Model Reference Adaptive Control Using a Neural Compensator to Drive an Active Knee Joint Orthosis

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***Abstract*— This paper presents an adaptive control approach of an actuated orthosis for the human knee joint rehabilitation. The objective of the proposed technique is to help patients to follow the guidelines of movement imposed by the therapists in terms of position and velocity. This is achieved by a system consisting of a mechanical orthosis actuated by an electrical driven motor. No needed prior knowledge concerning patients (height, weight, etc.). To prove the stability of the system, composed of the shank and the orthosis, in closed loop, we consider known its dynamic model structure. A Radial-Basis-Function Neural Network (RBFNN) is used to approximate online, a part of unknown dynamics and other unmodeled effects. In the goal to avoid abrupt transitions that can harm the wearer, we have used a reference model that can be constructed by an expert. The stability study conducted according to Lyapunov's approach guarantees that the proposed control remains stable even in the presence of bounded or assistive disturbances. The good performances of the proposed controller allow us to conclude with its effectiveness for trajectory tracking. In this work and for safety reasons, an adequate dummy has been used to perform real tests and detect any possible anomaly.**

I. INTRODUCTION

Hemiparesis is most often due to an accident occurring on one or both hemispheres of the brain. It engenders motor impairments characterized by a partial loss of one-half of the body motor skills (right or left). As the recovery by classical methods of medicine is insufficient, a physical therapy [1] is required to recover and realize voluntary movements. These can be achieved by physiotherapy sessions with the objective to mobilize the affected limbs. In general, these sessions are often long and repetitive with a high cost.

Exoskeletons and activated orthoses provide appropriate answers to the above-mentioned problems. These wearable robots are driven by actuators that can be assimilated to artificial muscles. This robotic system is intended to be worn by different parts of the human body (knee, arm, pelvis, etc.). Among various application fields of these machines, one can notate the rehabilitation services, assistance and the possible total replacement of the affected limbs. They can even be used for daily tasks to improve life comfort (gardening, carry heavy loads, climb stairs, walk long, etc.).

Several civilian and military applications of exoskeletons have been developed in recent years. For instance, the University of Agriculture and Technology of Tokyo has designed an exoskeleton to help the wearer to perform agricultural work considered difficult and tough [2]. The Berkeley Lower Extremity Exoskeleton (BLEEX) allows to carry heavy loads [3][4][5].

Hercules is a complete exoskeleton that concerns both lower and upper limbs and it has been proposed in order to improve the performance of soldiers [6]. Moreover, the references [7] and [8] contain an interesting state of the art about exoskeletons and their applications.

The complexity of the dynamic system consisting of the exoskeleton and its wearer makes the control design a real challenge. Classical controllers are obviously inefficient in the case of non-modelled external disturbances.

Some of the control techniques proposed in the literature are efficient when the exoskeleton is dedicated to a unique person and used in a stationary environment. These methods are generally based on prior identification [9] or on a known dynamic model of the overall system to be controlled. For other approaches that are adaptive, for instance, they can be applied to exoskeletons used by several persons, which can have different morphologies [10][11]. In nonlinear control theory, in general, one can find various proposition dedicated to controlling exoskeletons [12][13][14].

In this article, we propose to construct and experiment a new nonlinear adaptive controller for an active knee joint orthosis. The considered system, consisting of an actuated orthosis and a knee of the wearer, has a dynamic not obvious to model. The main objective is to help patients to follow the desired therapist trajectories in terms of position and velocity. No needed prior knowledge concerning patients (height, weight, etc.). Furthermore, only the structure of the dynamic model is employed to guarantee the stability of the system (active orthosis + wearer) in closed loop. A Radial Basis Functions Neural Network (RBFNN) approximation is chosen to estimate some unknown dynamic parts of the model and other unmodeled effects [15]. The desired dynamic can be described a priori by an expert using an adequate reference model and specific desired trajectories [16].

The rest of the article is presented as follows. The used knee joint orthosis is described in section II. The section III is dedicated to the RBFNN approximation, and the controller

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design is developed in section IV. The section V regroups experimental results and comments. We conclude and give some future works in section VI.

