_d$ as $t \longrightarrow \infty$. To summarize, if all the dynamic model of the robot (1) and the dynamics of its actuators (2) are known, the voltage control input (11) ensures the stability of the robot system.

B. *Adaptive Tracking Controller*

Practically, all dynamic and actuators' parameters of the exoskeleton robot are not easily obtained. In this subsection, we consider that the dynamic model and the actuators' parameters are not perfectly known. Let us, without loss of generality of (2), rewrite:

$$\begin{cases} R_e = R_{e0} + \Delta R_e \\ L = L_0 + \Delta L_0 \end{cases} \tag{13}$$

where R_{e0} and L_0 are respectively the known constant resistance and inductance actuator matrices. ΔR_e and ΔL_0 are the uncertain parts. Equation (2) can be rewritten as follows:

$$L_0 \dot{I} + R_{e0} I + D = u \tag{14}$$

where $D = \Delta L_0 \dot{I} + \Delta R_e I + K_e \dot{\theta} - \Delta u$. Due to the known terms ΔL_0, ΔR_e , K_e and Δu, D is also unknown. Next, considering **Lemma 2**, (3), and using **Property 1** and **Assumption 1**, one can obtain:

$$\|\dot{D}\| \leq \sigma \tag{15}$$

where σ is an unknown positive constant.

Remark 2: To apply **Lemma 2**, the functions $\beta_{max} sign(u)$ and u in saturation constraints defined in (3) are considered piecewise functions. Here, we can distinguish two cases. In the first case, the control input u meets its known bound β_{max} according to the definition of input saturation constraints (3), $\beta(u)$ remains bounded and constant; then, $\Delta u = \beta(u) - u$ fulfills **Lemma 2**. In the second case, if the actuators are not in saturation range, their outputs are continuous and smooth with $\Delta u = 0$. In this case, the term D is employed to adapt the uncertain parts. Incorporating both cases, the term Δu can be found to always fulfill **Lemma 2**.

Instead of presenting the matrices of the dynamics given in (1) by FAT approaches [88, 9] , let us eliminate the use of basis function as follows:

$$\begin{cases} M_e = M - \varepsilon_M \\ C_e = C - \varepsilon_C \\ G_e = G - \varepsilon_G \end{cases} \tag{16}$$

where $M_e \in R^{7\times 7}$, $C_e \in R^{7\times 7}$, and $G_e \in R^7$ are considered respectively the best approximation of the inertia matrix, the Coriolis and centrifugal matrix, and the gravitational vector. $\varepsilon_M \in R^{7\times 7}$, $\varepsilon_C \in R^{7\times 7}$, and $\varepsilon_G \in R^7$ are the bounded approximation errors of the inertia matrix, the Coriolis and centrifugal matrix, and the gravitational vector. By using (16) we can rewrite (5) as follows:

$$M\dot{s} + Cs + M_e\zeta + C_e\vartheta + G_e - \varepsilon = K_n I \tag{17}$$

where $\varepsilon \in R^7$ is the compound approximation error. We aim to find a desired current control I_d so that the suitable voltage control input u can be designed to achieve $I \longrightarrow I_d$. Since the parameters of (17) of the robot are unknown so that the desired current (6) is not appropriate.

Remark 3: it is important to mention that ε_M, ε_C, and ε_G cannot be ignored. However, their variations are available bounded and represented by the compound approximation error ε, where this lumped error satisfies: $\|\varepsilon\| \leq \gamma$.

In such case, let us propose the following desired current:

$$I_d = K_n^{-1}\left(\widehat{M}_e\zeta + \widehat{C}_e\vartheta + \widehat{G}_e - K_1 s\right) \tag{18}$$

where $\widehat{M}_e, \widehat{C}_e$ and $\widehat{G}_e$ are estimate of M_e, C_e and G_e respectively. By using (18), we can find the closed loop dynamics as follows:

$$M\dot{s} + Cs + K_1 s = K_n(I - I_d) - \widetilde{M}_e\zeta - \widetilde{C}_e\vartheta - \widetilde{G}_e + \varepsilon \tag{19}$$

