A Terminal Sliding Mode Control using EMG Signal: Application to an Exoskeleton- Upper Limb System

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Abstract: This paper presents a robust terminal sliding mode control using the EMG signal. The application deals with an exoskeleton- upper limb system, used for rehabilitation. The considered system is a robot with one degree of freedom controlling the flexion/ extension movement of the elbow. The different stages of the EMG signal extraction were presented. Then, a second order terminal sliding mode algorithm has been developed to control the exoskeleton- upper limb system. A Stability study is realized and a robustness analysis is done using Monte Carlo simulation in presence of parametric uncertainties. Simulation results are provided to prove performance and effectiveness of the second order terminal sliding mode algorithm when tracking the EMG signal extracted from the human arm.

1 INTRODUCTION

Muscle signals are biomedical signals that measure the electrical currents generated in muscles when they contract and represent their neuromuscular activities. These acquired muscle signals require state-of-the-art methods for detection, decomposition, and processing to control a mechanical system (Teena et al., 2011), (Satoshi et al., 2001).

Electromyography is a technique used to capture signals produced by the nerves in the target muscles. The field of electromyography is studied in biomedical engineering. The instrument from which the EMG signal is obtained is known as electromyography and the resulting record is known as electromyogram.

The electrical signal produced during muscle activation, known as the myoelectric signal, is produced from small electrical currents generated by ion exchange across muscle membranes and detected with the aid of electrodes.

EMG signal is present in different areas of applications (Reaz, et al., 2006). It is used clinically for the diagnosis of neurological, neuromuscular disorders and for biofeedback diagnosis or ergonomic assessment by laboratories and clinicians. EMG is also used in many types of research laboratories, including those involved in biomechanics, neuromuscular physiology, movement disorders, postural control (Christian et al., 2006), and physiotherapy.

In this context, we will use this signal to control an exoskeleton system.

Exoskeleton is defined as a mechatronic system placed on the user's arm and acts as amplifier that augments, reinforces or restores human performances (Sana et al., 2017), (Sana et al., 2018). The objective of controlling an exoskeleton is to follow the movements of a healthy human, 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 different control laws.

In the literature and referring to (Frank et al., 2017), a sliding mode was used to control the exoskeleton of the upper limbs. A mixed force and position controller which mixes, for the same degree of freedom, the force and position information is used by the author in (Nathanael, 2011). Pre-calculated torque control (using the PID corrector) is a simple nonlinear control method and is often used for the control of exoskeletons developed by the authors in (Sana et al., 2018), (Thierry, 2012).

Robotic systems, in general, suffer from two main components of uncertainties. The first is that of

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parameter variations. The second major source of uncertainty is the external interaction forces on the suspended body, which are generally unknown. So, robustness analysis becomes important for such systems.

The different developed controllers used in literature are obtained at the cost of certain disadvantages like the performance when tracking the desired trajectories and the robustness in presence of uncertainties and disturbances.

The contribution of this paper is to control an exoskeleton- upper limb system using a terminal sliding mode algorithm and the EMG signal as desired trajectories. In presence of parametric uncertainties and to study the robustness as well as the performance of the proposed controller, a Monte Carlo simulation was used.

The paper is organized as follows: section 2, deals with the different stages of EMG signal extraction. Section 3 describes the modeling of the exoskeleton- upper limb system, the control and the stability study using the terminal sliding mode as well as the robustness analysis using Monte Carlo simulation. In section 4, simulation results and discussions are given. Finally, section 5 is reserved for the conclusion and future work.

2 EMG SIGNAL EXTRACTION

As a control signal, the EMG muscle signal is sensitive to electrical noise since it is at the mV scale. This produces interference during the measurements, for this reason it must be highly transformed.

The muscle signal is acquired and amplified in a first stage and then filtered in a second stage in order to remove the DC component, it will be sent to a third stage where the high frequency noise will be eliminated (Reaz et al., 2006).