II. Considered System

Two jointed segments (upper and lower) composed the active orthosis considered in this paper. On the upper part of the orthosis are placed the actuator, the mechanical part and the sensor measuring the flexion/extension displacements. By its actuator, the orthosis generates a torque ensuring flexion/extension movements of the lower part (the leg of the wearer + the lower part of the orthosis). To avoid all undesirable behavior of the orthosis, the knee joint motion is constrained to be between 0 and 135^o. In Figure 1, is presented the knee joint orthosis worn by a healthy person.

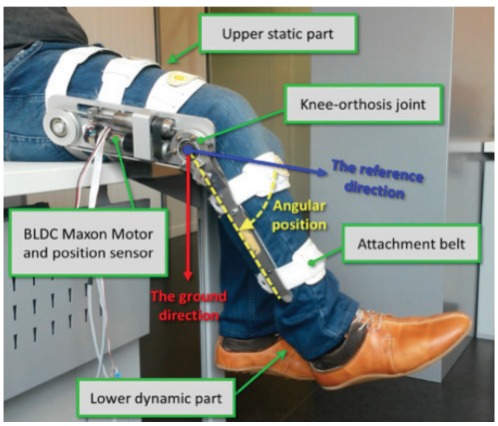

Fig. 1. EICoSI (Exoskeleton Intelligently Communicating and Sensitive to Intention) of LISSI laboratory worn by a healthy subject.

A brushless DC motor (BLDC) is used to actuate the orthosis joint. The applied torque is increased via a mechanical transmission. The characteristics of the regulation system of the BLDC motor leads us to write :

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

where u is the electrical current of the BLDC motor, τ is the applied torque and μ_m is a positive constant. 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 (Figure 2). Where 0 corresponds to the full knee extension and 90^o represents the resting position.

The dynamic model is given as follows [17]:

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

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

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

where :

- τ is the orthosis generated torque;
- τ_h represents the human torque and is bounded

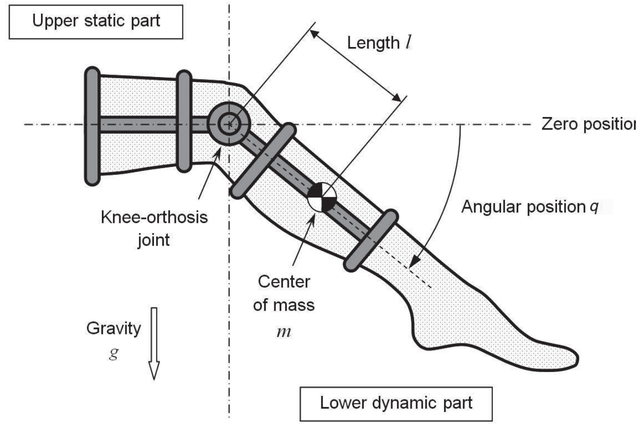

Fig. 2. Position of the joint orthosis

- $J = J_{or} + J_h$ is the inertia of the system (orthosis (or) + knee (h));
- $\beta\dot{q} = (\beta_{or} + \beta_h)\dot{q}$ is the viscous friction torque;
- $H(q, \dot{q})$ represents all other dynamics (gravitational torque, solid friction torque and all other unknown dynamics)
- q is the actual knee joint position
- $\dot{q}$ is the actual knee joint velocity
- $\ddot{q}$ is the actual knee joint acceleration

III. RBFNN Approximation

In the adaptive controller developed in section IV, the function:

$$\psi^*(x) = H_\mu(x) = \frac{1}{\mu_m}H(x) \tag{5}$$

$$x = \left[\begin{array}{cc} q & \dot{q} \end{array} \right]^T$$

is considered unknown and we propose to identify it using the RBFNN which is a universal approximator. So it can be written:

$$\begin{aligned}
\psi^*(x) &= W^{*T}\varphi(x) + \epsilon \\
\varphi(x) &= \left[\begin{array}{cccc} \varphi_1(x) & \varphi_2(x) & \cdots & \varphi_n(x) \end{array} \right]^T \in \mathbb{R}^{n\times 1} \\
W^* &= \left[\begin{array}{cccc} W_1^* & W_2^* & \cdots & W_n^* \end{array} \right]^T \in \mathbb{R}^{n\times 1} \\
\varphi_i(x) &= e^{-\pi\left(\frac{||x-\eta_i||^2}{\sigma^2}\right)} \quad x = \left[\begin{array}{c} q \\ \dot{q} \end{array} \right] \\
\sigma &= \left[\begin{array}{c} \sigma_q \\ \sigma_{\dot{q}} \end{array} \right] \quad \eta_i = \left[\begin{array}{c} \eta_{iq} \\ \eta_{i\dot{q}} \end{array} \right] \\
i &= 1, n \quad n \text{ is the number of neurons}
\end{aligned}$$

