Current Progress on Pathological Tremor Modeling and Active Compensation using Functional Electrical Stimulation

Ferdinan Widjaja, Cheng Yap Shee, Dingguo Zhang, Wei Tech Ang, Philippe Poignet, Antonio P. L. Bo and David Guiraud

Abstract— **Pathological tremor is an involuntary and roughly periodic movement of a body part. It is the most common movement disorder and its incidence increases with aging. Upper limb tremor can cause difficulties in performing simple activities of daily living like buttoning, inserting a key into a keyhole and writing. The proposed active tremor compensation method involves 3 stages: sensing, filtering and actuation. Tremor and intended motion are observed by means of motion and neuromuscular sensors and a filtering algorithm is applied to separate such movements. Then, the antagonist of the trembling muscle is actuated in anti-phase with respect to the tremor signal using Functional Electrical Stimulation (FES). The project long term goal is to provide a wearable tremor suppression orthosis for the upper limb. This paper reports the current progress in each portion of the project.**

I. Introduction

TREMOR is the most common movement disorder [1], defined as the involuntary rhythmic or semi rhythmic body part oscillation resulting from alternating simultaneous antagonistic muscle group contractions [2]. The two major types of tremors are physiological and pathological tremor. Pathological tremor, whose incidence is higher on the upper limb, is classified into rest (e.g. Parkinson's disease), postural (essential tremor) and kinetic tremor (multiple sclerosis).

The patient with pathological tremor on the upper limb, specially on the hands, has difficulties in performing activities of daily living, like buttoning, inserting a key to keyhole and writing. This condition may even lead to social embarrassment and isolation. Moreover, considering that the pathology is more common in elder patients, tremor diseases increase economic and social costs of elderly care.

Two common options for tremor treatment are medication and surgery. Medication is individualized for each patient and normally conducted in a trial and error method. Side effects, addiction and withdrawal symptoms are common risks [3]. Also, about 50% of the tremor patients do not present adequate response to pharmacological therapy. When medication fails and tremor is severe, brain stereotactic surgery, such as Deep Brain Stimulation (DBS), although risky and expensive, may be undertaken. Good results have been achieved with this technique, but adverse effects may still occur, like brain hemorrhage, seizures, marked cognitive problems and death.

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F. Widjaja, C. Y. Shee and W. T. Ang are with Biorobotics Lab, School of Mechanical and Aerospace Engineering in Nanyang Technological University, Singapore (e-mail: ferd0003, cyshee, wtang@ntu.edu.sg).

D. Zhang, A. P. L. Bo, D. Guiraud and P. Poignet* are with LIRMM Robotics Department, University of Montpellier II in France (e-mail: dingguo.zhang, antonio.bo, poignet, david.guiraud@lirmm.fr). *Corresponding author

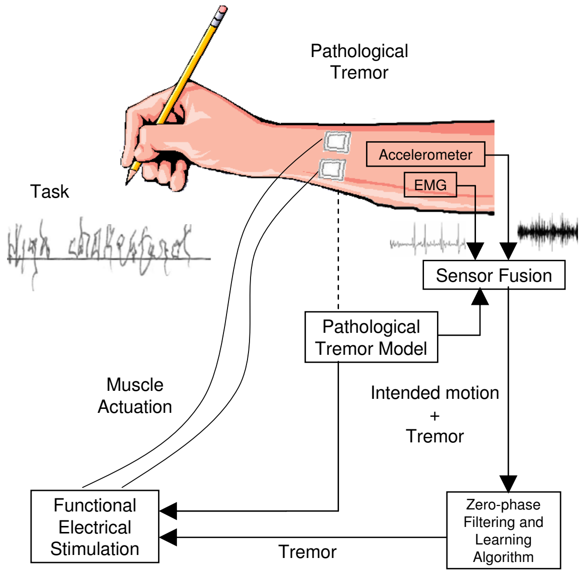

Fig. 1. Active tremor compensation using wearable orthosis.

The recent rise of assistive technology gives alternatives for tremor suppression. Recent examples include the Bionic Glove [4], DRIFTS [5] and Micron [6]. Our approach employs the same paradigm in DRIFTS and Micron, i.e. sensing-filtering-actuation. The tremor suppression method is given in Fig. 1. Motion (accelerometer) and neuromuscular (sEMG) information from the sensing module contain tremor and intended motion, hence a filtering algorithm is applied to separate such movements. Then, the antagonist of the trembling muscle is actuated using Functional Electrical Stimulation (FES) in order to attenuate the tremor, but still allowing the performance of intended motions.