The extraction of the EMG muscular signal is done through three stages (Abolfazl and Pourmin, 2016). These different stages (Fig. 1) are:

- Acquisition and differential amplification of the muscular signal: The EMG signal is acquired thanks to the differential amplification technique. The differential amplifier must have a high input impedance and a very low output impedance. Ideally, the differential amplifier has infinite input and zero output impedance.
  Indeed, the differential amplification is obtained using an instrumentation amplifier. The latter performs the differential amplification by subtracting the voltages V1 and V2. In this way, the noise signal which is common to V1 and V2 (potentials collected by the input electrodes) for example the disturbance of the supply line will be eliminated.
- Remove the DC component: an active high-pass first order filter will be used to get rid of any DC offset. The use of the active component can isolate the filtering from the rest of the circuit. We need a high-pass filter to remove low frequencies. In fact, the cutoff frequency of the filter is the frequency below which all frequencies are eliminated. All frequencies above this value are reported.
- High Frequency Noise Suppression: This stage uses a low pass filter to smooth our signal and remove high frequency noise. In this floor we will use a low-pass filter. The concept of low-pass filters is quite opposite to that of high-pass filters. In these filters, only the frequencies that are lower than the cutoff frequency are transmitted.

G_1 and G_2 presented respectively the amplification gain of the first and the second stages.
The EMG signal (Fig.2) was recorded during flexion movement of the elbow.
This signal will be used in the next section as a desired trajectory to control the elbow articulation of the exoskeleton- upper limb system.

3 EXOSKELETON- UPPER LIMB SYSTEM CONTROL

In this section, we aim to control the exoskeleton-upper limb system by the terminal sliding mode in order to track the desired trajectories defined by the EMG signal extracted from the human arm during the flexion movement of the elbow joint.
The considered system is presented by figure 3.
The modeled system is a robot with two degrees of freedom (controlling the shoulder and the elbow). We will be interested only in the articulation of the elbow. So the other articulation will be fixed in the next part.

Based on Euler Lagrange equation, the dynamic model of the system having two degrees of freedom (DoF) given by Fig.1 in the presence of friction can be expressed using the following second-order nonlinear differential equation:

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

Where:

$$F(q, \dot{q}) = f_v \dot{q} + k_i \,\text{sign}(\dot{q}_i) \qquad (2)$$

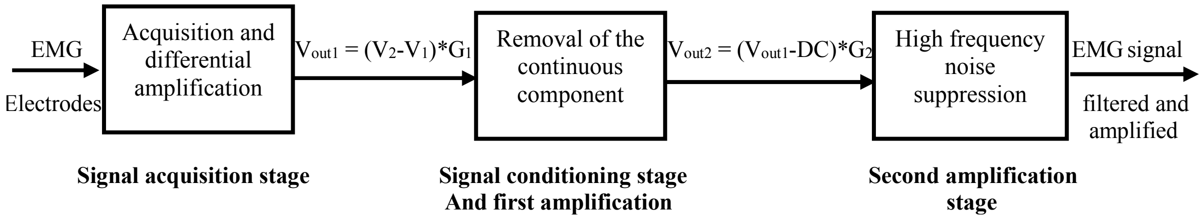

Figure 1: Different stages of the muscular signal extraction.

