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MLPNN Adaptive Controller Based on a Reference Model to Drive an Actuated Lower Limb Orthosis

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Abstract— **In this paper we propose to drive an actuated orthosis using an adaptive controller based on a reference model. It is not necessary to know all the functions of the dynamic model. Needing only the global structure of the dynamic model, we use a specific adaptive controller to obtain good performance in terms of trajectory tracking both in position and in velocity. A Multi-Layer Perceptron Neural Network (MLPNN) is used to estimate dynamics related to inertia, gravitational and frictional forces along with other unmodeled dynamics. The Lyapunov formalism is used for stability study of the system (shank+orthosis) in closed loop and to determine adaptation laws of the neural parameters. To treat the non-linearties related to the MLPNN, we have used first order Taylor series expansion. Experimental results have been obtained using a real orthosis worn by an appropriate dummy. Several tests have been realized to verify the effectiveness and the robustness of the proposed controller. For instance, our proposed orthosis model has given robust tracking performance under assistive as well as resistive forces.**

I. INTRODUCTION

Wearable robots (exoskeletons/orthoses), which are used in various fields such as rehabilitation of upper or lower human members, are becoming a mature research field [1]. These wearable robots are represented by a weared actuated system and animated by actuators that can be assimilated to artificial muscles. Exoskeletons can also be used to improve comfort and provide assistance in daily tasks (gardening, carrying heavy loads, climbing stairs, etc.). One of the main scientific issues addressed for this type of robot, is related to the design of efficient controllers. The identification of parameters or dynamic behaviors is also considered. More generally, the challenge now is to improve the cognitive abilities of exoskeletons to enable them to learn, adapt and make decisions based on their own mistakes in the same way as humans.

For research purposes, several exoskeletons have been developed and experimented like Vanderbilt exoskeleton [2][3]. For exoskeletons that are already marketed, we can cite the exoskeleton namely Ekso [4]. It has been conceived by bionic society and allows its wearer, having any lower limb deficiency, to easily realize basic movements as for instance, stand up and walking [5]. Unfortunately the problem of lateral stability remains unsolved for these exoskeletons. The University of Berkeley has recently developed a lower limb exoskeleton called BLEEX that allows the holder to carry heavy loads [6]. Another kind of exoskeleton namely "Hercules" has been made to improve the performance of soldiers [7]. Furthermore, a good state of the art on the exoskeletons and their applications is given in [8][9].

For these complex systems composed of exoskeleton and its wearer, it is not certain that conventional controllers ensure the expected performance mainly if the wearer develops assistive or resistive efforts. These controllers become clearly inefficient in case of external disturbances. So, to construct robust controllers taking into account of all these unmodeled dynamics constitutes a real challenge from robotic point of view. In this context, several control techniques are proposed in the literature. Some of them are based on a preliminary identification of the dynamic parameters of exoskeleton and its wearer [10][11]. This kind of technique can be efficient when the exoskeleton is to be worn by the same person in an invariant environment. Some other approaches are adaptive and can be dedicated to generic exoskeletons that can be worn by humans of different morphologies [12][13]. We can also find several works on nonlinear control of exoskeletons [14][15].

In this work, we propose to develop and experiment a new nonlinear adaptive controller to drive an actuated lower limb orthosis. The orthosis considered here has been conceived for rehabilitation reasons. The overall system composed of this actuated orthosis and the knee of wearer, has a complex dynamic that is not obvious to express by conventional differential equations. The goal here is to help the wearer to follow the desired trajectories both in position and in velocity. A therapist having served in rehabilitation of human lower limbs, has the task of defining these trajectories. In the developpement of the proposed adaptive controller, no prior knowledges are needed about the human asked to wear the actuated orthosis. These knowledges can be the height and the weight of the patient, etc. Only the structure of the dynamic model is needed and we use the Lyapunov formalism to guarantee the system stability in closed loop. A MLPNN, considered as a universal approximator [16][17], is chosen to estimate unknown dynamics. It is associated to a Proportional Derivative (PD) gains to avoid any undesirable behavior predominately at the initialization step. An expert using an adequate reference model [19] can describe, a priori, the desired dynamic. As the proposed controller is adaptive, different wearers having not the same morphologies can wear the actuated orthosis.