Where :

- ϵ is the RBFNN approximation error
- $\varphi_i(x)$ is a Gaussian function
- σ_q : width of the Gaussian function in q direction
- $\sigma_{\dot{q}}$: width of the Gaussian function in $\dot{q}$ direction
- η_{iq} : center i of the Gaussian function in q direction.
- $\eta_{i\dot{q}}$: center i of the Gaussian function in $\dot{q}$ direction.

Each two successive centers related to the position q are separated by a distance Δ_q, and each two successive centers related to the velocity $\dot{q}$ are separated by a distance $\Delta_{\dot{q}}$. If the desired position vary between q^d_{min} and $q^d_{max} \Rightarrow \eta_{0q} = q^d_{min}$ and $\eta_{nq} = q^d_{max}$. Also, if the desired velocity vary between $\dot{q}^d_{min}$ and $\dot{q}^d_{max} \Rightarrow \eta_{0\dot{q}} = \dot{q}^d_{min}$ and $\eta_{n\dot{q}} = \dot{q}^d_{max}$.

IV. Adaptive Controller Design

In order to improve our previous work [18], we have used another type of neural network to compensate only a part of the system dynamics. Compared to our previous work, two advantages are focused by the present controller. The first one is to limit and reduce the effect of the neural initialisation to random values especially when there is no prior identification. The second one is about the learning capacity of the RBFNN. In fact, unlike the MLPNN (Multi Layer Perceptron Neural Network) that has the characteristic to learn globally, the RBFNN has the property to learn locally and for this reason it can have a very faster convergence. For our system, having a reduced number of entries, the RBFNN is better-suited.

This section deals with the proposed robust adaptive control design and the stability study of the controlled system in closed loop. The proposed controller allows the overall system (orthosis + shank) to track desired trajectories both in position and velocity. As the orthosis is dedicated for rehabilitation reasons, flexion/extension are the movements to be realized. The control law is composed of three variable parameters and the RBFNN. The adaptive laws obtained via the Lyapunov stability study are used to update these parameters and the weights of the RBFNN. A part of the unknown dynamics (gravitational and frictional forces) is estimated by the RBFNN, and the other parameters are used to compensate the other dynamics, inertia for instance.

A. State representation

Consider $x \in \mathbb{R}^{2\times 1}$ the following state vector:

$$x = \begin{bmatrix} q \\ \dot{q} \end{bmatrix} \tag{6}$$

In order to derive the proposed controller, we have to rewrite the dynamic model (4) under its state form as follows:

$$\dot{x} = Ax + B(u + \frac{\tau_h}{\mu_m}) + C \tag{7}$$

$$A = \begin{bmatrix} 0 & 1 \\ 0 & -\frac{\beta}{J} \end{bmatrix} B = \begin{bmatrix} 0 \\ \frac{\mu_m}{J} \end{bmatrix} C = \begin{bmatrix} 0 \\ -\frac{1}{J}H(q,\dot{q}) \end{bmatrix} \tag{8}$$

Let the following reference model:

$$\dot{x}_m = A_m x_m + B_m r \tag{9}$$

$$A_m = \begin{bmatrix} 0 & 1 \\ a_{m1} & a_{m2} \end{bmatrix} B_m = \begin{bmatrix} 0 \\ b_m \end{bmatrix}$$
$$a_{m1}, a_{m2}, b_m \in \mathbb{R}$$

Concretely, the state vector given in (7) must track the state vector of the reference model given in (9) (reference trajectory). In experimentation section, the input signal r is chosen having a quasi-sinusoidal shape. Then, the reference model output $x_m = [q_m, \dot{q}_m]$ is used as the desired trajectory. By choosing appropriate values of the variables a_{m1}, a_{m2} and b_m, the reference model (9) works as a stable second-order system.

