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Robustness analysis of an upper-limb exoskeleton controlled by an adaptive sliding mode

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***Abstract*— This paper presents an adaptive sliding mode algorithm controlling an upper limb exoskeleton, used for rehabilitation, in presence of uncertainties. The considered system is a robot with three degrees of freedom. The objective is to control the flexion/ extension movement of the shoulder, the elbow and the wrist. To prove the performance of the proposed adaptive sliding mode, a comparison of this law with the adaptive and sliding mode controllers is done. An Input-to-State Stability study is realized to demonstrate the stability of the system. A robustness analysis in the presence of disturbances and uncertainties using Monte Carlo simulation is developed. Simulation results are provided to prove the performances and the effectiveness of the adaptive sliding mode algorithm and the stability of the system face to disturbances and uncertainties.**

***Keywords*— upper-limb exoskeleton, adaptive sliding mode controller, Input-To-State Stability, Monte Carlo, uncertainties, disturbances, robustness analysis.**

I. Introduction

The partial or complete loss of function of the upper limbs due to a partial loss of the motor capacities of one half of the body causes hemiparesis. Referring to the World Health Organization (Mackay and Mensah) [1], fifteen million people worldwide suffer from cerebral vascular accidents every year. Of these, more than five million are left handicapped. Since the number of such cases is constantly increasing and the duration of treatment is more and more long, the development of a robotic exoskeleton for the rehabilitation of the upper limbs could make a significant contribution to the success of these interventions.

Exoskeleton is a mechatronic system placed on the user's body and acts as amplifiers that augment, reinforce or restore human performances. It is an articulated mechanical structure made up of the various components such as sensors, actuators and control unit. This unit performs the acquisition and processing of the information delivered by the sensors and of controlling the actuators according to control laws guaranteeing the effectiveness of the assistance movement and the stability of the system.

Exoskeleton robots are used in different fields of applications. In military applications, exoskeletons are used in order to increase the physical endurance of soldiers and help them lift heavy loads. In this context, we find the development of Harvard's exoskeleton which allows soldiers to walk longer distances carrying heavy loads with less effort, while also minimizing risk of injury [3]. Around 2010, two major exoskeleton projects for the military were brought to the public's attention. The first one is the HULC (Human Universal Load Carrier) developed by Ekso Bionics and Lockheed Martin. The second one is the XOS and XOS2 developed by Sarcos and Raytheon which were both full body suits for solider mobility augmentation.

In the medical context, while ability to move is very necessary to ensure basic activities of daily living and the number of hemiplegic people is constantly increasing the development of robotic exoskeletons which are systems in physical interaction with the human being used in order to help the patient to realize his movement and to improve more comfort becomes a powerful solution. In this field, Saga University developed "SUEFUL-7" exoskeleton used to control all the axes of the upper limb [4]. The Space Systems Laboratory in collaboration with the Georgetown University Imaging Science and Informations Systems have designed an exoskeleton which allows an adaptation to the complex of the shoulder in order to propose a larger workspace [2].

The goal of controlling an exoskeleton is to follow the movements of a healthy user, to increase his physical abilities for specific tasks in a relatively safe and transparent manner. To achieve this, it is necessary to apply a suitable controller. The complexity of the exoskeleton-upper limb dynamic system has led researchers to develop many control laws.

In the literature and referring to [9], authors use sliding mode to control the exoskeleton of the upper limbs. This controller has proved its effectiveness through several theoretical studies and has ensured satisfactory performances in terms of continuity of trajectory in position and speed. There is another type of control called a mixed force and position controller which mixes, for the same degree of freedom, the force and position information used by the author in [7].

Pre-calculated torque control (using the PID corrector) is a simple nonlinear control method and is often used for the control of exoskeletons used by the author in [1]. However, this method performs well when the model is accurate. However, in this case, the model contains inaccuracies which could make this method of control less efficient. We find the development of several other modes of control, such as universal approaches to fuzzy logic or neural network approaches [6] which require offline learning to avoid undesirable behaviour of the robot.

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Like any robotic system, exoskeletons suffer from two main components of uncertainty. The first is that of parameter variations (parametric uncertainties). The second important source of uncertainty is the external interaction forces on the suspended body, which are generally unknown. So, it is necessary to study the stability and the robustness of the considered system face to these uncertainties.