The paper is organized as follows. In section II, the description of the used actuated knee orthosis is given. The section III is dedicated to the controller design. The

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experimental results with analysis, are given in section V. Finally, the section VI is the conclusion of the present work.

II. Active orthosis system

We consider for our experimentations an actuated orthosis worn by a dummy. Two jointed segments (upper and lower) compose the active orthosis. The actuator and the mechanical part are placed on the upper part of the orthosis. The torque generated by the orthosis permits to realize flexion/extension movements of the lower part composed by the shank of the wearer and the lower part of the orthosis. For security reason, the knee joint motion is imposed between 0 and $\frac{2\pi}{3}$rad. In Figure 1, we present an actuated knee joint orthosis worn by a dummy.

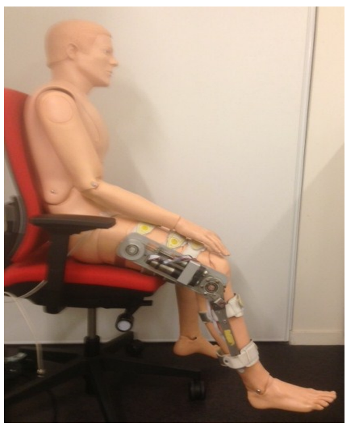

Fig. 1. An actuated knee joint orthosis worn by a dummy

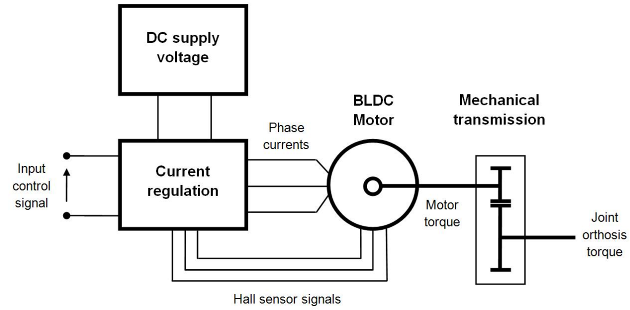

Fig. 2. Electrical architecture of the joint orthosis actuator

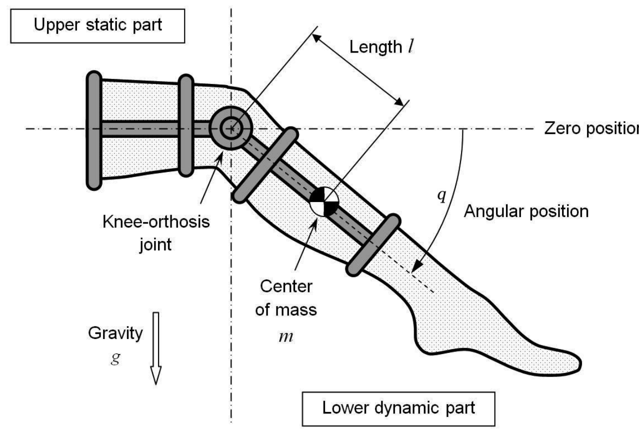

Fig. 3. Position of the joint orthosis

A. Electrical part

The joint of the orthosis is actuated by a brushless DC motor (BLDC). A power supply and an adequate electrical system are used to provide the motor's current regulation. A mechanical transmission is used to increase the orthosis applied torque. Furthermore, we assume neligible the time constant of the electrical system compared to the mechanical time constant. With this assumption and according to regulation system characteristics of the BLDC motor, we can write the following equation:

$$\tau = \mu_m u \tag{1}$$

where u is the electrical current of the BLDC motor, τ is the applied torque and μ_m is a positive constant. Fig. 2 shows the schematic diagram of the used electromechanical system.