B. Control law synthesis

Let as consider the following tracking errors :

$$e = (x_m - x) \in \mathbb{R}^{2\times 1},\ x_m = x + e,\ s = \Lambda e$$
$$\Lambda = [\lambda \ \ 1] \in \mathbb{R}^{1\times 2} \quad \lambda \in \mathbb{R}^+$$

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

The adaptive controller is given by the following equation:

$$u = Kx + Le + Nr + \psi + \rho s \tag{10}$$

where $\rho \in \mathbb{R}^+$, $K \in \mathbb{R}^{1\times 2}, L \in \mathbb{R}^{1\times 2}, N \in \mathbb{R}$, are respectively the estimated parameters of K^*, L^*, N^* given later (equations (12), (13) and (14)). ψ is a RBFNN estimator of ψ^* (equation (15)).

C. Stability study

Let the following Lyapunov function with $\alpha = \frac{J}{\mu_m}$:

$$V = \frac{\alpha}{2}s^2 + \frac{1}{2\theta_1}\tilde{K}\tilde{K}^T + \frac{1}{2\theta_2}\tilde{L}\tilde{L}^T + \frac{1}{2\theta_3}\tilde{N}^2 + \frac{1}{2\theta_4}\tilde{W}^T\tilde{W}$$

with:

$$\theta_i > 0 \quad (i = 1, 4)$$

$$\tilde{K} = -K^* + K \quad \tilde{L} = -L^* + L$$
$$\tilde{N} = -N^* + N \quad \tilde{W} = -W^* + W$$
$$\dot{\tilde{K}} = \dot{K} \quad \dot{\tilde{L}} = \dot{L} \quad \dot{\tilde{N}} = \dot{N} \quad \dot{\tilde{W}} = \dot{W}$$

The derivative of V with respect to the time is given by:

$$\dot{V} = \alpha s\dot{s} + \frac{1}{\theta_1}\tilde{K}\dot{K}^T + \frac{1}{\theta_2}\tilde{L}\dot{L}^T + \frac{1}{\theta_3}\tilde{N}\dot{N} + \frac{1}{\theta_4}\tilde{W}^T\dot{W}$$

To simplify the writing; we calculate $\alpha\dot{s}$ with $\tau_{h\mu} = \frac{\tau_h}{\mu_m}$:

$$\begin{aligned}\alpha\dot{s} &= \alpha\Lambda\dot{e} \\ &= \alpha\Lambda\{A_m x_m + B_m r - Ax - B(u + \tau_{h\mu}) - C\}\end{aligned} \tag{11}$$

As $x_m = x + e$ and by substituting (10) in (11), we get:

$$\begin{aligned}\alpha\dot{s} &= \alpha\Lambda\{(A_m - A)x + A_m e + B_m r\} \\ &\quad - \alpha\Lambda B(Kx + Le + Nr + \psi + \rho s) - \alpha\Lambda B\tau_{h\mu} - \alpha\Lambda C\end{aligned}$$

As $\alpha\Lambda B = 1$ and $-\alpha\Lambda C = H_\mu$, we have:

$$\begin{aligned}\alpha\dot{s} &= \alpha\Lambda\{(A_m - A)x + A_m e + B_m r\} \\ &\quad - Kx - Le - Nr - \psi - \rho s - \tau_{h\mu} + H_\mu\end{aligned}$$

By commutativity and as $\alpha\Lambda B_m = \alpha b_m$, we obtain:

$$\begin{aligned}\alpha\dot{s} &= (\alpha\Lambda(A_m - A) - K)x + (\alpha\Lambda A_m - L)e \\ &+ (\alpha b_m - N)r - \psi - \rho s - \tau_{h\mu} + H_\mu\end{aligned}$$

Multiplying by s:

$$\begin{aligned}\alpha s\dot{s} &= s(\alpha\Lambda(A_m - A) - K)x + s(\alpha\Lambda A_m - L)e \\ &+ s(\alpha b_m - N)r - \rho s^2 + (H_\mu - \psi)s - \tau_{h\mu}s\end{aligned}$$