Recent advances in technology have seen a growth of interest in wearable sensors and systems [7]. The interest is also fostered by the increasing challenge in providing continuous healthcare outside the clinical environment. Hence, the implementation of the proposed method will in a wearable orthosis for the upper limb expected. However, since the project is still on its starting phase, the current sensing system is not portable yet. Once the whole concept has been successfully implemented and proved, the sensing, filtering and actuation subsystems will be miniaturized into the wearable device. In this paper, the current progresses on the three main portions of the project and also the expected future works are presented.

II. SENSING

Tremor detection and quantification are of clinical interest for neurological disorders diagnostics and objective evaluation of their treatment. To prescribe proper therapy for pathological tremor, clinicians have to correctly classify different types of pathological tremor and distinguish it from other movement disorders. When the patient's condition is advanced, diagnosis is easier due to the presence of other distinctive symptoms.

A sensing system for quantification of tremor has been developed [8]. It consists of accelerometers (ACCs) and surface electromyography (sEMG) system, both of them "self-contained" and, therefore, suitable for a wearable system. In clinical settings, ACCs and sEMG have already been used to gain more understanding about pathological tremor. In [9], the source of bilateral tremor (tremor on both limbs) was investigated based mainly on EMG data and ACCs data as the mechanical reference. ACC and EMG signals have also been used for differentiation of pathological tremors with statistical techniques [10], using data mining methods [11] and to identify functional activity [12].

An optical tracking system is used as reference for the aforementioned sensors. This system will be useful for clinical diagnosis of tremor patients, as it can provide quantitative assessment of the tremor. For engineering purpose, the data obtained by the system can be used to model the tremor. The experiment setup for the sensing system is shown in Fig. 2.

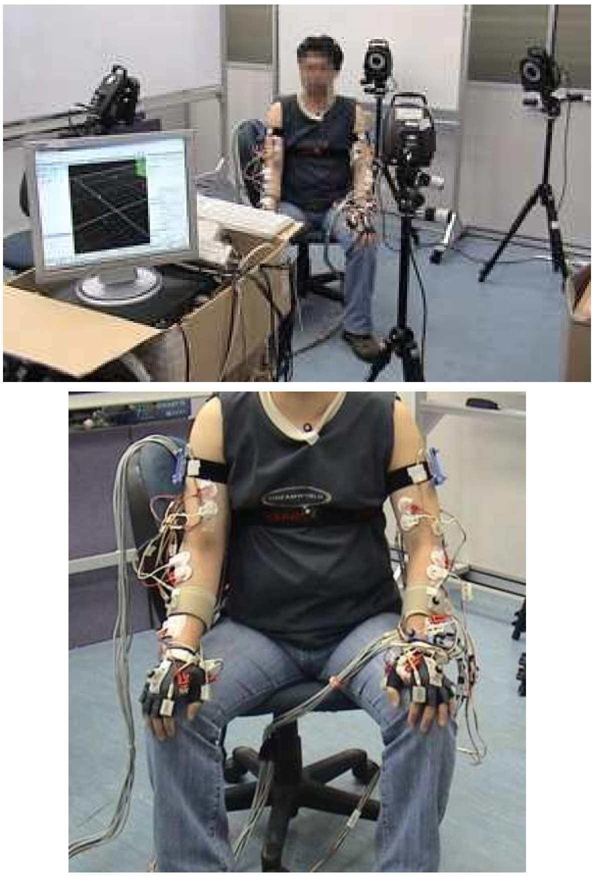

Fig. 2. The whole setup for the sensing system developed.

A. Data analysis

The sensing system developed has been used to record the data from normal subjects and patients with tremor. Subject recruitment was done with the help of our collaborators at local institutes. In the first phase of data collection, 7 Parkinson's Disease (PD) patients, 7 Essential Tremor (ET) patients, 2 psychogenic tremor patients, 3 Holmes' Tremor (HT) patients and 1 stroke patients have participated. Data from 18 normal subjects has also been collected. In this section, the measurement results from a PD patient is shown. The data was taken at resting position and the focus will be at wrist flexion-extension of the right hand. In addition, comments are added concerning data acquired from a HT patient.