The contribution of this paper is to develop an adaptive sliding mode algorithm to control the upper-limb exoskeleton. In presence of disturbances and to study the robustness as well as the performance of the proposed control, we use the Input-to-State Stability (ISS) and Monte Carlo simulation.

The paper is organized as follows: section 2, deals with the modelling and the control of the upper-limb exoskeleton. Section 3 describes the Input-to-State Stability studies and the robustness analysis of the system affected by uncertainties and disturbances. In section 4, simulation results and discussions are given. Finally, section 5 is reserved for the conclusion and future work.

II. MODELLING AND CONTROL OF THE UPPER LIMB EXOSKELETON

The objective of the proposed adaptive sliding mode law is to operate the upper limb exoskeleton in order to help the patient to make desired movements. The proposed system treats the actuated joints shoulder, elbow and wrist.

A. Dynamic model of the upper-limb exoskeleton

Referring to Lagrange equation [8], the dynamic model of an exoskeleton having three degrees of freedom (DoF), presented by Fig.1. is given by the following equation

$$M(q)\,\ddot{q} + C(q,\dot{q})\,\dot{q} + G(q) + F(q,\dot{q}) = \tau \qquad (1)$$

Where $q \in \mathbb{R}^3$ is the vector of joint positions; $\dot{q} \in \mathbb{R}^3$ is the vector of joint velocities; $\ddot{q} \in \mathbb{R}^3$ is the vector of joint accelerations; $M(q)\in\mathbb{R}^{3*3}$ is the inertia matrix; $C(q,\dot{q})\in\mathbb{R}^{3*3}$ is the Coriolis matrix, $G(q) \in \mathbb{R}^3$ is the gravitational vector; $F(q,\dot{q}) \in \mathbb{R}^3$ is the force generated by friction and $\tau \in \mathbb{R}^3$ is the control vector.

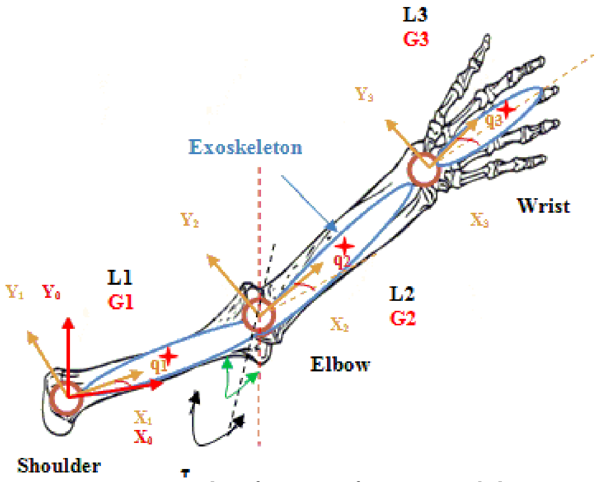

Fig.1 General configuration of a 3 DoF exoskeleton

We synthesize then the algorithms laws used to control the exoskeleton in order to follow the desired trajectories.

B. Control of the upper-limb exoskeleton

In this part, we started with the control of our exoskeleton using the adaptive and the sliding mode algorithms. By the following, we have combined these two laws to obtain the adaptive sliding mode.

B.1. Adaptive mode controller

We use the adaptive mode to respond to uncertainties by adjusting the controller parameters in real time.
The control law can be written as follows [4]

$$\boldsymbol{\tau} = \underbrace{M(q)\,\ddot{q}_d + C(q,\dot{q})\,\dot{q}_d + G(q)}_{Y(q,\,\dot{q},\,\dot{q}_d,\,\ddot{q}_d)\,a} + F(q,\dot{q}) + \underbrace{k_d(\dot{q}_d - \dot{q})}_{k_d\,s}$$

$$\boldsymbol{\tau} = Y(q,\dot{q},\dot{q}_d,\ddot{q}_d)\,a + F(q,\dot{q}) + k_d\,s \qquad (2)$$

Where a presents the robot constant parameters vector and $Y(q,\dot{q},\dot{q}_d,\ddot{q}_d)$ is the matrix according to positions, speeds and accelerations.
Since the parameters of the vector a are unknown, we pose

$$\boldsymbol{\tau} = Y(q,\dot{q},\dot{q}_d,\ddot{q}_d)\,\hat{a} + F(q,\dot{q}) + k_d\,s \qquad (3)$$