B. Mechanical part

The mechanical structure scheme of the considered active orthosis is given by Fig. 3. Let q, $\dot{q}$ and $\ddot{q}$ respectively the angular position, the angular velocity and the angular acceleration of the knee joint-orthosis in the sagittal plane. Where 0 corresponds to the maximum knee extension and $\frac{\pi}{2}rad$ represents the resting position.

The dynamic model is given as follows :

$$\tau + \tau_h = J\ddot{q} + H(q, \dot{q}) \tag{2}$$

This equation can be expressed as:

$$\ddot{q} = \frac{1}{J}(\tau + \tau_h) - \frac{1}{J}H(q, \dot{q}) \tag{3}$$

$$\ddot{q} = \frac{\mu_m}{J}(u + \frac{\tau_h}{\mu_m}) - \frac{1}{J}H(q, \dot{q}) \tag{4}$$

where :

- τ is the orthosis generated torque;
- τ_h represents the human torque and is bounded
- $J = J_{or} + J_h$ is the inertia of the system (orthosis (or) + knee (h)). (J is considered unknown)
- $H(q, \dot{q})$ represents all dynamics (gravitational torque, solid friction torque and all other unkown dynamics). (H is considered unknown).

III. Adaptive Controller design

The purpose of this section is to design a robust adaptive controller in position and in velocity to drive an active orthosis for rehabilitation reasons. The stability study of the system (orthosis + wearer) in closed loop is conducted using the Lyapunov approach. The MLPNN weights are to be updated using appropriate adaptive laws. The given controller is designed such that the state vector of the equation (6) tracks the state vector of the reference model given in equation (8) (reference trajectory). Indeed, the MLPNN is used to estimate inertia, gravitational and frictional forces and other non-modeled dynamic effects.

A. State representation of the dynamic model

Let $x \in \mathbb{R}^{2\times 1}$ be the state vector defined by:

$$x = \begin{bmatrix} q \\ \dot{q} \end{bmatrix} \tag{5}$$

To derive the control laws, the dynamic model given in (3) must be rewritten under the form of a state equation:

$$\dot{x} = Ax + B(u + \frac{\tau_h}{\mu_m}) + C \tag{6}$$

$$\begin{cases} A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \\ B = \begin{bmatrix} 0 \\ \frac{\mu_m}{J} \end{bmatrix} \\ C = \begin{bmatrix} 0 \\ -\frac{1}{J}H(x) \end{bmatrix} \end{cases} \tag{7}$$

Let us consider the following reference model:

$$\dot{x}_m = A_m x_m + B_m r \tag{8}$$

$$\begin{cases} A_m = \begin{bmatrix} 0 & 1 \\ a_{m1} & a_{m2} \end{bmatrix} \\ B_m = \begin{bmatrix} 0 \\ b_m \end{bmatrix} \end{cases}$$

$$a_{m1}, a_{m2}, b_m \in \mathbb{R}$$

For experiments, the reference trajectory is obtained by choosing the input signal r with quasi-sinusoidal shape. The output of the reference model denoted by x_m=$[q_m \ \dot{q}_m]^T$is then used as a desired trajectory in the control scheme. The values a_{m_1}, a_{m_2} and b_m are chosen so that the reference model (8) works as a stable second-order system.