The cardinal feature in PD patients is resting tremor (resembling pill-rolling) with a frequency of 3-6 Hz [13]. Therefore, it is expected to see this feature from the recordings at resting posture. The tremor in PD patients is also usually asymmetric. However, since tremor is not the only symptoms of PD, this does not mean that the patient's performance is as good as normal subjects aside from the resting position tremor. The other two prominent features are muscle rigidity and bradykinesia, the effects of which can be seen from tests such as finger tapping, alternating movement and fist closing and opening.

All the data shown in Fig. 3 have been passed through a bandpass filter to remove the noise at higher frequency and the slow movement (intentionally or not) which is not tremor. The cutoffs frequencies used are 1 and 15 Hz for the high and low pass filters respectively. The filter implemented is a zero-phase Butterworth filter as given by Matlab.

The burst frequency (recorded from each sensor) is given in the figures (4.785 Hz for sEMG, 4.785 Hz for ACC and 4.736 Hz for Vicon MX), so we can see that there is a visible resting tremor in the region of 4.8 Hz. Because the frequencies of the flexor and extensor EMG signals are the same, we can use cross correlation function to calculate the delay between those two signals. Calculating the correlation between the flexor and extensor EMG signals, we obtain a delay of 3 samples. With 50 Hz sampling rate and a signal of roughly 5 Hz, 3 samples of delay corresponds to about 90^o phase difference. By using the cross correlation function, it can also be observed that during the postural position there is a window of time when the flexor and extensor EMG signals are actually in phase. The delay calculated from the cross correlation function is zero and using visual inspection the zero delay is also observed. Clinically this can explain the rigidity suffered by the patient.

Another data set was obtained from a HT patient. In

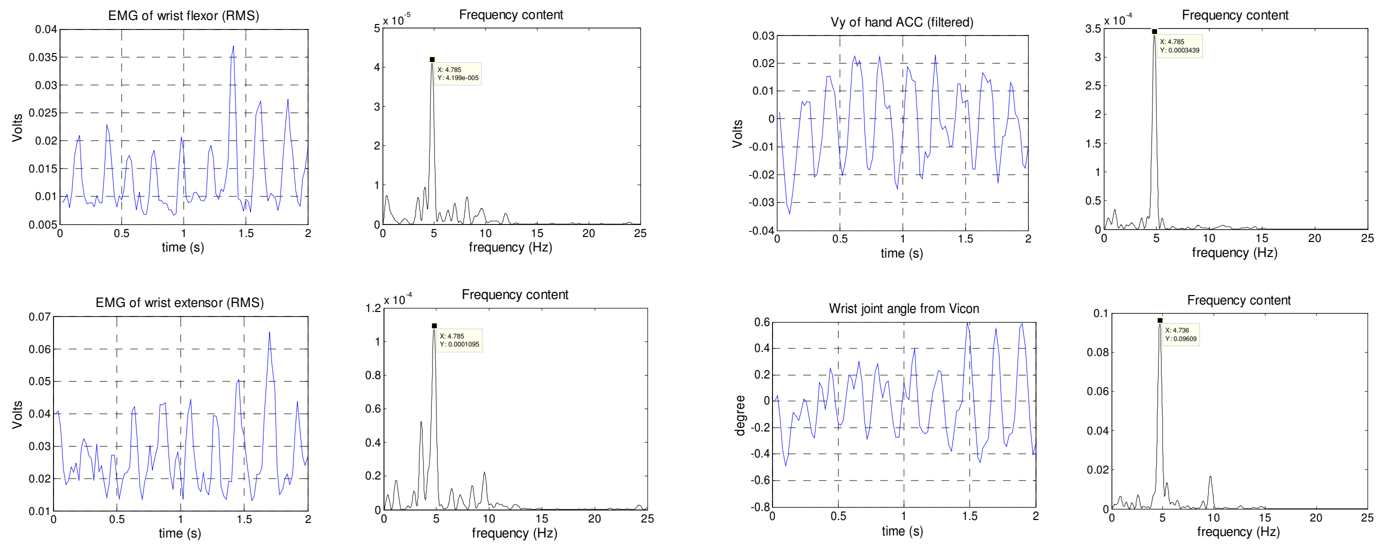

Fig. 3. Measurement result of PD patient during resting and its power spectrum from EMG, ACC and Vicon.

that data, the amplitude of the wrist flexor EMG signal is irregular, whereas for the extensor it is more regular. One of the possible clinical explanations for that fact is the existence of a tremor at the wrist extensor muscle and that the nervous system is constantly trying to compensate the tremor by sending a counter signal to the wrist flexor. The jerky behavior of the wrist flexor can be explained by the the irregularity in amplitude commonly found on Holmes' tremor.