Using this result to simplify $\dot{V}$:

$$\begin{aligned}\dot{V} &= s(\alpha\Lambda(A_m - A) - K)x + s(\alpha\Lambda A_m - L)e \\ &+ s(\alpha b_m - N)r - \rho s^2 + (H_\mu - \psi)s - s\tau_{h\mu} \\ &+ \frac{1}{\theta_1}\tilde{K}\dot{K}^T + \frac{1}{\theta_2}\tilde{L}\dot{L}^T + \frac{1}{\theta_3}\tilde{N}\dot{N} + \frac{1}{\theta_4}\tilde{W}^T\dot{W} \\ &= \dot{V}_1 + \dot{V}_2 + \dot{V}_3 + \dot{V}_4\end{aligned}$$

where:

$$\begin{aligned}\dot{V}_1 &= s(\alpha\Lambda(A_m - A) - K)x + \frac{1}{\theta_1}\tilde{K}\dot{K}^T \\ \dot{V}_2 &= s(\alpha\Lambda A_m - L)e + \frac{1}{\theta_2}\tilde{L}\dot{L}^T \\ \dot{V}_3 &= s(\alpha b_m - N)r + \frac{1}{\theta_3}\tilde{N}\dot{N} \\ \dot{V}_4 &= (H_\mu - \psi)s + \frac{1}{\theta_4}\tilde{W}^T\dot{W} - \rho s^2 - \tau_{h\mu}s\end{aligned}$$

Let us consider:

$$\alpha\Lambda(A_m - A) = K^* \tag{12}$$
$$\alpha\Lambda A_m = L^* \tag{13}$$
$$\alpha b_m = N^* \tag{14}$$
$$H_\mu = \psi^* \tag{15}$$

As we have not the real values of $K^*, L^*,\ N^*$and ψ^*, they will be replaced respectively by their estimated ones $K, L,\ N$ and ψ. So we have:

$$\begin{aligned}\dot{V}_1 &= s(K^* - K)x + \frac{1}{\theta_1}\tilde{K}\dot{K}^T \\ \dot{V}_2 &= s(L^* - L)e + \frac{1}{\theta_2}\tilde{L}\dot{L}^T \\ \dot{V}_3 &= s(N^* - N)r + \frac{1}{\theta_3}\tilde{N}\dot{N} \\ \dot{V}_4 &= (\psi^* - \psi)s + \frac{1}{\theta_4}\tilde{W}^T\dot{W} - \rho s^2 - \tau_{h\mu}s\end{aligned}$$

Choosing the following adaptation laws:

$$\dot{K}^T = \theta_1 sx \quad \dot{L}^T = \theta_2 se \quad \dot{N} = \theta_3 sr$$

It becomes:

$$\begin{aligned}\dot{V}_1 &= -s\tilde{K}x + \frac{1}{\theta_1}\tilde{K}\dot{K}^T = 0 \\ \dot{V}_2 &= -s\tilde{L}e + \frac{1}{\theta_2}\tilde{L}\dot{L}^T = 0 \\ \dot{V}_3 &= -s\tilde{N}r + \frac{1}{\theta_3}\tilde{N}\dot{N} = 0\end{aligned}$$

As $\dot{V}_1 = \dot{V}_2 = \dot{V}_3 = 0$, we can write:

$$\begin{aligned}\dot{V} = \dot{V}_4 &= (\psi^* - \psi)s + \frac{1}{\theta_4}\tilde{W}^T\dot{W} - \rho s^2 - \tau_{h\mu}s \\ &= (-\tilde{W}^T\varphi(x) + \epsilon)s + \frac{1}{\theta_4}\tilde{W}^T\dot{W} - \rho s^2 - \tau_{h\mu}s\end{aligned}$$

Consider the adaptation law for the RBFNN weights :

$$\dot{W} = \theta_4\varphi(x)s$$

We obtain :

$$\dot{V} = -\rho s^2 + \epsilon s - \tau_{h\mu}s$$

To conclude with the stability study, let us consider the following two cases:

Case 1: The wearer is completely passive and the RBFNN approximation error is negligible:

$$\dot{V} = -\rho s^2 \leq 0$$

As $\dot{V}$ is checked definite negative, it can be concluded that s goes to zero (Barbalat's Lemma). Consequently, the stability of the system in closed loop is ensured by applying the proposed control law (10). Furthermore, the dynamic imposed by the reference model is reproduced by the controlled system.

Case 2: Neural approximation errors, and muscular effort are different from zero:

$$\dot{V} = \dot{V}_4 = -\rho s^2 + s\epsilon - s\tau_{h\mu}$$

This equation can be transformed to :

$$\dot{V} \leq -\rho s^2 + |s|\left(|\epsilon| + |\tau_{h\mu}|\right)$$

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

$$\rho s^2 \geq |s|\left(|\epsilon| + |\tau_{h\mu}|\right) \implies |s| \geq \frac{|\epsilon| + |\tau_{h\mu}|}{\rho}$$

So here it can be concluded with the overall stability of the system in closed loop. The tracking errors converge towards a bounded region of radius $\frac{|\epsilon|+|\tau_{h\mu}|}{\rho}$ because ϵ and τ_h are bounded. The proposed controller ensures that s never goes outside this region.