where $\widetilde{M}_e = M_e - \widehat{M}_e$, $\widetilde{C}_e = C_e - \widehat{C}_e$ and $\widetilde{G}_e = G_e - \widehat{G}_e$. $\varepsilon \in R^7$ is the compound approximation error. If we select a suitable voltage control input u and appropriate update laws of $\widehat{M}_e$, $\widehat{C}_e$ and $\widehat{G}_e$, we can easily show that $I \longrightarrow I_d$, $\widetilde{M}_e \longrightarrow 0$, $\widetilde{C}_e \longrightarrow 0$, and $\widetilde{G}_e \longrightarrow 0$, hence the dynamics of equation 22 can achieve the desired performance. Now, according to (11) and (14), we can select the voltage input such that:

$$u = \widehat{D} + L_0\dot{I}_d + R_{e0}I - K_2 e_I \tag{20}$$

where $\widehat{D}$ is the estimate of D. By replacing (20) into (14), we find:

$$L_0\dot{e}_I + K_2 e_I = \widehat{D} - D \tag{21}$$

By selecting a suitable update law for $\widehat{D}$, we can obtain that $I \longrightarrow I_d$. Next, a nonlinear observer of the uncertainties can be developed in order to estimate the term D. Let us define the auxiliary error as follows:

$$e_D = k_3 I - D \tag{22}$$

where $k_3 \in R^{7\times 7}$ is a diagonal positive-definite matrix. The derivative of e_D taking into account (14) and (22):

$$\begin{aligned}\dot{e}_D &= k_3\dot{I} - \dot{D}\\ &= k_3 L_0^{-1}(u - R_{e0}I - D) - \dot{D}\end{aligned} \tag{23}$$

However, e_D is not available due to the unknown variable $D(t)$. An estimator is designed to obtain the value of e_D as follows:

$$\dot{\hat{e}}_D = k_3 L_0^{-1}\left(u - R_{e0}I - \widehat{D}\right) \tag{24}$$

where $\hat{e}_D$ is the estimated value of e_D. From (22), the value of the uncertain function D can be obtained such that:

$$\widehat{D} = k_3 I - \hat{e}_D \tag{25}$$

One can obtain easily:

$$\tilde{e}_D = \hat{e}_D - e_D = \widehat{D} - D = \widetilde{D} \tag{26}$$

The time derivative of (26), taking into consideration (23) and (24), gives:

$$\dot{\widetilde{D}} = \dot{\tilde{e}}_D = \dot{\hat{e}}_D - \dot{e}_D = -\dot{D} - k_3 L_0^{-1}\widetilde{D} \tag{27}$$

To prove the stability of the robot system, we consider the second Lyapunov function candidate as:

$$\begin{aligned}V_2 = \tfrac{1}{2}s^T M s + \tfrac{1}{2}e_I^T L_0 e_I + \tfrac{1}{2}\tilde{e}_D^T\tilde{e}_D + \tfrac{1}{2}Tr\big(\widetilde{M}_e^T\Lambda_M\widetilde{M}_e +\\ \widetilde{C}_e^T\Lambda_C\widetilde{C}_e + \widetilde{G}_e^T\Lambda_G\widetilde{G}_e\big)\end{aligned} \tag{28}$$

where $\tilde{e}_3 = \widetilde{D}$; $\Lambda_M \in R^{7\times 7}, \Lambda_C \in R^{7\times 7}$ and $\Lambda_G \in R^{7\times 7}$ are diagonal positive-definite matrices. The time derivative of V_2 is given by:

$$\begin{aligned}\dot{V}_2 = s^T M\dot{s} + \tfrac{1}{2}s^T\dot{M}s + e_I^T L_0\dot{e}_I + \widetilde{D}^T\dot{\widetilde{D}} +\\ Tr\left(\dot{\widetilde{M}}_e^T\Lambda_M\widetilde{M}_e + \dot{\widetilde{C}}_e^T\Lambda_C\widetilde{C}_e + \dot{\widetilde{G}}_e^T\Lambda_G\widetilde{G}_e\right)\end{aligned} \tag{29}$$

