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Estimation of Instantaneous Tremor Parameters for FES–Based Tremor Suppression

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***Abstract*— Pathological tremor constitutes the most common movement disorder, and is increasing its prevalence with ageing. Treatment forms range from drugs to surgery in those patients refractory to drugs, however, tremor is not effectively managed in about 25% of patients. According to this, new management techniques such as wearable robots that take advantage of selective biomechanical loading seem an interesting alternative. Our objective is to design robotic exoskeletons which suppress tremor, letting the user perform a voluntary movement, by means of intelligent control approaches that include accurate tremor models. In this context, we propose a two–stage algorithm for real–time estimation of time varying tremor amplitude and frequency. It is based on the assumption that tremor alters voluntary motion in an additive manner, and happens in a higher frequency band. The two–stage algorithm first generates an estimation of voluntary movement based on its inherent slower dynamics, and then removes it from the total motion, directly providing an estimate of tremor. This tremor estimation is then fed into an adaptive filter, which provides instantaneous tremor characteristics. Accurate and robust tremor amplitude and frequency estimates are obtained.**

I. Introduction

Tremor is commonly defined as an involuntary, approximately rhythmic, and roughly sinusoidal motion around a joint, [1]. It constitutes the most common movement disorder, and is strongly increasing its incidence and prevalence with ageing. Although pathological tremor is not life-threatening, it is cause of functional disability and social embarrassment. In fact, more than 65 % of the population suffering from upper limb tremor presents serious difficulties in performing their activities of daily living (ADL), [2]. Current strategies in the treatment of tremors are based on drugs (mainly the front–line agents primidone and propranolol), and surgery (thalamotomy and deep brain stimulation) in those patients being refractory to drugs. However, 1) tremor is not managed effectively or sufficiently in about 25 % of patients, 2) the drugs used may be contra–indicated, or may present potential side effects that make their use more difficult, and 3) surgery is associated with a risk of hemorrhage and psychiatric manifestations. Therefore, further research and new therapeutic options are required to manage tremor most effectively.

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In this regard, functional compensation of pathological tremor via biomechanical loading emerges as a promising treatment alternative. This approach relies on the fact that most types of tremor respond to modification of the limb impedance, [2]. In particular, an increase of damping and/or inertia in the upper limb leads to an effective tremor reduction, [3]. Recently, the concept of tremor suppression by means of a wearable exoskeleton that estimates in real–time the amount of biomechanical load to be applied, has been validated both clinically and functionally, [4]. However, the use of wearable robots as functional compensation devices often results in bulky and considerably unesthetic solutions. In fact, during the evaluation of the above mentioned exoskeleton, users reported that such device would cause social exclusion, [4], and thus were not supportive of using it outside their houses. According to this, the EU project TREMOR aims at designing a textile–based wearable robot, which applies selective biomechanical loads through Functional Electrical Stimulation (FES) to compensate tremor. Tremor suppression by means of FES has already proven to be a successful approach. In [5], the authors designed a controller that stimulated the tremorogenic muscles out of phase, attenuating the tremor without significantly affecting concomitant voluntary movement. The TREMOR project aims at extending this approach by generating dynamic stimulation patterns, which counteract time–varying tremor based on an accurate model of its instantaneous characteristics, without impeding the user perform his ADL.

Regarding the state of the art on tremor modelling, most works focus on suppression of physiological tremor in human–machine interfaces, e.g. for enhanced precision in hand held microsurgery, [6], [7]. These approaches rely on adaptive methods that fit a time varying Fourier series to an adequately processed input signal. Estimation of tremor characteristics in patients suffering from pathological tremors is typically based on off–line analysis of recorded data. Kinematic (i.e. recorded with accelerometers or gyroscopes) or electromyographic information is examined in order to estimate tremor frequency, and less commonly, amplitude. Signal processing approaches range from classical Fourier analysis, [1], to adaptive filtering algorithms, [6], blind source separation, and nonlinear techniques such as Empirical Mode Decomposition, [8].

This paper presents a two–stage algorithm for estimation of tremor parameters. It provides robust estimation of instantaneous tremor amplitude and frequency with inherent zero phase. Mean amplitude estimation error is 0.141 rad/s (less than 10 % of the peak to peak tremor value), and frequency estimation coincides with the one observed in spectrograms. The paper is organized as follows. First, the experimental protocol is briefly summarized, discussing patients, tasks, and sensor selection. Next the two stage algorithm is presented and evaluated. Finally, we discuss the results, and provide conclusions summarizing our work.