With $\hat{a}$ is an estimator of the parameters vector of a.
Eq.3 can be rewritten as

$$\boldsymbol{\tau} = Y(q,\dot{q},\dot{q}_d,\ddot{q}_d)\,a - Y(q,\dot{q},\dot{q}_d,\ddot{q}_d)\,\tilde{a} + F(q,\dot{q}) + k_d\,s$$

$$\boldsymbol{\tau} = M(q)\,\ddot{q}_d + C(q,\dot{q})\,\dot{q}_d + G(q) + F(q,\dot{q}) + k_d\,s - Y(q,\dot{q},\dot{q}_d,\ddot{q}_d)\,\tilde{a} \qquad (4)$$

With $\tilde{a} = a - \hat{a}$.
The control law applied to the dynamic of our system gives the following dynamics of s

$$M(q)\,\dot{s} + C(q,\dot{q})\,s + k_d\,s = Y(q,\dot{q},\dot{q}_d,\ddot{q}_d)\,\tilde{a} \qquad (5)$$

The adaptation law is considered as

$$\dot{\hat{a}} = \sigma\,Y(q,\dot{q},\dot{q}_d,\ddot{q}_d)\;s \qquad (6)$$

Where σ is a gain matrix that must be symmetric and positive.
Supposed that the parameters of the vector a are constant, then we will get

$$\dot{\tilde{a}} = \dot{a} - \dot{\hat{a}} = -\dot{\hat{a}} = -\sigma\,Y(q,\dot{q},\dot{q}_d,\ddot{q}_d)\;s \qquad (7)$$

B.2. Sliding mode controller

The objective of this controller is to develop a control law U(t) in order to achieve and maintain the sliding mode surface S = 0.
The sliding surface which ensures the convergence of a variable to its desired value is given by

$$S = \lambda\,e + \dot{e}$$

Where $e = q_d - q$ is the tracking error and λ is the vector of parameters for setting the discontinuous control.

The system checked the tracking error when the sliding surface S = 0 is reached. This error is represented by the following equation

$$\lambda e + \dot{e} = 0 \quad (8)$$

The dynamic model of the system presented by Eq.1 can be rewritten in the following form

$$\ddot{q} = M^{-1}(q)\,[\tau - C(q,\dot{q})\,\dot{q} - G(q) - F(q,\dot{q})] \quad (9)$$

Calculating the derivative of S with respect to time

$$\dot{S} = \lambda \dot{e} + \ddot{e} \quad (10)$$

The sliding mode control applied to the robot is given by

$$U = U_{eq} + U_n \quad (11)$$

With U_{eq} corresponds to the equivalent command proposed by Filipov and U_n is determined to check the convergence condition.
To calculate U_{eq}, it is necessary that $\dot{S}= 0$, which give

$$U_{eq} = M\,(\lambda \dot{e} + \ddot{q}_d) + G(q) + C(q,\dot{q})\,\dot{q} + F(q,\dot{q}) \quad (12)$$

The main purpose of this command is to check the attractiveness conditions.

$$U_n = -k\,sign\,(S) = -k\,sign\,(\lambda e + \dot{e}) \quad (13)$$

Where k is the gain matrix chosen to guarantee stability, speed and to overcome external disturbances that may affect the system.

Referring to Eqs. 12 and 13, the sliding mode controller is given by the following equation

$$U = M(q)\,(\lambda \dot{e} + \ddot{q}_d) + G(q) + C(q,\dot{q})\dot{q} + F(q,\dot{q}) - (k\,sign\,(\lambda e + \dot{e})) \quad (14)$$

B.3. Adaptive sliding mode controller

The objective of using an adaptive sliding mode is to ensure a dynamic adaptation of the control gain in order to be as small as possible while sufficient to counter the uncertainties and disturbances.
The adaptive control is used for its speed and ease of implementation, and the sliding mode for its theoretical foundations reassuring in terms of stability and robustness.
The adaptive sliding mode control tries to drive the sliding vector σ (x, t) to a vicinity of zero in a finite time. The dynamic of σ is given by

$$\dot{\sigma} = \frac{\partial \sigma}{\partial x}\dot{x} + \frac{\partial \sigma}{\partial t} = \underbrace{\frac{\partial \sigma}{\partial t} + \frac{\partial \sigma}{\partial x} f(x)}_{\Psi(x,t)} + \underbrace{\frac{\partial \sigma}{\partial x} g(x)}_{\Gamma(x,t)} \quad (15)$$