Substituting $M\dot{s}$ from (17) and $L_0\dot{e}_I$ from (21), using the control input (18) and (27), hence the (29) becomes:

$$\begin{aligned}\dot{V}_2 = s^T\left(\tfrac{1}{2}\dot{M} - C\right)s - s^T K_1 s - s^T\widetilde{M}_e\zeta - s^T\widetilde{C}_e\vartheta -\\ s^T\widetilde{G}_e + s^T\varepsilon - e_I^T K_2 e_I + e_I^T\widetilde{D} + \widetilde{D}^T\dot{\widetilde{D}} +\\ Tr\left(\dot{\widetilde{M}}_e^T\Lambda_M\widetilde{M}_e + \dot{\widetilde{C}}_e^T\Lambda_C\widetilde{C}_e + \dot{\widetilde{G}}_e^T\Lambda_G\widetilde{G}_e\right)\end{aligned} \tag{30}$$

Using **Property 2**, **Notation 1** and substituting (27) into (30), one can obtain:

$$\begin{aligned}\dot{V}_2 = -s^T K_1 s - e_I^T K_2 e_I - \widetilde{D}^T k_3 L_0^{-1}\widetilde{D} + s^T\varepsilon -\\ \widetilde{D}^T\dot{D} + e_I^T\widetilde{D} + Tr\left(\left(\dot{\widetilde{M}}_e^T\Lambda_M - \zeta s^T\right)\widetilde{M}_e +\right.\\ \left.\left(\dot{\widetilde{C}}_e^T\Lambda_C - \vartheta s^T\right)\widetilde{C}_e + \left(\dot{\widetilde{G}}_e^T\Lambda_G - s^T\right)\widetilde{G}_e\right)\end{aligned} \tag{31}$$

Utilizing the case that $\left(\dot{\tilde{\cdot}}_e\right) = \left(\dot{\cdot}_e\right) - \left(\dot{\hat{\cdot}}_e\right)$. Equation (31) becomes:

$$\begin{aligned}\dot{V}_2 = -s^T K_1 s - e_I^T K_2 e_I - \widetilde{D}^T k_3 L_0^{-1}\widetilde{D} + s^T\varepsilon -\\ \widetilde{D}^T\dot{D} + e_I^T\widetilde{D} + Tr\left(\left(\dot{\widehat{M}}_e^T\Lambda_M - \zeta s^T\right)\widetilde{M}_e\right) +\\ Tr\left(\left(\dot{\widehat{C}}_e^T\Lambda_C - \vartheta s^T\right)\widetilde{C}_e\right) + Tr\left(\left(\dot{\widehat{G}}_e^T\Lambda_G - s^T\right)\widetilde{G}_e\right)\end{aligned} \tag{32}$$

To prove the stability of the system using **Lemma 1**, let us select the update laws as follows:

$$\begin{aligned}\dot{\widehat{M}}_e^T &= -\left(\zeta s^T + \mu_M\widehat{M}_e^T\right)\Lambda_M^{-1}\\ \dot{\widehat{C}}_e^T &= -\left(\vartheta s^T + \mu_C\widehat{C}_e^T\right)\Lambda_C^{-1}\\ \dot{\widehat{G}}_e^T &= -\left(s^T + \mu_G\widehat{G}_e^T\right)\Lambda_G^{-1}\end{aligned} \tag{33}$$

where $\mu_{(.)}$ is determined as $\lim_{t\to\infty}\mu_{(.)} = 0$, $\int_0^t \mu_{(.)}(w)dw = Q_i < \infty$. In simulation, we choose $\mu_{(.)} = \frac{1}{1+t^2}$. Substituting update laws (33) into (32), we find:

$$\begin{aligned}\dot{V}_2 = -s^T K_1 s - e_I^T K_2 e_I - \widetilde{D}^T k_3 L_0^{-1}\widetilde{D} + s^T\varepsilon -\\ \widetilde{D}^T\dot{D} + e_I^T\widetilde{D} + \mu_M Tr\left(\widehat{M}_e^T\widetilde{M}_e\right) + \mu_C Tr\left(\widehat{C}_e^T\widetilde{C}_e\right) +\\ \mu_G Tr\left(\widehat{G}_e^T\widetilde{G}_e\right)\end{aligned} \tag{34}$$