II. Experimental Protocol

A representative group of patients affected by the most common disorders that cause tremor was selected. The group of patients was compound of four men and one woman, with an average age of 63 years old. Two of them suffered from essential tremor, and the others from idiopathic Parkinson's, extrapyramidal syndrome, and paraneoplastic syndrome. Tremor severity ranged from 1 to 3 in Faher scale. All patients agreed to participate in the experiments and gave written informed consent. Ethical approval for this research was given by the Ethical Committee of the Hôptial Erasme.

Wrist flexion–extension movement was recorded, because tremors are more explicit in distal joints, [9]. We employed miniaturized MEMS gyroscopes as they provide directly joint angular velocity without any external reference, [8]. MEMS sensors provide a low weight and small size solution, which is mandatory for our application, as large sensors interfere with the user's movement, and the addition of mass alters the characteristics of tremors. MEMS gyroscopes are manufactured by Technaid S.L., weigh roughly 40 g, and provide an orientation error less than 1 °. Proper alignment between the gyroscope axis and the wrist was ensured before the recordings. Each patient was asked to perform four tasks, three repetitions each. They were selected because they constitute typical tasks in functional and clinical assessment of tremors, as they stimulate the pathologies that cause different types of tremors, they are: 1) Keeping the arms outstretched (AO): hold both arms against gravity, 2) Finger to nose test (FN): touch alternatively the nose and knee with the fingertip, 3) Resting the arms on the lap (RE), and 4) Pouring water from a regular bottle into a glass (WG).

III. Instantaneous Estimation of Tremor Parameters

As tremor is defined as an approximately rhythmic and roughly sinusoidal motion [1], it seems appropriate to model it as some kind of oscillator. In fact, most of the algorithms for real–time tremor tracking are built upon an adaptive Fourier series, [6], [7]. However, the performance of these techniques degrades if the input signal is affected by undesired sources such as voluntary movement, because the algorithm attempts to track these low frequency components. According to this, we propose a two–stage algorithm that first removes concomitant voluntary motion from the input signal, and afterwards estimates instantaneous tremor amplitude and frequency from a clean tremor estimate. The tremor estimate is immediately obtained after removing voluntary movement from the input signal, Fig. 1, because from a signal processing point of view, tremor alters volitional motion in an additive manner. Regarding the separation of voluntary and tremorous movements, both the literature and our studies establish that ADL are performed at lower frequencies that tremors, [8]. For example in [10] it is shown that most of the activities of daily living involve a frequency range between 0 and 1 Hz. The remainder of the paper presents a detailed description of the implementation of the two stage algorithm for online tremor modelling.

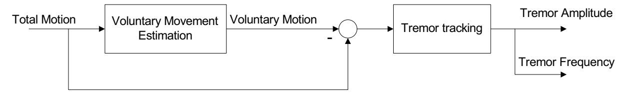


Fig. 1. Block diagram depicting the two–stage algorithm for real–time tremor amplitude and frequency tracking.

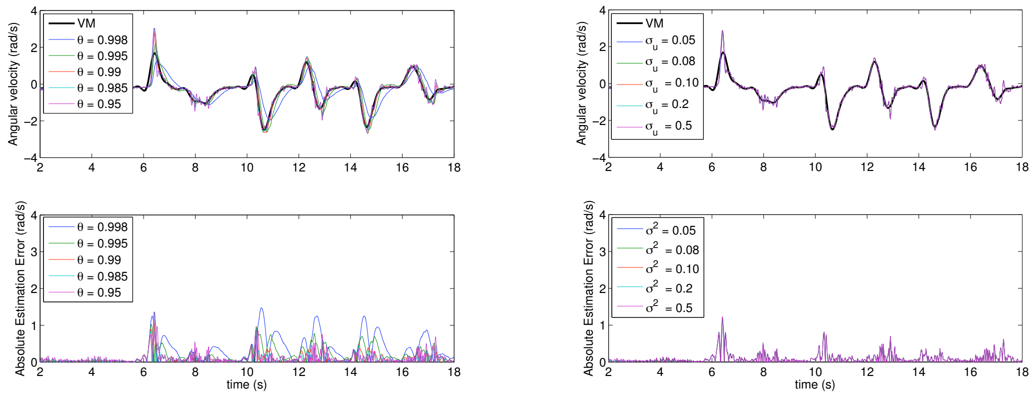
A. Voluntary Motion Tracking

As voluntary motion is considered as superimposed to tremorous motion, and happens in a lower frequency band, voluntary movement estimation can be assimilated to a tracking problem, where only tracking of the slow component of the signal is sought. As tremor happens at higher frequencies (3–12 Hz), it will be ignored. The most immediate approach would be to use digital low pass filters with cut off frequency 2 Hz. However this approach introduces phase distortion in the signal, degrading the subsequent tremor estimate. Thus we implemented and evaluated based on adequate figures of merit, two tracking filter.