B. Control law

Before giving the control law expression, consider the following errors:

$$e = x_m - x \in \mathbb{R}^{2\times 1} \tag{9}$$

$$x_m = x + e \tag{10}$$

$$s = \Lambda e \tag{11}$$

$$\Lambda = [\lambda \quad 1] \in \mathbb{R}^{1\times 2} \quad \lambda \in \mathbb{R}^{+}$$

$$\dot{s} = \Lambda \dot{e} = \Lambda(\dot{x}_m - \dot{x}) \in \mathbb{R}$$

The proposed control law is given by the following equation and its principle scheme in figure (4).

$$u = \digamma(\theta) + Ks \tag{12}$$

$$K \in \mathbb{R}^{+}$$

$$\theta = [x, e, r]^T \tag{13}$$

Taking:

$$\tau_{h\mu} = \frac{\tau_h}{\mu_m}, \qquad \alpha = \frac{J}{\mu_m}, \qquad H_\mu = \frac{H(x)}{\mu_m}$$

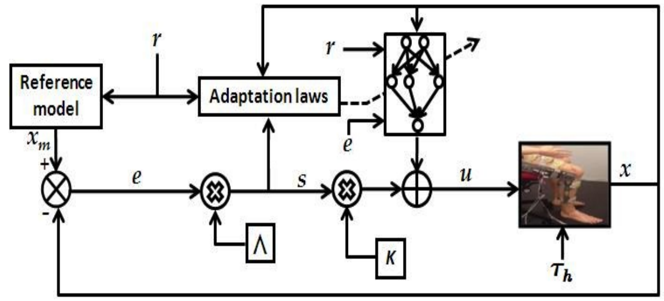

Fig. 4. The proposed adaptive controller scheme.

where $\digamma(\theta)$ is a $MLPN$ that the parameters are updated using the stability study in Lyapunov sense. For the stability analysis of the system in closed loop, we calculate:

$$\begin{aligned} \alpha\dot{s} &= \alpha\Lambda\{A_m x + B_m r - Ax - B(u + \tau_{h\mu}) - C\} \\ &= \alpha\Lambda\{A_m x + B_m r - Ax\} - \alpha\Lambda B(u + \tau_{h\mu}) - \alpha\Lambda C \end{aligned} \tag{14}$$

as $\alpha\Lambda B = 1$ and $-\alpha\Lambda C = H_\mu$, we can write:

$$\alpha\dot{s} = \alpha\Lambda\{A_m x + B_m r - Ax\} - u - \tau_{h\mu} + H_\mu$$

Using (12):

$$\begin{aligned} \alpha\dot{s} &= \alpha\Lambda\{(A_m - A)x + A_m e + B_m r\} - \digamma(\theta) \\ &- Ks + H_\mu - \tau_{h\mu} \\ &= \alpha\Lambda(A_m - A)x + \alpha\Lambda A_m e + \alpha\Lambda B_m r \\ &+ H_\mu - \tau_{h\mu} - \digamma(\theta) - Ks \end{aligned} \tag{15}$$

Consider the following function depending on θ :

$$\digamma^*(\theta) = \Lambda\alpha((A_m - A)x + A_m e + B_m r) + H_\mu$$

Then the equation (15) becomes :

$$\begin{aligned} \alpha\dot{s} &= -\digamma(\theta) + \digamma^*(\theta) - Ks - \tau_{h\mu} \\ &= -\tilde{\digamma}(\theta) - Ks - \tau_{h\mu} \end{aligned} \tag{16}$$

where:

$$\tilde{\digamma}(\theta) = \digamma(\theta) - \digamma^*(\theta)$$

The function $\digamma^*(\theta)$ considered unknown can be represented by a MLPNN as follows :

$$\digamma^*(\theta) = V^{*T}\varphi(W^{*T}\theta) + \epsilon \tag{17}$$

where ϵ is the neural approximation error and $W^{*T} \in \mathbb{R}^{n\times m}$ and $V^{*T} \in \mathbb{R}^{1\times n}$ are the weight matrices between the input and the hidden layer and between the hidden layer and the output of the MLPNN respectively, with:

- n the number of neurons in the hidden layer.
- m : size of θ
- φ represents the activation function and has a sigmoidal form.

$\digamma^*$ can be estimated by $\digamma$ as follows:

$$\digamma(\theta) = V^T\varphi(W^T\theta) \tag{18}$$

where the neural parameters W and V are the estimations of W^* and V^* respectively. As we will see later, these parameters are adjusted according to an adaptation law based on the Lyapunov stability analysis.