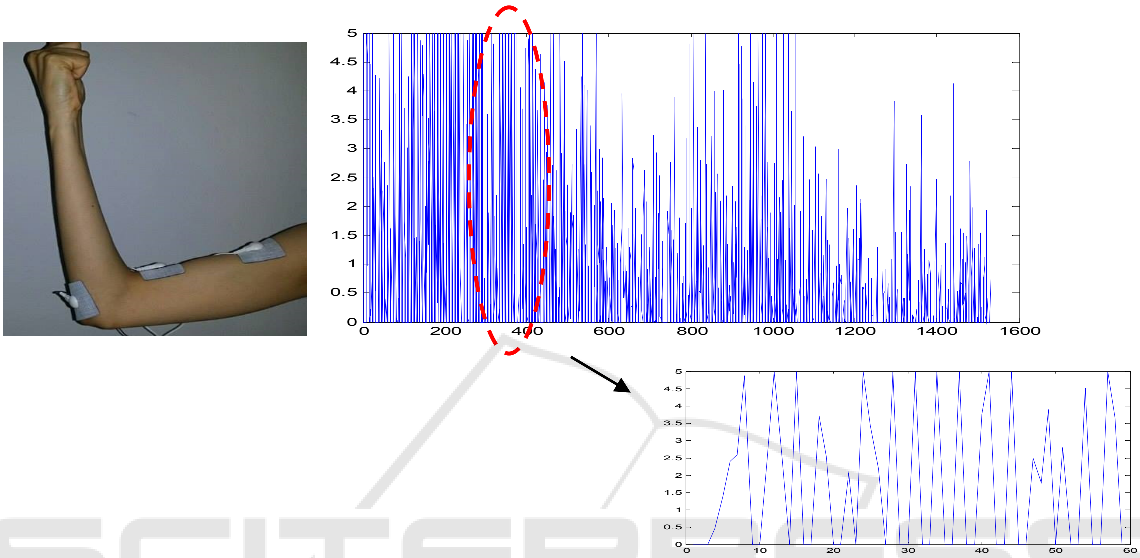

Figure 2: EMG signal obtained for a contraction movement of the elbow.

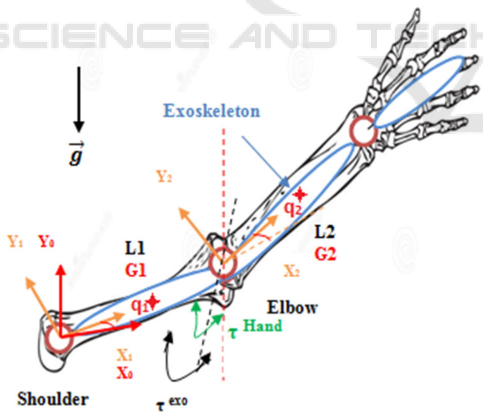

Figure 3: General configuration of a 2 DoF exoskeleton.

With:

- $q \in \mathbb{R}^2$ is the vector of joint positions;
- $\dot{q} \in \mathbb{R}^2$ is the vector of joint velocities;
- $\ddot{q} \in \mathbb{R}^2$ is the vector of joint accelerations;
- $M(q) \in \mathbb{R}^{2x2}$ is the inertia matrix;
- $C(q,\dot{q}) \in \mathbb{R}^{2x2}$ is the Coriolis matrix;
- $G(q) \in \mathbb{R}^2$ is the gravitational vector;
- $F(q,\dot{q}) \in \mathbb{R}^2$ is the force generated by friction;
- $\tau^{exo} \in \mathbb{R}^2$ is the control vector applied by exoskeleton;
- $\tau^{arm} \in \mathbb{R}^2$ is the torque applied by the human;
- $\tau^{ext} \in \mathbb{R}^2$ is the external torque.

a. A Terminal Sliding Mode Control.

Instead of using a linear sliding surface, the Terminal Sliding Mode Control (TSMC) with a nonlinear sliding surface has been proposed (Behnamgol and Vali, 2015), (Chaoxu and Haibo, 2018), (Yuqiang et al., 1998).The terminal sliding mode was developed by adding the nonlinear fractional power element to the sliding phase to provide some superior properties, such as finite state convergence of state variables, faster and better tracking accuracy.

A nonlinear sliding variable in TSMC can also improve static performances.

Terminal Sliding mode control adds non-linear functions to the design of the sliding top plane (Yong and Zhihong, 2002). Thus, a terminal sliding surface is constructed and tracking errors on the sliding surface converge to zero in a finite time.

For the terminal sliding mode control, the sliding surface is defined by:

$$S_t = x_2 + \lambda x_1^{q/p} \tag{3}$$

With: $\lambda > 0$; q and $p > 0$; $0 < q < p$.