V. Results and Discussion

The purpose of the conducted experimentations is to ensure the good performance of the actuated orthosis to help therapists in their rehabilitation program in real conditions by using our control strategy. We implemented the control law on a PC equipped with a dSpace DS1103 PPC real-time controller card, using dSpace Control Desk software and Matlab/Simulink. The experiment considers a dummy subject weighing $25kg$ and measuring $1.70m$. In order to reduce the measurement noise effect, a low pass first order filter has been applied to the joint position. The controller parameters are selected as follows :

θ_1	θ_2	θ_3	θ_4	λ	ρ	n
5	5	5	2	30	0.8	10

Sampling time	Δ_q	$\Delta_{\dot{q}}$
10^{-3} sec	$0.05 rad$	$0.05 rad/s$

For the parameters, which concern RBFNN, they have been chosen so that the workspace (both in position and velocity) is covered by the use of a sufficient number of Gaussian functions. For the other parameters, the unique condition is that they should be strictly positive and they are chosen heuristically. In our case, several tests were conducted in simulations and the gains values which have given the best results were selected for experimentations.

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

The figure 3 shows a good quality of trajectory tracking in joint position. In the first time and in order to verify the robustness of our controller, a resistive effort has been applied on the leg of the dummy. After a few seconds of operation of the orthosis, an assistive effort has been applied in the same sense as the desired movement. Since the dummy itself does not exert these efforts, they can be viewed as external disturbances. In that cases, even if the tracking error increases both in position and velocity, the quality of trajectory tracking remains satisfactory. As a comparison between the two situations : resistive efforts and assistive efforts, the tracking error is smaller in the case of the assistive force applied in the same direction of the movement. The

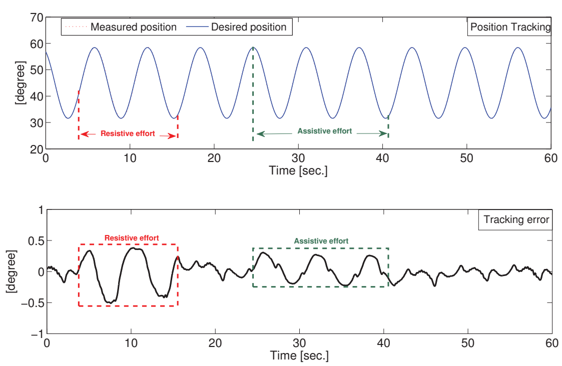

Fig. 3. Position tracking

proposed control preserves good performances in terms of disturbance rejection and trajectory tracking. One can notice the similar performances as for the position concerning the velocity trajectory tracking. The tracking error is smaller when an assistive effort is applied than in the free case when there is no external effort (figure 4). On the other hand, if a resistive effort is applied, the tracking error increases slightly but remains bounded and small enough maintaining a good quality of trajectory tracking both in position and velocity. The proposed controller by its adaptive nature allows to the active orthosis to keep a stable behavior. As shown in figure 5, the applied control input is not important which makes the actuator not heavily used. Furthermore, the proposed controller handles properly resistive and assistive efforts. This can be explained by the increasing of the electrical current input in the resistive case and its decreasing in the assistive case. If the assistive effort goes upper than the necessary control input, it becomes a resistive effort. When this last exceeds the capacity of the actuator, the controller becomes saturated and the trajectory tracking may deteriorate. On the other hand if the resistive effort cannot be countered by the calculated control input, the actuator becomes in its maximal capacity and logically the quality of the trajectory tracking deteriorates.

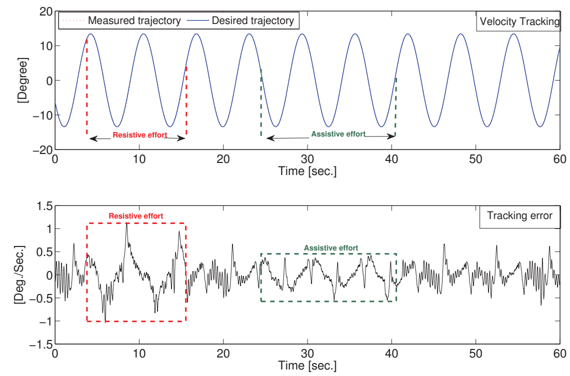

Fig. 4. Velocity tracking.