Using (15), **Remark 3** and the following inequality:

$$\begin{aligned}-\widetilde{D}^T\dot{D} &\leq \tfrac{\widetilde{D}^T\widetilde{D}}{2} + \tfrac{\|\sigma\|^2}{2}\\ e_I^T\widetilde{D} &\leq \tfrac{e_I^T e_I}{2} + \tfrac{\widetilde{D}^T\widetilde{D}}{2}\\ s^T\varepsilon &\leq \tfrac{s^T s}{2} + \tfrac{\|\gamma\|^2}{2}\end{aligned} \tag{35}$$

$$Tr\left((\tilde{\cdot})^T(\breve{\cdot})\right) \le \frac{1}{2}Tr\left((\cdot)^T(\cdot)\right) - \frac{1}{2}Tr\left((\tilde{\cdot})^T(\tilde{\cdot})\right)$$

Equation (25) becomes such that:

$$\dot{V}_2 \le -s^T\left(K_1 - \tfrac{1}{2}I_{7\times7}\right)s - e_I^T\left(K_2 - \tfrac{1}{2}I_{7\times7}\right)e_I - \tilde{D}^T(k_3L_0^{-1} - I_{7\times7})\tilde{D} - \tfrac{\mu_M}{2}Tr\left(\left(\tilde{M}_e\right)^T\left(\tilde{M}_e\right)\right) - \tfrac{\mu_C}{2}Tr\left(\left(\tilde{C}_e\right)^T\left(\tilde{C}_e\right)\right) - \tfrac{\mu_G}{2}Tr\left(\left(\tilde{G}_e\right)^T\left(\tilde{G}_e\right)\right) + \tfrac{\|\sigma\|^2}{2} + \tfrac{\|\gamma\|^2}{2} + \tfrac{\mu_M}{2}Tr\left((M_e)^T(M_e)\right) + \tfrac{\mu_M}{2}Tr\left((C_e)^T(C_e)\right) + \tfrac{\mu_M}{2}Tr\left((G_e)^T(G_e)\right) \quad (36)$$

$$\dot{V}_2 \le -\alpha_1 V_2 + \alpha_2$$

where: $\alpha_1 = \min\left(\gamma_{min}\left(K_1 - \frac{1}{2}I_{7\times7}\right), \gamma_{min}\left(K_2 - \frac{1}{2}I_{7\times7}\right), \gamma_{min}(k_3L_0^{-1} - I_{7\times7}), \frac{\mu_M}{2}, \frac{\mu_C}{2}, \frac{\mu_G}{2}\right)$ and $\alpha_2 = \frac{\|\sigma\|^2}{2} + \frac{\|\gamma\|^2}{2}$. Since $\frac{\mu_M}{2}Tr\left((M_e)^T(M_e)\right) + \frac{\mu_M}{2}Tr\left((C_e)^T(C_e)\right) + \frac{\mu_M}{2}Tr\left((G_e)^T(G_e)\right) \longrightarrow 0$ as $t \longrightarrow \infty$ due to the definition of $\mu_{(.)}$ in (33). By verifying the following condition: $k_1 - \frac{1}{2}I_{7\times7} > 0$, $k_2 - \frac{1}{2}I_{7\times7} > 0$, and $k_3L_0^{-1} - I_{7\times7} > 0$ this implies that $\dot{V}_2 \le 0$ wherever $V_2 > \frac{\alpha_2}{\alpha_1}$, which means the robot system is stable. According to **Lemma 1** and (25), the signals s, e_I, $\tilde{M}_e$, $\tilde{C}_e$, $\tilde{G}_e$ and $\tilde{e}_D$ are bounded.

Theorem 2: Considering the exoskeleton robot system (1) that satisfies the mentioned properties and assumptions, with the proposed adaptive voltage controller (20) with desired current input (18). If the previous conditions are verified with the bounded initial condition, the robot system is stable and the errors of the system e_1, e_2 and $\tilde{e}_3$ are bounded.

The structure of the proposed control scheme is shown in Fig. 2.