The Taylor series expansion of function $\varphi(W^{*T}\theta)$ on the estimated parameter $(W^T\theta)$ can be written as follows [21]:

$$\varphi(W^{*T}\theta)) = \varphi(W^T\theta) - \acute{\varphi}(W^T\theta)\tilde{W}^T\theta - O_s$$
$$\varphi(W^T\theta) - \varphi(W^{*T}\theta)) = \acute{\varphi}(W^T\theta)\tilde{W}^T\theta + O_s$$

$$\acute{\varphi}(W^T\theta) = \begin{bmatrix} \acute{\varphi}(W_1^T\cdot\theta) & 0 & \dots & 0 \\ 0 & \acute{\varphi}(W_2^T\cdot\theta) & & \vdots \\ \vdots & & \ddots & \\ 0 & \dots & & \acute{\varphi}(W_n^T\cdot\theta) \end{bmatrix}$$

$$W^T = \begin{bmatrix} W_{11} & W_{12} & \dots & W_{1m} \\ W_{21} & W_{22} & \dots & W_{2m} \\ \vdots & & \ddots & \vdots \\ W_{n1} & W_{n2} & \dots & W_{nm} \end{bmatrix} = \begin{bmatrix} W_1^T \\ W_2^T \\ \vdots \\ W_n^T \end{bmatrix}$$

$$\tilde{W} = W - W^*$$
$$\tilde{V} = V - V^*, \quad V \in \mathbb{R}^{n\times 1}$$
$$W_{ij} \in \mathbb{R}\,\{i = 1..n; j = 1..m\}$$

where $\acute{\varphi}(\vartheta) = \left.\frac{d\varphi(\varrho)}{d\varrho}\right|_{\varrho=\vartheta}$ and $O_s$are the superior-order term with:

$$O_s = (\varphi - \varphi^*) - \acute{\varphi}\tilde{W}^T\theta = \tilde{\varphi} - \acute{\varphi}\tilde{W}^T\theta$$

To simplify writing, consider:

$$\varphi = \varphi(W^T\theta) \qquad \varphi^* = \varphi(W^{*T}\theta)$$
$$\acute{\varphi} = \acute{\varphi}(W^T\theta)$$

Finally we can write:

$$\begin{aligned} \tilde{F}(\theta) &= V^T\varphi - (V^{*T} + V^T - V^T)\varphi^* - \epsilon \\ &= V^T(\varphi - \varphi^*) + (V^T - V^{*T})\varphi^* - \epsilon \\ &= V^T\acute{\varphi}\tilde{W}^T\theta + V^TO_s + \tilde{V}^T\varphi^* - \epsilon \\ &= V^T\acute{\varphi}\tilde{W}^T\theta + \tilde{V}^T(\varphi - \acute{\varphi}\tilde{W}^T\theta - O_s) + V^TO_s - \epsilon \\ &= V^T\acute{\varphi}\tilde{W}^T\theta + \tilde{V}^T\varphi + \epsilon_\varphi - \epsilon \end{aligned} \tag{19}$$

$$\epsilon_\varphi = -\tilde{V}^T\acute{\varphi}\tilde{W}^T\theta + V^{*^T}O_s \tag{20}$$

ϵ_φ represents the approximation errors rising from the first order Taylor series expansion. From (20), we can state that if $\tilde{W} \to 0$ and $\tilde{V}$ is bounded, then $\epsilon_\varphi \to 0$. Equation (19), is used in the next section to calculate the adaptation laws of neural network parameters.