Those hypothetical explanations require further investigation in order to confirm whether the phenomena observed are explained by them. However, those examples show already that the system may be used to help tremor analysis and diagnose, as the tremor may be better appreciated compared to observation by naked eye only and other traditional techniques.

B. *Sensor fusion*

The next step after the tremor data is available is to fuse the signals from accelerometers and surface electromyography. The integration of ACCs and sEMG data may provide a better estimation of the tremor. Also, it is important during the operation of the compensation system, since the accelerometers are mainly used to provide information about the compensated motion and the sEMG information used to continuously provide estimates of the trembling muscles states.

One of the most common sensor fusion algorithms is the Kalman filter, but extensive literature concerning its application to the fusion of motion and neuromuscular data is not available. In [14], a first attempt to develop Kalman filtering algorithms to fuse the data from both sensing modalities in order to estimate the joint angle of the affected limb was presented. This effort provided promising results for further exploration.

The tremor model developed employs the fact that tremor is approximately rhythmic and roughly sinusoidal. If $y(k)$ is defined as the joint angle of the trembling limb, then the tremor may be modeled as a single sinusoidal signal, i.e.

$$y(k) = r\sin(\omega k T), \tag{1}$$

where r is the tremor amplitude, ω is the tremor fundamental frequency in rad/s and T is the sampling time in s. Both r and ω are assumed to be constant in that initial study. The state vector for the KF is the joint angle and its angular velocity as shown in (2).

Thus, the process model in (3) uses the sinusoidal signal as the predictor, while the EMG and ACC measurements in (4) serve as the corrector:

$$\mathbf{x}(k) = \begin{bmatrix} y(k) & \dot{y}(k) \end{bmatrix} \tag{2}$$

$$\mathbf{x}(k+1) = \begin{bmatrix} \cos(\omega T) & \frac{\sin(\omega T)}{\omega T} \\ -\omega T\sin(\omega T) & \cos(\omega T) \end{bmatrix} \mathbf{x}(k) + \mathbf{w}(k) \tag{3}$$

$$\begin{aligned} \mathbf{z}(k) &= \begin{bmatrix} EMG(k) \\ ACC(k) \end{bmatrix} \\ &= \begin{bmatrix} c_{EMG}(1) & 0 \\ c_{ACC}(1) & 0 \end{bmatrix} \mathbf{x}(k) + \begin{bmatrix} c_{EMG}(2) \\ c_{ACC}(2) \end{bmatrix} + \mathbf{v}(k), \end{aligned} \tag{4}$$

where $EMG(k)$ and $ACC(k)$ are the measurements from both EMG and ACC, respectively. The coefficients $\mathbf{c}_{EMG}$ and $\mathbf{c}_{ACC}$ in (4) are calculated *a priori* by applying linear regression between both EMG and ACC data with joint angle data obtained by the optical tracking system. This implies the relationships between them are modeled as linear first order polynomials, although the relationships are definitely nonlinear, as discussed in [14]. Lastly, the process noise, $\mathbf{w}(k)$, and the measurement noise, $\mathbf{v}(k)$, are considered additive and mutually independent white Gaussian noise with zero mean.

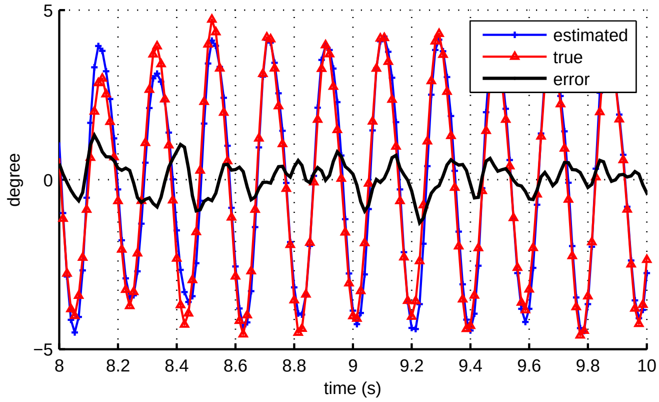

Fig. 4. Result of Kalman filter from a PD patient [14].