We consider the following system:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = f(x) + g(x)\, u \end{cases}$$

We have:

$$\dot{x}_2 = f(x) + g(x)\, u \Longrightarrow u = -\, g^{-1}\, [f(x) - \dot{x}_2] \tag{4}$$

For $S_t = 0$, we get:

$$x_2 = -\lambda x_1^{\,q/p} \tag{5}$$

$$\dot{x}_2 = -\lambda \frac{q}{p} x_1^{\,q/p-1} \dot{x}_1 = -\lambda \frac{q}{p} x_1^{\,q/p-1} x_2 \tag{6}$$

We have:

$$u = -\, g^{-1}\, [f(x) - \dot{x}_2] \tag{7}$$

$$u = -\, g^{-1}\, [f(x) + \lambda \frac{q}{p} x_1^{\,q/p-1} x_2] \tag{8}$$

$$u_t = -\, g^{-1}\, [f(x) + \lambda \frac{q}{p} x_1^{\,q/p-1} x_2 + k\, \mathrm{sign}(S_t)] \tag{9}$$

b. Stability Proof.

Consider the Lyapunov candidate function:

$$V = \frac{1}{2} S_t^2 \tag{10}$$

$$\dot{V} = S_t\, \dot{S}_t \tag{11}$$

We calculate $\dot{S}_t$:

$$\dot{S}t = \dot{x}2 + \lambda \frac{q}{p} x1\ (q/p)\text{-}1x2 \tag{12}$$

$$\dot{S}_t = f(x) + g(x)\, u + \lambda \frac{q}{p} x_1^{\,(q/p)-1} x_2 \tag{13}$$

With:

$$g(x\ u = \dot{x}_2 - f(x) = -\, \lambda \frac{q}{p} x_1^{\,(q/p)-1} x_2 - f(x) - k\ \mathrm{sign}(S_{t)} \tag{14}$$

So:

$$\dot{S}_t = f(x) - \lambda \frac{q}{p} x_1^{\,q/p-1} x_2 - f(x) + \lambda \frac{q}{p} x_1^{\,(q/p)-1} x_2 - k\ \mathrm{sign}\ (S_t) \tag{15}$$

$$\dot{S}_t = -\, k\ \mathrm{sign}\ (S_t) \tag{16}$$

We get:

$$\dot{V} = S_t\, \dot{S}_t = -\, S_t\, k\ \mathrm{sign}\ (S_t) < 0 \tag{17}$$

As:

- The term $-kS_t$ sign (S_t) is negative because: $k \geq 0$ and since the sign function is constant in pieces so $S_{t,}$sign $(S_t) = +1$, $\forall S_t$.

Then $\dot{V}$ is semi-definite negative.

Like $V \geq 0$ and $\dot{V} \leq 0$, the system is asymptotically stable.

Applying this command to our system, we obtain:

$$u_t = -\, g^{-1}\, [f(x) + \lambda \frac{q}{p} x_1^{\,(q/p)-1} x_2 + k\ \mathrm{sign}(S_t)] \tag{18}$$

The system is presented by:

$$\ddot{q} = f(q, \dot{q}) + g(q\, , \dot{q})\, u \tag{19}$$

With:

- $f(q, \dot{q}) = -\, M^{-1}(q\, , \dot{q})\ (C(q\, , \dot{q})\, \dot{q} + G(q))$
- $g(q\, , \dot{q}) = M^{-1}(q\, , \dot{q})$

We get:

$$u_t = C(q\ \dot{q})\, \dot{q} + G(q) - M^{-1}\, [\lambda \frac{p}{p} (\dot{q}_d - \dot{q})^{\,(q/p)-1}\, \ddot{q}_d + k\ \mathrm{sign}(S_t)] \tag{20}$$

c. Robustness Analysis.

To study the performance and the robustness of the proposed controller face to parametric uncertainties, we used the Monte Carlo method which is a probabilistic technique based on the use of a large number of random disturbances.

The Monte Carlo method (Gersende, 2009) refers to any calculation technique that involves successive resolutions of a deterministic system incorporating uncertain parameters modeled by random variables (Laura and Robert, 1993). It is a powerful and very general mathematical tool which has earned it a wide range of applications.