C. Stability study

Consider the following Lyapunov function:

$$L = \frac{\alpha}{2}s^2 + \frac{1}{2\delta_1}tr(\tilde{W}^T\tilde{W}) + \frac{1}{2\delta_2}\tilde{V}^T\tilde{V} \tag{21}$$
$$\delta_1 > 0 \quad \delta_2 > 0$$

By differentiating (21), we get:

$$\dot{L} = \alpha s\dot{s} + \frac{1}{\delta_1}tr(\tilde{W}\dot{W}^T) + \frac{1}{\delta_2}\tilde{V}\dot{V}^T \tag{22}$$

using the equations (16) and (19), we get:

$$\begin{aligned} \alpha s\dot{s} &= -s\tilde{F}(\theta) - Ks^2 - \tau_{h\mu}s \\ &= -sV^T\acute{\varphi}\tilde{W}^T\theta\varphi + s\epsilon - s\epsilon_\varphi - Ks^2 - \tau_{h\mu}s \end{aligned}$$

From (16), we can write :

$$\begin{aligned} \dot{L} = &-sV^T\acute{\varphi}\tilde{W}^T\theta - s\tilde{V}^T\varphi + s\epsilon - s\epsilon_\varphi - Ks^2 - \tau_{h\mu}s \\ &+ \frac{1}{\delta_1}tr(\tilde{W}\dot{W}^T) + \frac{1}{\delta_2}\tilde{V}\dot{V}^T \end{aligned}$$

Le us consider the follwing adaptation laws:

$$\begin{aligned} \dot{W} &= \delta_1\theta sV^T\varphi' \\ \dot{V} &= \delta_2\varphi s \end{aligned} \tag{23}$$

We can then have:

$$\dot{L} = -Ks^2 + s\epsilon - s\epsilon_\varphi - s\tau_{h\mu}$$

To finalise the stability study we have to consider two cases :

1) There is no neural approximation errors:

$$\dot{L} = -Ks^2 \leq 0$$

Invoking Barbalat's Lemma, we can say that s goes to zero because $\dot{L}$ is checked definite negative. The system controlled by the (12) is asymptotically stable and tracks the same dynamics as the reference model.

2) Neural approximation errors are different from zero:

$$\dot{L} = -Ks^2 + s\epsilon - s\epsilon_\varphi - \tau_{h\mu}s$$
$$\dot{L} \leq -Ks^2 + |s||\epsilon - \epsilon_\varphi - \tau_{h\mu}|$$

For $\dot{V}$ to be negative or zero:

$$Ks^2 \geq |s||\epsilon - \epsilon_\varphi - \tau_{h\mu}|$$
$$s^2 \geq \frac{|s||\epsilon - \epsilon_\varphi - \tau_{h\mu}|}{K}$$
$$|s| \geq \frac{|\epsilon - \epsilon_\varphi - \tau_{h\mu}|}{K}$$

In this case, overall stability and convergence is ensured towards a bounded region of radius $\frac{|\epsilon - \epsilon_\varphi - \tau_{h\mu}|}{K}$ because $\epsilon, \epsilon_\varphi$ and $\tau_{h\mu}$ are bounded. Every time s tries to get out of this region, $\dot{L}$ becomes negative and the controller draws it immediately back in.

IV. Experimental results and analysis

The performed experimentations have the goal to ensure the good performance of the actuated orthosis worn by a human for rehabilitation reasons. The parameters of the reference model used here, can be quite fixed by a doctor. The proposed control strategy aims to apply any rehabilitation program in good conditions. Furthermore, we have used a PC equipped of a dSpace DS1103 PPC real-time controller card and dSpace Control Desk software and Matlab/Simulink. For these first experiments, an appropriate dummy weighing $25kg$ and measuring $1.70m$ have been used. The considered experimental setup is given in Fig. 5.