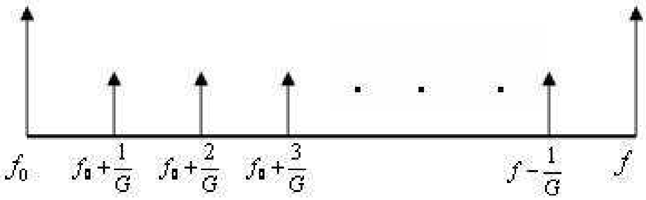

Fig. 5. Bandlimited-Multiple FLC [16].

The result of applying the KF equations to data from the same PD patient whose data has been presented is shown in Fig. 4. The KF algorithm estimates the wrist flexion-extension angle from the ACC (placed on dorsum of hand) and EMG data (wrist flexor and extensor). Then the angle estimate is compared with the joint angle obtained from the optical tracking system. From the data, the RMS error between the actual angle (recorded by the optical tracking system) and the estimated angle (from Kalman filtering) is about 0.65°, while the tremor is about 8° peak-to-peak.

Present work related to ACC and sEMG sensor fusion concerns the use of different sensor fusion algorithms. Modifications of Kalman Filter, such as Extended Kalman Filter and Unscented Kalman Filter [15] are currently pursued. Also, different models to describe tremor motion are being evaluated, like Fourier series or harmonic models and also Auto-Regressive (AR) models. The goal is also to design a sensor fusion algorithm that performs online estimation of the model parameters.

III. Filtering

The key technical challenge in tremor filtering is the real-time criterion of the application. In order to filter intended motion from the composed motion to obtain its pathological component, one approach would be to apply classical low-pass filters. However, most classical frequency selective filters cause phase shift in the filtered signal, which means that the filtered pathological motion that we attempt to cancel would be a time delayed version of the actual physical motion. Therefore, adaptive zero-phase filtering algorithms are studied and proposed to overcome this problem.

One possible alternative is to use a mathematical model to characterize tremor and perform an online identification of that model with the low-pass filtered tremor signal. The Weighted-Fourier Linear Combiner (WFLC) [17] is an algorithm that may be used with that purpose, modeling tremor as an harmonic model. It may be considered, in this case, as a zero-phase adaptive notch or band-stop filter with the stop band centered at the dominant fundamental frequency estimated by the filter. This zero-phase characteristic of the filter and its iterative nature are crucial for developing a real-time tremor compensation system as shown in Fig. 1. The algorithm estimates the unknown tremor frequency, tracking its modulation in order to maintain the proper notch frequency.

WFLC itself is able to estimate the dominant frequency and the amplitude of a tremor signal. However, for the case of tremor with high frequency variation or multiple components, the performance of the WFLC will deteriorate. Hence, a modification of the WFLC has been presented in [16]. The proposed algorithm (Bandwidth-Limited FLC) is able to track modulated signals with multiple frequency components with better performance. Instead of adopting a Fourier series model, where the harmonics frequencies are multiples of the fundamental frequency, it uses a nonharmonic model. Firstly, the frequency band of interest is divided into a finite number of divisions $L = (f - f_0)G$, where $G(\geq 1) \in N$ is the scaling number that decides the step-size of the series (Fig. 5). For estimation of the unknown signal, we then form the following series comprising of sine and cosine components:

$$y_k = \sum_{r=0}^{L} a_r \sin(2\pi(f_0 + \frac{r}{G})k) + b_r \cos(2\pi(f_0 + \frac{r}{G})k). \quad (5)$$

In (5), if G is increased, the divisions become smaller and the accuracy in estimation can be increased according to the tremor complexity. We then adopt the LMS algorithm to adapt the weights a_r and b_r in accordance with the unknown tremor signal. The algorithm equations are the following:

$$\begin{aligned} x_{rk} &= \begin{cases} \sin(2\pi(f_0 + \frac{r-1}{G})k) & ,1 \leq r \leq L \\ \cos(2\pi(f_0 + \frac{(r-L)-1}{G})k) & ,L+1 \leq r \leq 2L \end{cases} \\ \epsilon_k &= s_k - \mathbf{w}_k^T \mathbf{x}_k \\ \mathbf{w}_{k+1} &= \mathbf{w}_k + 2\mu \mathbf{x}_k \epsilon_k. \end{aligned} \quad (6)$$

The algorithm has been tested in real physiological tremor signal and the results are shown in Table I. It is clear that BMFLC outperforms the WFLC in the presence of two frequencies.