To conduct a Monte Carlo simulation, it is necessary to identify the type of distribution of the uncertainties applied to the input system.

In this case, an uniform random distribution is applied to the system which will have the following form in presence of parametric uncertainties:

$$\ddot{q} = (f\, (q, \dot{q}, t) + \Delta_f) + (g\, (q) + \Delta_g\,)\, u(t) \tag{21}$$

4 SIMULATION AND RESULTS

Simulation results are provided to prove the efficiency of the proposed controller law.

In a first time, the EMG signal extraction of the elbow flexion movement is done from a healthy person. Then this signal was used as a desired trajectory.

The measured and the desired trajectories of the released tests as well as the tracking errors trajectories are given in Figs. 4 and 5.

Figs. 6 and 7 present the velocities tracking and errors of the tested algorithm.

From these figures, we can clearly note that using the second order terminal sliding mode controller, we get a good position as well as velocity tracking of the desired trajectories defined by the EMG signal in presence of parametric uncertainties.

In order to prove the robustness and the performance of the tested controller, we applied some disturbances and we calculate the Root-Mean-Square (RMS), the mean (Mean) and the standard deviation (Std).

The RMS is calculated using the following expression:

$$q_{RMS} = \sqrt{\frac{1}{N}\sum_{n=1}^{N}|q\,n|^2} \qquad (22)$$

The Std can be expressed by:

$$\Sigma_q = \sqrt{E[q - E[q])^2]} = \sqrt{E[q^2] - E[q]^2} \qquad (23)$$

And the sample mean is defined as:

$$\bar{q} = \frac{1}{m}\sum_{i=1}^{m} q_i \qquad (24)$$

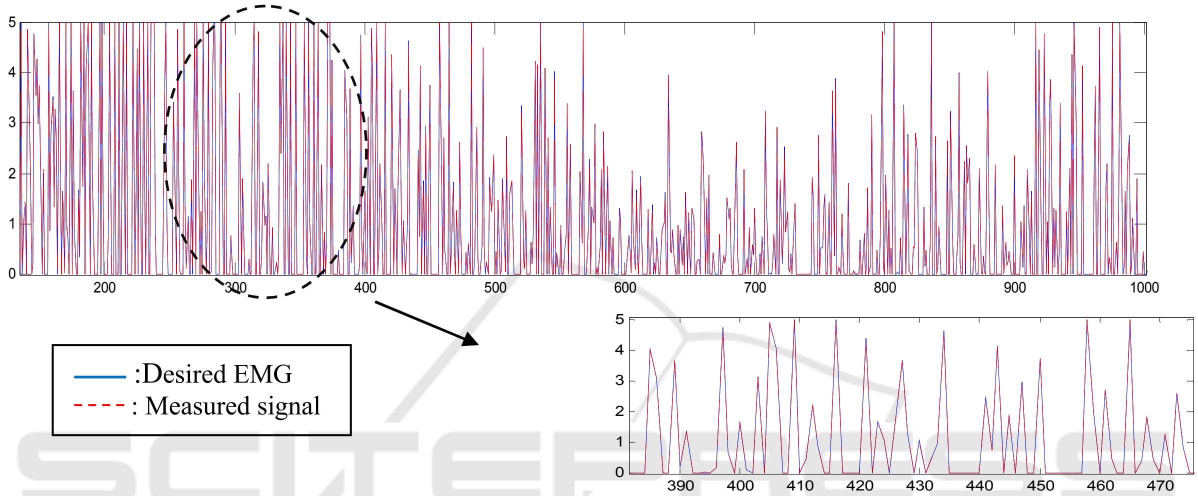

Figure 4: Simulation results of the desired EMG signal and the measured signal during the flexion movement of the elbow in position.