IV. SIMULATION AND COMPARATIVE STUDY

A. Simulation Set-up

A simulation session was created to validate the proposed control approach. The simulation was done in Matlab 2016. We used Sim-Mechanics toolbox to bring simulation closer to our real physical system. The control of the system consists of two units. The first unit uses the proposed controller as well as the adaptation of the dynamic model based on FAT approach, at a sampling time of 0.01µs. The second unit is where the torque is transformed to current. It uses a voltage control input and a nonlinear observer control loop to maintain motor current as required by the main controller. Each joint of the ETS-MARSE is powered by a brushless DC motor (Maxon EC-45, EC-90) combined with harmonic drives.

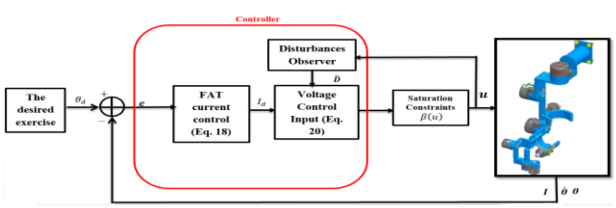

Fig. 2. General schematic of proposed control.

In this section, the exoskeleton performed the basic joint physiotherapy task (all joints of the robot) using the designed control. The initial position of the robot is given with the elbow joint position at 90 degrees. In the comparative study, the robot repeated the same exercise with a conventional approach (PI Controller), which doesn't need the dynamic model of the robot.

B. Simulation Results

The adaptive tracking control is implemented with modified FAT approach and designed nonlinear observer. The dynamics of the exoskeleton is assumed unknown with the presence of non-smooth nonlinear constraints. The control parameters were chosen manually as follows: $\lambda = 22.9I_{7\times7}$, $k_1 = 180.31I_{7\times7}$, $k_2 = 50I_{7\times7}$, $k_3 = 2.5I_{7\times7}$, $L_0 = 0.5I_{7\times7}$, $R_{e0} = 0.25I_{7\times7}$, $\Lambda_{(.)} = 12I_{7\times7}$. $K_n = diag([0.18, 0.18, 0.13, 0.14, 0.15, 0.3, 0.3])$. Saturation boundaries are selected for all motors as follows: $\beta_{max} = 5$ V.

The simulation results for the proposed task are presented in Fig. 3 to Fig. 7, using the proposed approach with the disturbance observer. From Fig. 3, it is easy to remark that the desired trajectory (red line) overlapped with the actual position (dashed blue line). The plots of Fig. 4 and Fig. 5 present the tracking errors of the position and the voltage control input, respectively. It can be seen that the voltage input (Fig. 5) is within the required motors range. Fig. 6 presents the current error which means that the proposed voltage control input is able to force the actual current to converge to the desired current *($I \longrightarrow I_d$)*. The evaluation of the outputs of the disturbance observer is given in Fig. 7. From this trial, it is clear that the proposed controller achieves the desired physiotherapy even if the dynamic parameters and the actuators dynamics were unknown.

From the comparison of results that are shown in Table IV, we remark three observations. The first one is that the tracking errors are smaller than the tracking error presented by the conventional controller, the second point is that the proposed voltage control input is relatively smaller than the control input given by PD controller. Finally, the third point is that the output of the disturbance observer respected the saturation of the motors. These observations prove that the proposed controller is very efficient when the dynamic model of the robot and its actuators is unknown. It also shows the feasibility of the combining the FAT approach and disturbance observer.

Table IV. Controller's evaluation

Root Mean Square (RMS)	Controllers	
	Conventional controller	***Proposed Controller***
$\|\tilde{\theta}\|_{position\ error}$	0.0559 (Deg)	0.0049 (Deg)
$\|e_I\|_{current\ error}$	0.2573 *mA*	0.0456 *mA*
$\|u\|_{Voltage}$	4.1274 V	2.7186 V

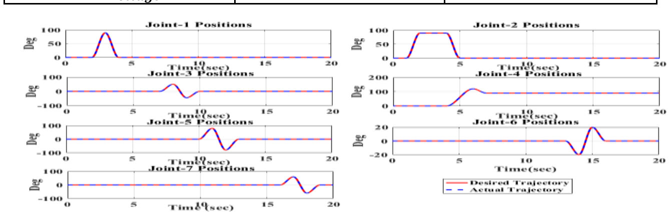

Fig. 3. Trajectory tracking of all joints of ETS-MARSE (red line desired trajectory and dashed blue line is measured trajectory).