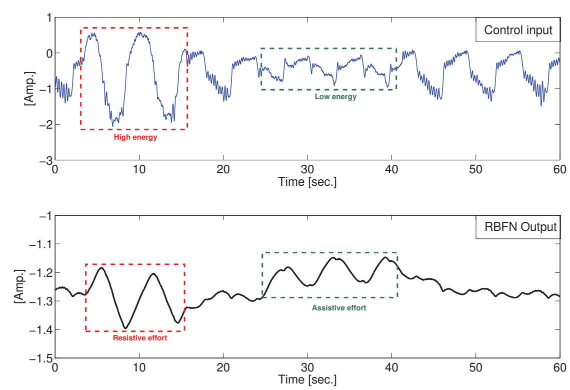

Fig. 5. Applied control input and RBFNN output.

Other adaptive control parameters also react to external disturbances that are represented here by assistive and resistive forces applied by the person to the shank of the dummy (figure 6). The parameter N that is not shown here, is very close to the value 0.8. 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.

On the other hand, we applied only the part ($u = \rho s$), which represents a Proportional Derivative (PD) controller, to show the importance of using a specific controller as the

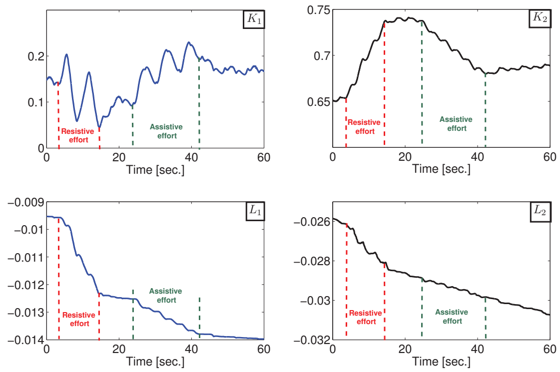

Fig. 6. Control parameters.

proposed one. One can notice on figures 7 and 8 that the PD controller is not sufficient for this kind of wearable robots. It justifies at the same time the use of the proposed neural network controller to obtain good performances in different situation (free movement, resistive effort or assistive effort).

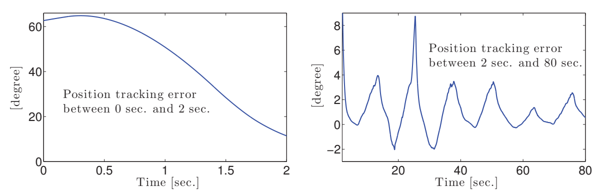

Fig. 7. PD controller : tracking errors in position using the same desired trajectory as for the proposed controller. Around the 25th second, a resistive effort has been applied

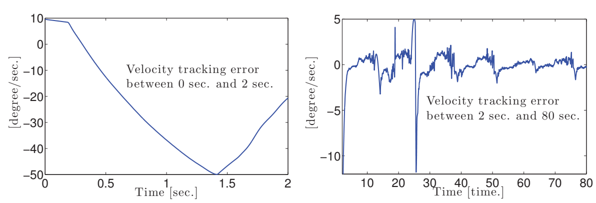

Fig. 8. PD controller : tracking errors in velocity using the same desired trajectory as for the proposed controller. Around the 25th second, a resistive effort has been applied

VI. Conclusion and Future Work

An adaptive control technique for an actuated knee-joint orthosis is presented in this work. The proposed controller has the properties of the universal estimation of nonlinear unknown functions thanks to use of RBFNN. This allowed to estimate some unknown parts of the model. The desired dynamic can be described beforehand by an expert using an adequate reference model and specific desired trajectories. Except the structure of its dynamical model, no prior knowledge is considered on the overall system. The adaptation of the control parameters is quite fast, which reduces the risk of undesirable behavior in the initial step and in the possible change on the system. The implementation of the control is easy due to the structure of the used approaches. Indeed, the RBFNN is linear on parameters and we have chosen the reference model as a simple dynamic system. Good performances have been obtained in the different conducted experiments. The control ensures the convergence of tracking position and velocity despite resistive or assistive bounded disturbances. For future work, collaborations are under investigation to apply the proposed controller on a person suffering of a real mobility problem.

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