Concerning present activities related to the filtering portion of the project, further improvement of WFLC based algorithms is being pursued. In addition, different algorithms are being evaluated for harmonic and nonharmonic models, like the EKF, and also different models to characterize tremor, like the AR model.

IV. Actuation

After the desired sensing information is acquired and the filtering algorithms processed, this information is used to

TABLE I
COMPARISON OF WFLC AND BMFLC IN MULTIPLE FREQUENCY SIGNAL [16]. FREQUENCY IN (HZ), ERROR IN (RMS) AND COMPENSATION IN (%).

f_1	f_2	WFLC		BMFLC	
		Error	**Compens.**	**Error**	**Compens.**
8	8	0.0135	98.7	0.117	96.16
8	8.2	0.5	84.22	0.117	96.16
8	8.6	0.56	81.5	0.116	96.17
8	9	0.765	75.06	0.116	96.17
8	10	1.22	59.83	0.116	96.19
6	12	2.33	23.48	0.124	95.91

regulate the stimulator in order to actuate on the trembling muscles appropriately. This section discusses some of the control algorithms studied and evaluated for this task.

Until today, due to some hardware challenges and the need for approval of the proposed medical protocols, only simulation studies have been carried out. Hence, great effort has been spent in the development of suitable musculoskeletal models for the project. The models developed take into account either the sEMG or the FES signal as inputs. Those models may be used not only to validate the control approaches in simulation, but also in the design of model-based controllers. For the models developed for control design, there is need for a compromise between model simplicity and estimation quality, while for compensation validation more precise models may be used.

Concerning the sEMG model, surface electromyography has a specific importance in the tremor suppression problem when compared with other available sensing signals, such as joint angle, angular velocity and acceleration. sEMG is a more stable index to continuously estimate pathological tremor while compensation is active, since the motion sensors measure the compensated motion and not the muscle trembling activity. Also, sEMG provides valuable information to indicate the muscle groups responsible for the tremor and hence allows a better characterization of tremor. Finally, there is a time delay between the sEMG signal and the actual contraction of the muscle (usually called electromechanical delay [14], between 20 and 100 ms). That means sEMG signals precedes the motion, which may also be a valuable information.

sEMG signal have been used to predict the acceleration of tremor based on a simplified musculoskeletal model [18], which is meaningful to design a model-based predictive control for tremor suppression in future. The main advantage of this model, compared to classical model, is the direct measurability of the angular acceleration. In classical Hill model, the output is torque and we cannot measure this directly. The model diagram is shown in Fig. 6. Equivalent muscles are modeled as Contractile Elements (CEs), as they are described in Hill's work, with a second order linear differential equation. They drive a phenomenological part consisting of virtual spring-damper system as shown in the

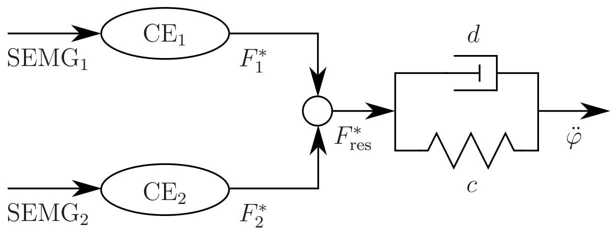

Fig. 6. Structure of the phenomenological motivated tremor-specific antagonistic muscle model consisting of two Contractile Elements (CE) feeding virtual force (F_1^*, F_2^*) into the virtual spring-damper system. [18]

figure.

$$\begin{aligned} F_1^* &= \frac{K_1\omega_1^2}{s^2+2\omega_1 s+\omega_1^2}e^{-sT_{d1}}.SEMG_1 \\ F_2^* &= \frac{K_2\omega_2^2}{s^2+2\omega_2 s+\omega_2^2}e^{-sT_{d2}}.SEMG_2 \\ F_{res}^* &= F_1^*+F_2^* \\ \ddot{\varphi} &= \frac{c}{s^2+ds+c}.F_{res}^* = \frac{\omega^2}{s^2+2D\omega_0 s+\omega_0^2}.F_{res}^*, \end{aligned} \tag{7}$$

where $-\omega_1$, $-\omega_2$, K_1, K_2, T_{d1} and T_{d2} are parameters to be identified because they are different from person to person. However, they can be determined in a simple identification procedure [18]. The tremor frequency is the ω_0.