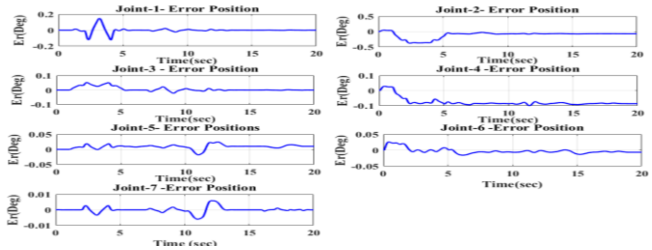

Fig. 4. Tracking of position errors of all joints of the exoskeleton robot.

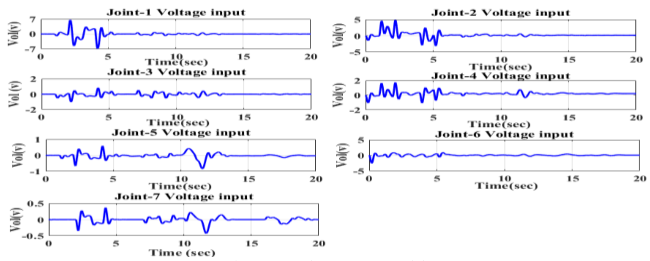

Fig. 5. Voltage control input.

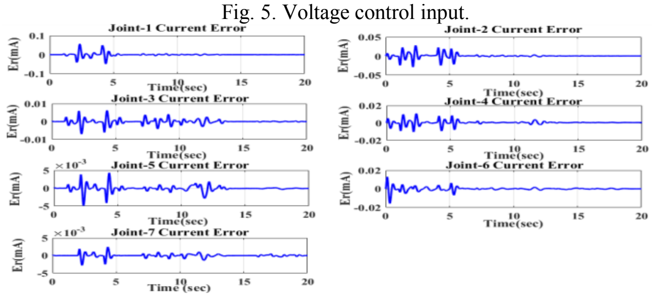

Fig. 6. Current error e_I ($I \longrightarrow I_d$).

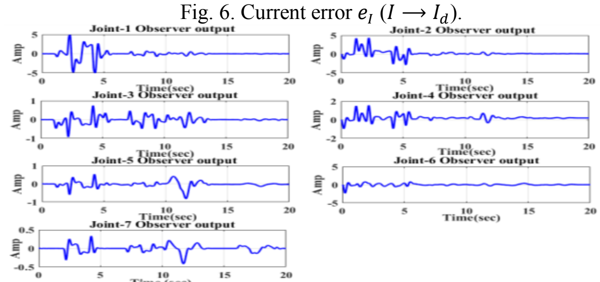

Fig. 7. Outputs of the disturbance observer.

To prove the feasibility of the proposed approach, we compared it with PD control strategy. The PD control is given as: $\tau = \ddot{\theta}_d - K_p e_1 - K_d \dot{e}_1$. The gains of the PD controller were chosen manually as: $K_p = 350 I_{7\times7}$, $K_d = 200 I_{7\times7}$. Saturation boundaries are selected for all motors as follows: $\beta_{\max} = 5\text{v}$. The comparison study is shown in Table IV.

V. Conclusion

In this paper, we proposed an adaptive tracking control for a 7-DOF exoskeleton robot taking into consideration the dynamics actuators. The proposed control is inspired from Function Approximation Technique (FAT). However, we tried to modify this technique to overcome its limit by eliminating the required use of basis functions in the estimation's law of the dynamic model. It can be seen that the basis function influences the accurate performance and time implementation of the conventional FAT approach. A nonlinear observer is designed to compensate the nonsmooth nonlinear constraints caused by the robot's actuators. The benefit of the proposed controller is that the full knowledge of the dynamic models of the robot and the actuators is not required. The stability analysis is formulated and proved based on Lyapunov theory. The simulation results are conducted with ETS-MARSE robot to show the feasibility and the effectiveness of the designed approach.