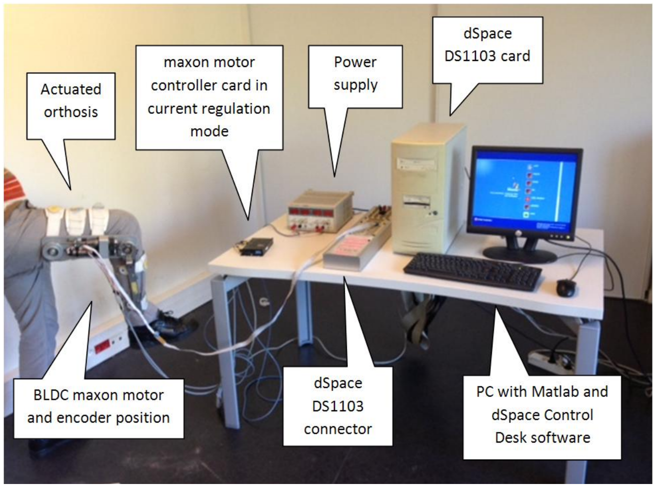

Fig. 5. Experimental setup

The real position is measured by incremental encoder. Furthermore, we applied a low pass first order filter in the goal to reduce the noise effect concerning the angular position measurement. The sampling time has been fixed to 10^{-3} sec. The reference model considered here is given by the following equation:

$$\dot{x}_m = \begin{bmatrix} 0 & 1 \\ -0.5 & -1 \end{bmatrix} x_m + \begin{bmatrix} 0 \\ 0.5 \end{bmatrix} r$$

The controller parameters are given in table 1. As we can

δ_1	δ_2	K	λ	n
5	5	40	2	3

TABLE I
CONTROLLER PARAMETERS

see on figure (6), the quality of tracking is satisfactory. To test the robustness of the proposed controller, we have applied in the first time a resistive effort on the shank of the dummy. In the second time an assistive effort has been applied. These efforts can be considered as external disturbances since they are not produced by the dummy itself. Even if the error increases in the case of unknown external disturbances, it remains bounded and small enough for a good trajectory tracking. The tracking error is greater in the case of the resistive force applied in the opposite direction of the movement. Nevertheless, the proposed control keeps good performances in term of trajectory tracking. For the velocity trajectory tracking, we notice the same performances as for the position. Concerning assistive effort, the tracking errors improve compared to the free case (no applied effort) as shown by figure (6). For the resistive case, the trajectory tracking error increases but remains limited and small enough

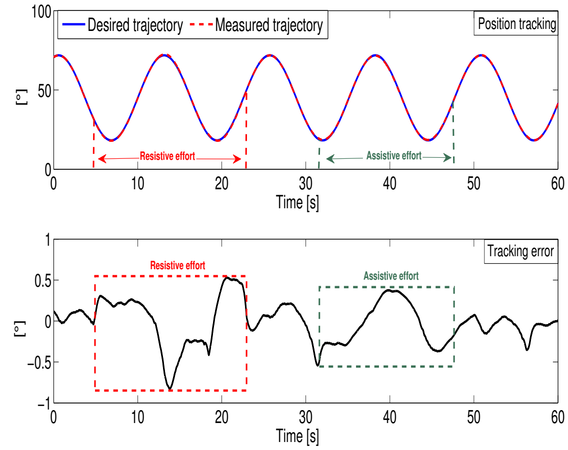

Fig. 6. Position tracking

to keep good performances. As the controller is adaptive, this error remains stable. As illustrated in figure (9), the control

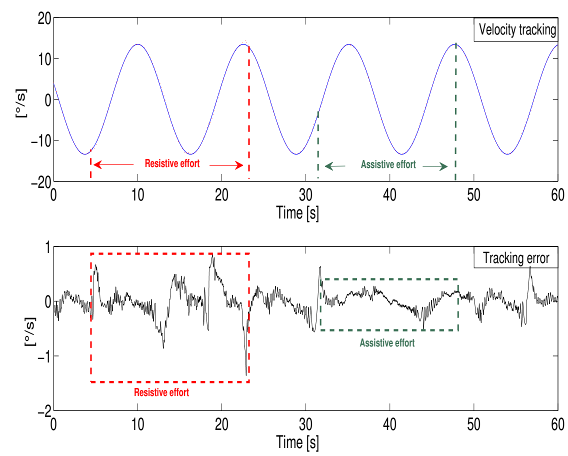

Fig. 7. Velocity tracking.