An essential problem when using sEMG on patients that are also receiving electrical stimulation is that the natural EMG is contaminated by FES. The stimulation artifacts (SA) and the corresponding M-wave must be filtered from the raw EMG as the sensor fusion and filtering algorithms proposed assume that the EMG signal is not corrupted by SA and M-wave.

A solution to this problem is proposed in [19]. In the paper, SA is eliminated via software using the blocking (blanking) window. The width of blocking window is set at 25 ms, and the EMG signals are zeroed during this period, which has the same function as the EMG amplifier being shut down. Therefore, the high amplitude SA can be effectively reduced. There is a compromise regarding the width of blocking window. If the width is too long, it can ensure the complete elimination of SA, but much of the natural EMG will also be lost. The ideal range for the blocking window width depends on the stimulation intensity and electrode position. Normally it is about 20 to 25 ms.

To eliminate the M-wave, the popular method ”comb filter” is used, which is a type of Infinite Impulse Response (IIR) filter. The algorithm is simple to be implemented:

$$y(k) = \frac{x(k)-x(k-T_s)}{\sqrt{2}} \tag{8}$$

$x(k)$ is the raw EMG signal, T_s is the inter-stimulus time between two neighboring electrical pulses and $y(t)$ is the filtered signal. The scale factor $\sqrt{2}$ is added to keep the same power in the signal before and after filtering. Result is shown in Fig. 7.

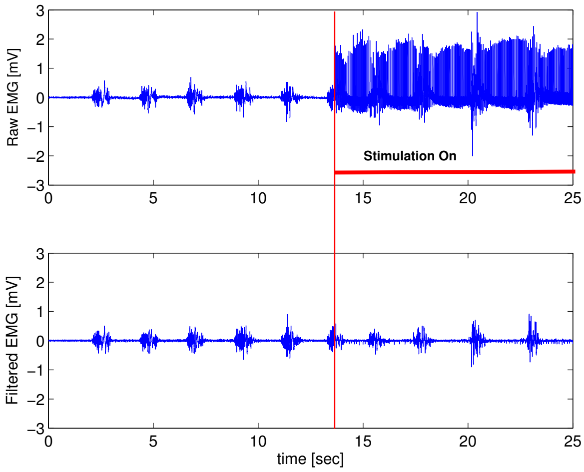

Fig. 7. Filter performance on the raw EMG of voluntary motion under FES. Stimulation intensity (pulse amplitude) is 20 mA. Raw EMG is shown in upper plot, and the filtered EMG is shown in lower plot. [19].

Regarding the FES modeling, a model specifically designed to simulation studies before the real experiments take place has been proposed in [20]. This musculoskeletal model is a one-joint elbow model containing two muscles, biceps and triceps. The muscle model is not represented by simple linear transfer functions as in [18]. It incorporates both the electrical (activation) and mechanical (contraction) properties of the real muscle and several physiological phenomena in order to improve the fidelity of the model. In the future, that model should be extended for multiple joints and muscles.

About the control approaches already evaluated, in [20], the angle and angular velocity of the joint affected by the pathological motion are used as feedback information for a multiloop controller, composed by a fuzzy logic and classical controllers. Also, using the model developed in [18], a model-based acceleration controller has been developed.

V. Conclusions and Future Works

This paper reports the current progress in the study conducted to evaluate the use of superficial FES on the active compensation of pathological tremor on the upper limb. The method would serve as an alternative to the other treatments available, like pharmacological treatment, DBS and externally actuated orthosis. Initial results are promising and in the future improvements are expected.

About the sensing part, quantitative online information about tremor is already provided and different sensor fusion algorithms and models will yet be explored. Concerning the real-time filtering requirements, similar models are being evaluated and improvements of WFLC pursued. Lastly, in the actuation portion of the project, different muscle models have been proposed in order to allow the design of model-based controllers and also the validation of the those control algorithms. The simulations have shown satisfactory results and current effort is concentrated on the confirmation of these results on real experiments.

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