The controller may be expressed as follows

$$u = -k\,sign\,(\sigma(x,t)) \quad (16)$$

Using the previous section, we consider the following sliding variable

$$\sigma = \lambda^2 (q_d - q) + 2\lambda\,(\dot{q}_d - \dot{q}) + \ddot{q}_d \quad (17)$$

III. Input-to-state stability STUDY AND ROBUSTNESS ANALYSIS

A. Input-to State-Stability

A.1. preliminary

In order to formalize a Lyapunov-type stability property of nonlinear systems by taking into account persistent inputs, we use the notion of input-to-state stability (ISS) which was introduced by Sontag [5].

Theorem 1: For $\alpha_1, \alpha_2, \alpha_3 \in \mathcal{K}_\infty$, $V \in \mathcal{R}^n$ and $V: \mathcal{X} \rightarrow \mathcal{R}_+$ a function defined with V (0) = 0, the following inequalities are considered

$$\alpha_1(||x||) \le V(x) \le \alpha_2(||x||) \quad (18)$$

$$V(f(x,u)) - V(x) \le -\alpha_3(||x||) \quad (19)$$

If the precedent inequalities are true for all $x \in X$ and $v \in V$, then the system is ISS *(X, V).*

Definition: The function V which satisfies the hypothesis of the preceding theorem is called an ISS-Lyapunov function.

Theorem 2: A system is ISS if and only if it has an ISS Lyapunov function.

A.2. ISS application for upper-limb exoskeleton

To prove the stability of the exoskeleton system, we can rewrite Eq.1 as

$$\ddot{q} = f(q,\dot{q}) + g(q,\dot{q})\,u$$

$$\ddot{q} = -M^{-1}(q)\,C(q,\dot{q})\,\dot{q} - M^{-1}(q)\,G(q) + g(q,\dot{q})\,u \quad (20)$$

We pose that $A = M^{-1}(q)\,C(q,\dot{q})$, $B = -M^{-1}(q)\,G(q)$, $x = \dot{q}$ and $\dot{x} = \ddot{q}$, we get the following form

$$\dot{x} = -Ax + B + g(x)\,u \quad (21)$$

We suppose that B = 0 (no gravity force) and in the presence of uncertainties and disturbances, the equation of the system becomes of the following form

$$\dot{x} = -A\,x + g(x)\,[u + \delta_1] + \delta_2 + \Delta I \quad (22)$$

Where δ_1 is the matched disturbances, δ_2 is the unmatched disturbances and ΔI presents the parametric uncertainties.

The candidate Lyapunov function is defined by

$$V(x) = \frac{1}{2}\,x\,x^T \quad (23)$$

With $\alpha_1(|(x)|) < V(x) < \alpha_2(|(x|)$ for all $x \in \mathcal{R}$

The derivative of V is written as

$$\dot{V}(x) = x\,\dot{x} = x\,(-A\,x + g(x)[u + \delta_1] + \delta_2 + \Delta I)$$

$$\dot{V}(x) = x\,\dot{x} = x\,(-A\,x + g(x)\,\delta_1 + \delta_2 + \Delta I) + g(x)\,u$$

$$\dot{V}(x) = -\,[A\,x^2(1-\theta) - g(x)\,\delta_1 + \delta_2 + \Delta I] - (A\,x^2\theta - x\,g(x)\,u)$$

$$\theta \in [0,1]$$

$$\dot{V}(x) < -\underbrace{(A\,x^2(1-\theta) - g(x)\,\delta_1 + \delta_2 + \Delta I)}_{\alpha_3(|x|)} \quad (24)$$

$$\text{for } (A\,x^2\,\theta - x\,g(x)\,u) > 0$$

Since A= $M^{-1}(q)\,C(q,\dot{q})$ is an invertible matrix, we get

$$|x| > \alpha_x(|u|) = \left[\frac{A^{-1}g(x)|u|}{\theta}\right] \quad (25)$$

$\dot{V}(x) < -\alpha_3(|x|)$ for all $x \in \mathcal{R}$, $u \in \mathcal{R}$, $|x| > \alpha_x(|u|)$.

$\alpha_i \in \mathcal{K}_\infty$, i = 1, 2, 3. The function V is therefore an ISS-Lyapunov function which proves that the system is input-state stable.