input calculated by the proposed controller shows that the actuator is not heavily used. Also, the external disturbances represented by the resistive and assistive efforts, are properly interpreted by the adaptive controller. This means that the calculated electrical current input is increased in the resistive case and considerably decreases in the assistive case. If the resistive force exceeds the capacity of the actuator, the controller becomes saturated and the trajectory tracking may deteriorate. For a real application on a human subject, these efforts are intrinsic and developed by the muscles. This may change the behavior of the control signal because the wearer feels perfectly the applied movements and forces. This means that it is not possible to apply an extern assistive effort (or an extern resistive effort) accurately as if it is done by the wearer himself. The last test made during the experimentation, is represented by the application of a resisitive effort exceeding the fixed capacity of the used brushless motor (± 2.5 A).

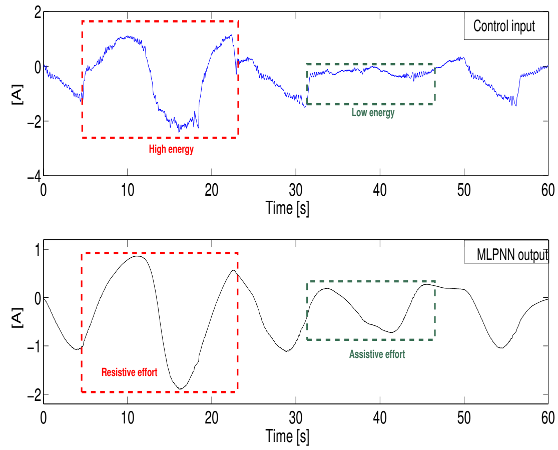

Fig. 8. Applied control input and MLPNN output.

Although the applied current is in saturation, the system maintains its stability and the quality of trajectory tracking remains good.

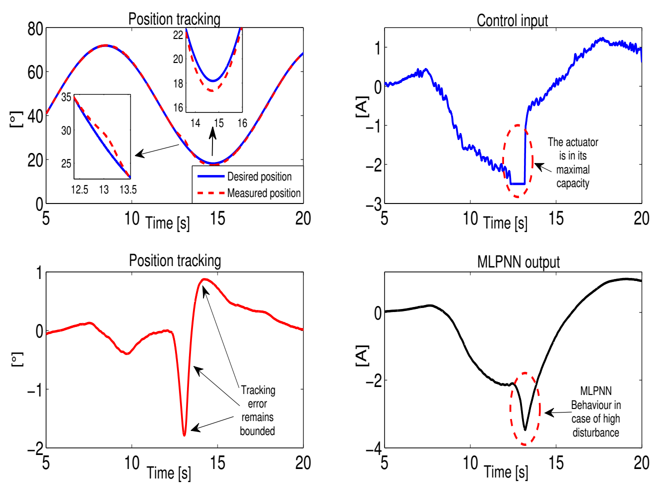

Fig. 9. Saturation.

V. Conclusion and Future Work

The control technique that we have proposed and validated on an active orthosis worn by an appropriate dummy, has given a good tracking performance. Our objective was to conceive a controller that requires no prior knowledge on the dynamic model, takes into account different situations of the wearer and is robust against external disturbances. We have chosen a strategy based on a reference model for its several possibilities including, for instance, the integration of the rehabilitation protocol that can be described beforehand by the doctor. We have also used an MLPNN for its characteristic of universal approximation of nonlinear unknown functions. As the MLPNN parameters are adaptive according to the laws issued from the stability study in Lyapunov sense, good performances have been obtained in different experiments. Furthermore, our expectations concerning the rapid adaptation to possible changes in the dynamics as well as the stability of the system in closed loop have been met. For future work, we shall prepare a specific protocol to experiment our approach on a person suffering from a problem of mobility, and are waiting the response from the competent authority.

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