References

[1] G. R. Philips, J. J. Daly, and J. C. Príncipe, "Topographical measures of functional connectivity as biomarkers for post-stroke motor recovery," *Journal of NeuroEngineering and Rehabilitation,* vol. 14, p. 67, 2017.

[2] J. Ueda, D. Ming, V. Krishnamoorthy, M. Shinohara, and T. Ogasawara, "Individual Muscle Control Using an Exoskeleton Robot for Muscle Function Testing," *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* vol. 18, pp.339-350, 2010.

[3] L. Byeong-Kyu, L. Hee-Don, L. Ji-yeong, S. Kyoosik, H. Jung-Soo, and H. Chang-Soo, "Development of dynamic model-based controller for upper limb exoskeleton robot," in *2012 IEEE International Conference on Robotics and Automation*, 2012, pp. 3173-3178.

[4] M. H. Rahman, M. Saad, J.-P. Kenné, and P. S. Archambault, "Control of an exoskeleton robot arm with sliding mode exponential reaching law," *International Journal of Control, Automation and Systems,* vol. 11, pp. 92-104, 2013.

[5] H. Yazarel and C.-C. Cheah, "Task-space adaptive control of robotic manipulators with uncertainties in gravity regressor matrix and kinematics," *IEEE Transactions on Automatic Control,* vol. 47, pp. 1580-1585, 2002.

[6] J.-J. E. Slotine, *Applied nonlinear control* vol. 199: Englewood Cliffs: Prentice Hall., 1991.

[7] A. Brahmi, M. Saad, G. Gauthier, B. Brahmi, W.-H. Zhu, and J. Ghommam, "Adaptive backstepping control of mobile manipulator robot based on virtual decomposition approach," in *Modelling, Identification and Control (ICMIC), 2016 8th International Conference on*, 2016, pp. 707-712.

[8] A.-C. Huang and M.-C. Chien, *Adaptive control of robot manipulators: a unified regressor-free approach*: World Scientific, 2010.

[9] M.-C. Chien and A.-C. Huang, "Adaptive impedance control of robot manipulators based on function approximation technique," *Robotica,* vol. 22, pp. 395-403, 2004.

[10] W. Chen, S. S. Ge, J. Wu, and M. Gong, "Globally stable adaptive backstepping neural network control for uncertain strict-feedback systems with tracking accuracy known a priori," *IEEE transactions on neural networks and learning systems,* vol. 26, pp. 1842-1854, 2015.

[11] Z. Li, C.-Y. Su, G. Li, and H. Su, "Fuzzy approximation-based adaptive backstepping control of an exoskeleton for human upper limbs," *IEEE Transactions on Fuzzy Systems,* vol. 23, pp. 555-566, 2015.

[12] B. Brahmi, M. Saad, C. O. Luna, P. Archambault, and M. Rahman, "Sliding mode control of an exoskeleton robot based on time delay estimation," in *Virtual Rehabilitation (ICVR), 2017 International Conference on*, 2017, pp. 1-2.

[13] B. Brahmi, M. Saad, C. Ochoa-Luna, and M. H. Rahman, "Adaptive control of an exoskeleton robot with uncertainties on kinematics and dynamics," in *Rehabilitation Robotics (ICORR), 2017 International Conference on*, 2017, pp. 1369-1374.

[14] X.-S. Wang, H. Hong, and C.-Y. Su, "Model reference adaptive control of continuous-time systems with an unknown input dead-zone," *IEE Proceedings-Control Theory and Applications,* vol. 150, pp. 261-266, 2003.

[15] X. Chen, C.-Y. Su, and T. Fukuda, "A nonlinear disturbance observer for multivariable systems and its application to magnetic bearing systems," *IEEE transactions on control systems technology,* vol. 12, pp. 569-577, 2004.

[16] M. H. Rahman, M. J. Rahman, O. Cristobal, M. Saad, J.-P. Kenné, and P. S. Archambault, "Development of a whole arm wearable robotic exoskeleton for rehabilitation and to assist upper limb movements," *Robotica,* vol. 33, pp. 19-39, 2015.

[17] Z. Li, C. Yang, and L. Fan, *Advanced control of wheeled inverted pendulum systems*: Springer Science & Business Media, 2012