B. Monte Carlo simulation

To study the performance and the robustness of the tested controllers face to uncertainties, we used the Monte Carlo method which is a probabilistic technique based on the use of a large number of random disturbances.
To conduct a Monte Carlo simulation, it is necessary to identify the type of distribution of the uncertainties applied to the input system. In our case, we choose to work with an uniform random distribution.

IV. SIMULATIONS AND RESULTS

To validate our approaches and show their efficiencies, we simulate the three algorithm lows used to control the exoskeleton by applying the desired trajectories as

- q_1= (pi/6) + (pi/10)*sin(2*pi*t),
- q_2= (pi/6) + (pi/10)* sin (2*pi*t),
- q_3= (pi/10)* sin (2*pi*t),

The initial conditions of the real trajectories are $q(0) = [-pi/2; 0; pi/4]^T$ and $\dot{q}(0) = [0; 0; 0]^T$.

The measured and the desired trajectories of the released tests as well as the errors of tracking trajectories are given in Figs. 2, 3 and 4. Figs.5, 6 and 7 present the velocities tracking and errors of the algorithms tested.

From these figures, we can clearly note that the best tracking of the desired trajectories in position and in velocities in presence of disturbances are given by the adaptive sliding mode controller.

To perform the tests and to prove the robustness of the proposed controller, the adaptive sliding mode was compared to the adaptive and the sliding mode approaches. Table.1 and Figs.8 and 9 present some statistics of the tracking recorded errors by the calculation of the Root-Mean- Square (RMS), the mean (Mean) and the standard deviation (Std).

The RMS is calculated using the following expression

$$X_{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}|X\,n|^2} \quad (27)$$

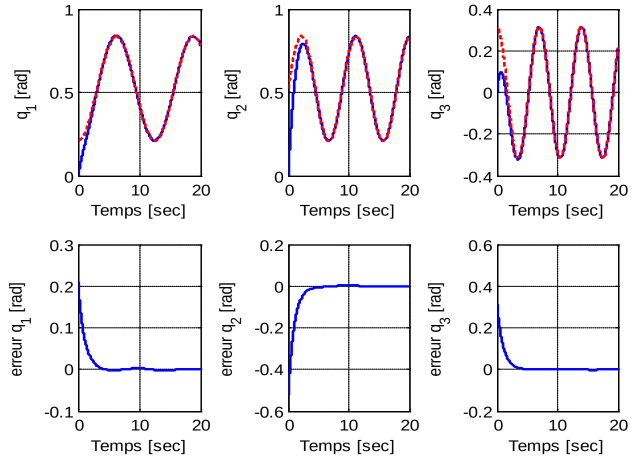

Fig.2 Simulation results of the trajectories and errors tracking of the joints q_1, q_2 and q_3 using adaptive mode controller

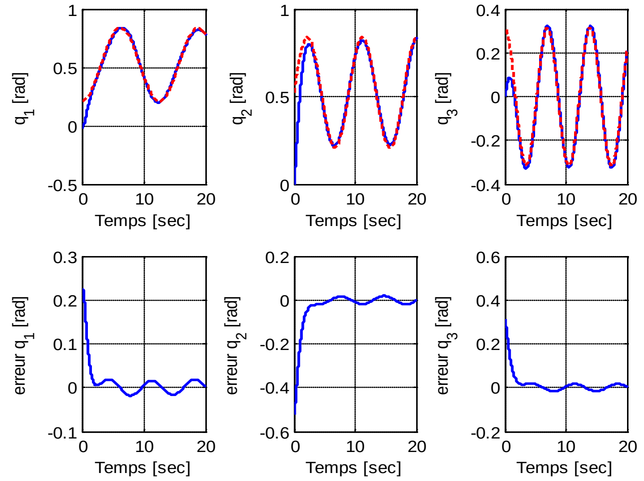

Fig.3 Simulation results of the trajectories and errors tracking of the joints q_1, q_2 and q_3 using sliding mode controller