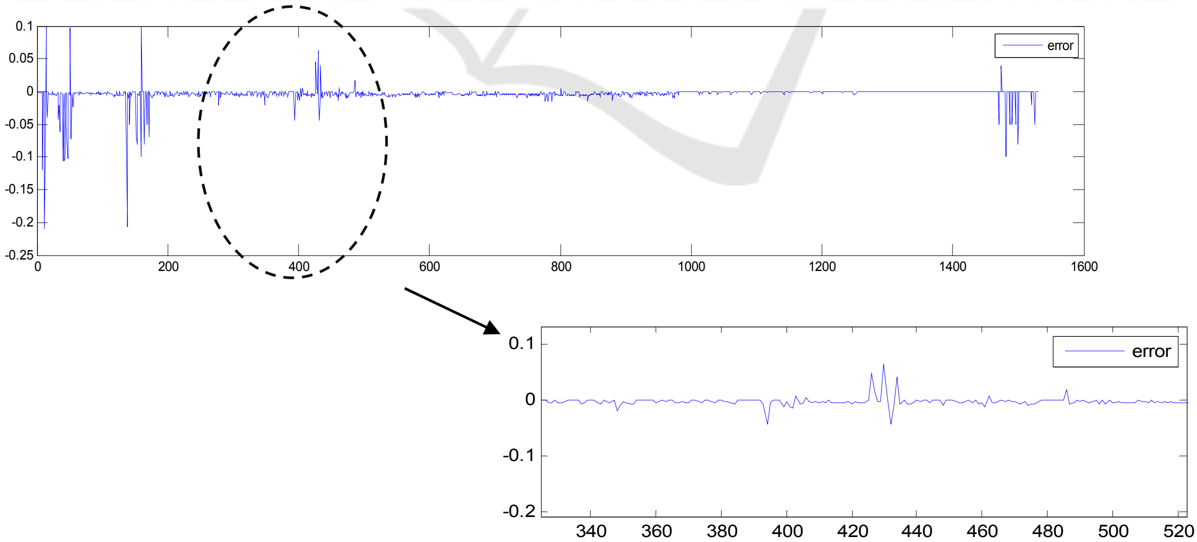

Figure 5: Measured error simulation when the tracking desired trajectories in position.

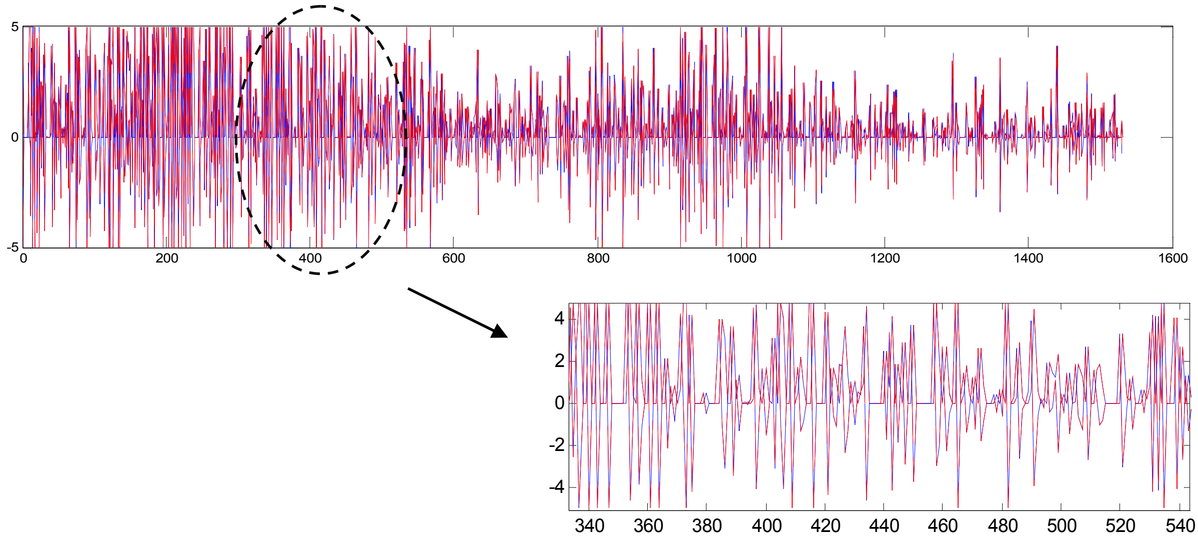

Figure 6: Simulation results of the desired EMG signal and the measured signal during the flexion movement of the elbow in velocity.