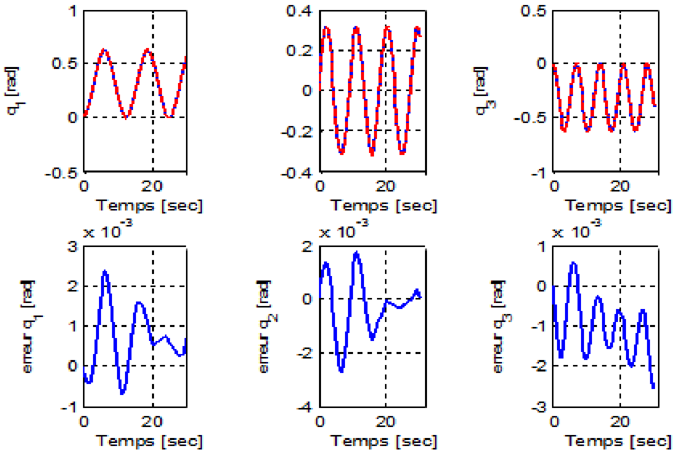

Fig.4 Simulation results of the trajectories and errors tracking of the joints q_1, q_2 and q_3 using adaptive sliding mode controller

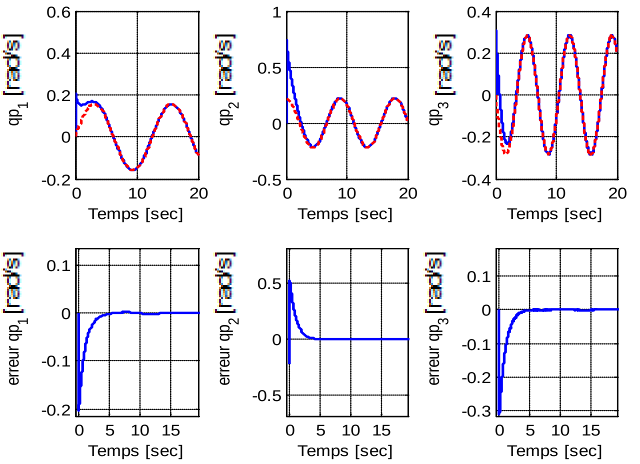

Fig.5 Simulation results of the velocities and errors tracking of the joints q_1, q_2 and q_3 using adaptive mode controller

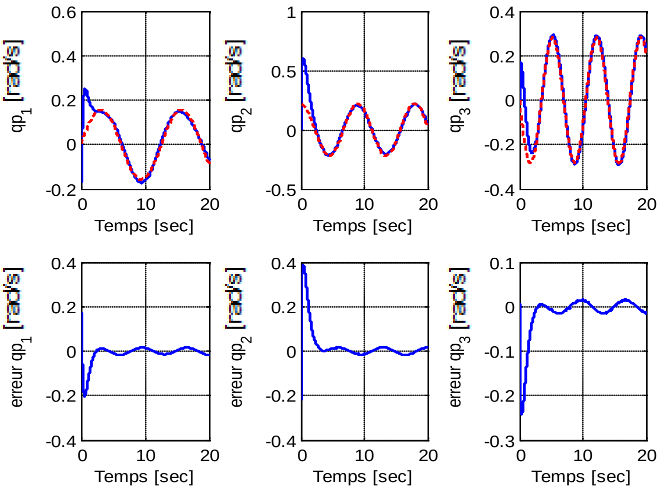

Fig.6 Simulation results of the velocities and errors tracking of the joints q_1, q_2 and q_3 using sliding mode controller

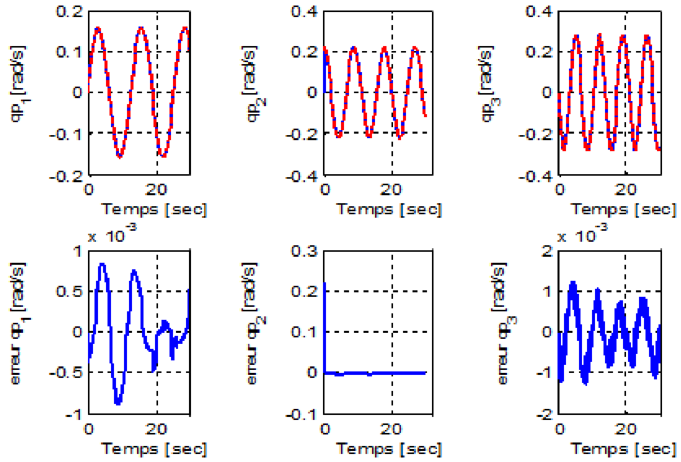

Fig.7 Simulation results of the velocities and errors tracking of the joints q_1, q_2 and q_3 using adaptive sliding mode controller

- - - : desired trajectory; —— : measured trajectory

The Std can be expressed by

$$\sigma_x = \sqrt{E[x - E[x])^2]} = \sqrt{E[x^2] - E[x]^2} \qquad (28)$$

And the sample mean is defined as

$$\bar{\theta} = \frac{1}{m} \sum_{i=1}^{m} \theta_i \qquad (29)$$

Table.1. Summary of the results of the RMS, mean error and standard deviation calculation for each articulation q_1, q_2 and q_3 using the adaptive mode, the sliding mode and the adaptive sliding mode controllers in case of tracking the desired trajectories in positions and velocities

		Position error			Velocity error		
10^{-3}		*Mean*	*RMS*	*Std*	*Mean*	*RMS*	*Std*
Adaptive mode	q_1	*11.9*	*35*	*33*	11	33	31
	q_2	*29*	*87*	*81*	28	86	81.4
	q_3	*17.9*	*52*	*49*	17	51	48
Sliding mode	q_1	*1.5*	*4.7*	*4.5*	1.1	4.5	4.4
	q_2	*3.4*	*6.1*	*6.9*	2.2	8.3	7.9
	q_3	*2.2*	*6.3*	*5.9*	1.4	4.9	4.7
Adaptive sliding mode	q_1	*0.67*	*0.11*	0.75	1.9	0.44	0.44
	q_2	*0.22*	*0.12*	0.11	0.22	0.64	0.61
	q_3	*0.11*	*0.12*	0.68	0.72	0.58	0.58

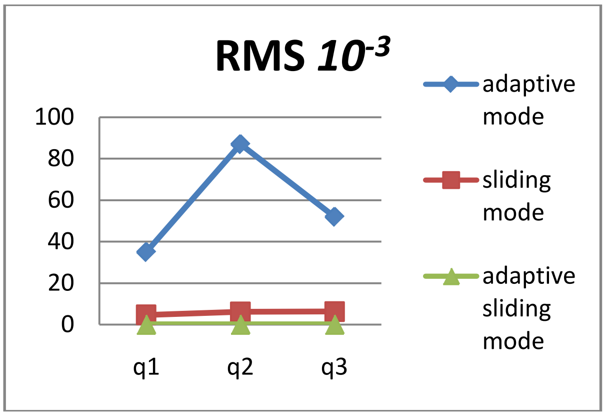

Fig.8 The RMS calculation of the joints q_1, q_2 and q_3 respectively when tracking the desired trajectories in positions by the three algorithms tested

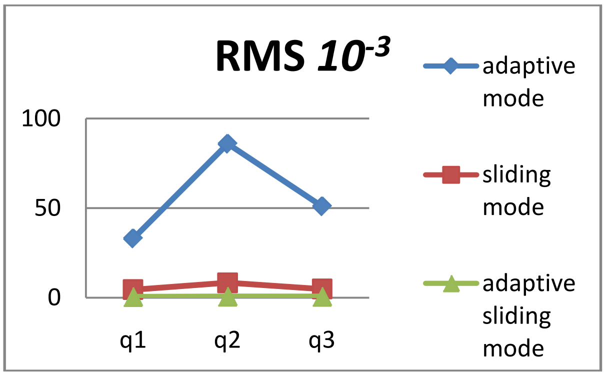

Fig.9 The RMS calculation of the joints q_1, q_2 and q_3 respectively when tracking the desired trajectories in velocities controlled by the three algorithms tested

In the course of our work, we choose the RMS as a criterion of performance and robustness against uncertainties and disturbances to compare the different used algorithms.

From the results of table.1 and Figs.8 and 9 which present the calculated RMS, it can be clearly found that the adaptive mode presents the highest value of RMS while the proposed adaptive sliding mode controller presents the best responses in term of rapidity, performances when tracking the desired trajectories and robustness in the presence of uncertainties.

V. CONCLUSION

This paper deals with the control, the stability study and the robustness analysis of a three degree of freedom exoskeleton used for rehabilitation of the upper limb in presence of uncertainties. A dynamical model of the robot was developed. Then, an adaptive sliding mode algorithm is used to control the system. An Input-to-State-Stability (ISS) and a robustness studies were done to analyse the performance of the exoskeleton in presence of disturbances and uncertainties. Referring to the simulation results, a comparison between three controllers' laws was done in order to prove the one the most performing when tracking the desired trajectories. As a future work, a stability study of the exoskeleton in interaction with the human upper limb will be done as well as a control of the system exoskeleton-upper limb.

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