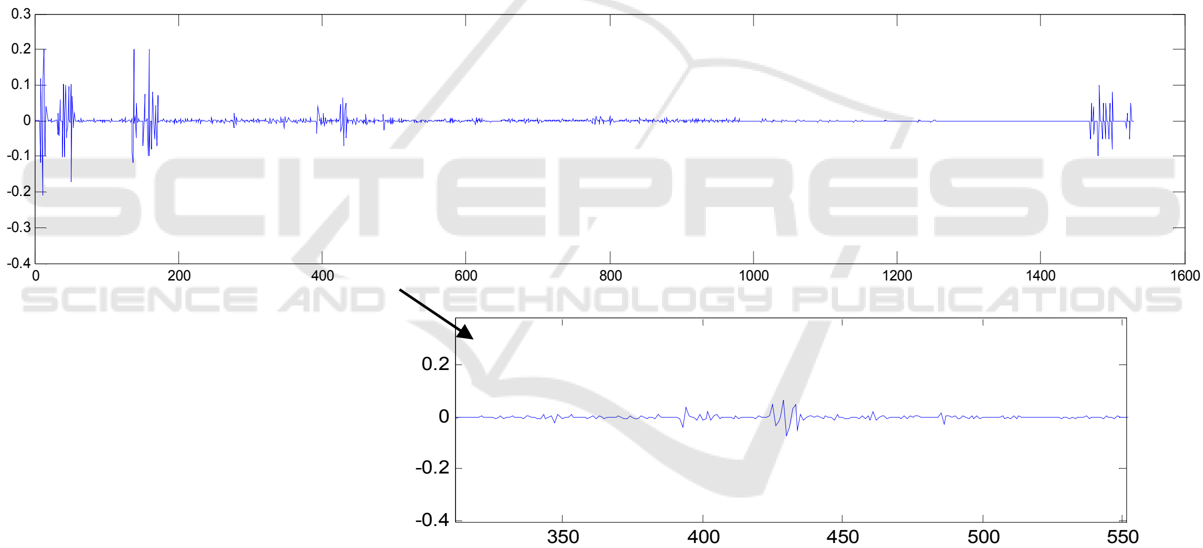

Figure 7: Measured error simulation when the tracking desired trajectories in velocity.

The uncertainties applied to the exoskeleton-upper limb system are uniform random distributions with Δ_f and $\Delta_g \in [0; 0.005]$ at t= 0.2s.

Table 1: Calculation of RMS, Mean and Std of the elbow joint of the exoskeleton- upper limb system during the elbow flexion movement.

Terminal Sliding Mode Control			
Position simulation		***Velocity simulation***	
RMS [rad]	0.0043	**RMS [rad/s]**	0.0037
Mean [rad]	0.0037	**Mean [rad/s]**	0.0028
Std [rad]	0.0021	**Std [rad/s]**	0.0012

The results (Table.I) are given when controlling the exoskeleton-upper limb system in the presence of parametric uncertainties.

We can clearly see from this table that the proposed algorithm gave a good tracking of the desired trajectories (RMS in order of 10^{-3}).

5 CONCLUSION

This paper deals with the control, the stability study and the robustness analysis of an exoskeleton-upper limb system, used for rehabilitation, in presence of uncertainties using the EMG signal. The different stages of the EMG signal extraction were presented. Then, a terminal sliding mode algorithm is used to control the system. A robustness study using Monte Carlo simulation was done to analyse the performance of the exoskeleton in presence of parametric uncertainties. Simulation results are provided to prove the performance and the robustness of the proposed algorithm when tracking the desired trajectories. As a future work, experimental results will be given when the exoskeleton is worn by the human upper limb.

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