1) Metrics for Evaluation of Voluntary Motion Estimation: Tracking performance is typically assessed by computing the absolute estimation error (AEE) or root mean square error between the filter estimation, $x_{k+1,k}$, and the reference signal, y_k, [11], [12]. These figures of merit, however, do not provide an insight on the physical cause of the error: they do not consider whether this error raises from undershoots or overshoots, estimation delays, or a noisy estimate. In this regard, the kinematic tracking error (KTE) provides a better approach, as it evaluates the smoothness, response time, and execution time of a tracking algorithm, (1), [4]. The KTE is an aggregate error composed by $\varphi_{|b^*|}$, the mean of the absolute estimation error, and $\sigma_{b^*}^2$, its variance. The former measures how fast the algorithm is capable of reacting when the velocity changes, whereas the latter quantifies the smoothness or filtering of the variable, [4]. Selection of filter parameters and comparison among tracking algorithms is carried out based in these figures of merit.

$$\kappa = \sqrt{\varphi_{|b^*|}^2 + \sigma_{b^*}^2} \qquad (1)$$

2) g–h Filters: g–h filters are simple recursive filters that estimate the future position and velocity of a variable based on constant velocity dynamic model. Measurements are used to correct these predictions, minimizing the estimation error. Despite of assuming zero acceleration, they provide good performance when this assumption is not fully satisfied. As in our case the sampling period is just 1 ms, and the second derivative of the angular velocity of the wrist during voluntary motion has a maximum of $2.5339 \cdot 10^{-4}$ rad/s^{-3},



(a) CDF estimation

(b) KF estimation. Measurement noise covariance is kept at σ_ω^2=0.0643.

Fig. 2. Critically Dampened filter (a) and Kalman filter (b) estimation of voluntary movement during a finger to nose test performed by patient 04. The upper plot shows the real voluntary motion (VM) obtained off–line and voluntary motion estimation for five different parameters. The lower plot shows the absolute tracking error for each case.

this assumption is satisfied, [12]. The g–h filter is formulated as follows:

$$x_{k,k} = x_{k,k-1} + g_k(y_k - x_{k,k-1}) \tag{2}$$

$$\dot{x}_{k,k} = \dot{x}_{k,k-1} + \frac{h_k}{T_s}(y_k - x_{k,k-1}) \tag{3}$$

$$x_{k+1,k} = x_{k,k} + T_s\dot{x}_{k,k} \tag{4}$$

$$\dot{x}_{k+1,k} = \dot{x}_{k,k} \tag{5}$$

Where $x_{k,k}$, $\dot{x}_{k,k}$, stand for the current position and velocity of the variable, and are estimated based on predicted position and velocity, $x_{k,k-1}$, $\dot{x}_{k,k-1}$, having current measurement y_k into account. Confidence on the measures is weighted by the gains g_k and h_k.

However, there exists a wide number of theoretically derived relationships to simplify selection of gains g_k and h_k. Among them, after a preliminary evaluation, the Critically Dampened Filter provides the best performance for our application. It provides better tracking than other algorithms such as the Benedict Bordner Filter, [4]. The Critical Dampened Filter (CDF) is based on finding the least-squares fitting line of the previous measurements, [12], giving the old data lesser significance when formulating the total error by weighting them by a factor θ, (6). Fig. 2(a) depicts CDF tracking of voluntary motion during a finger to nose test. CDF estimation for five different gains is shown. Computing the amplitude spectra, it is observed that the larger θ is, the smaller bandwidth the filter tracks. AEE and KTE were computed for five values of gain θ. The KTE for all gains is very similar (average around 0.6 rad/s), but the AEE increases with θ. According to this, the optimal gain is $\theta = 0.995$, because it provides the best trade–off between low KTE and low AEE.

$$\begin{aligned} g &= 1 - \theta^2 \\ h &= (1-\theta)^2 \end{aligned} \tag{6}$$

3) Kalman Filters: A Kalman Filter (KF) to estimate voluntary motion ignoring faster tremorous movement is developed. We define a state vector $\mathbf{x}(t)$ that includes a first order model of voluntary motion, composed by the variable to be estimated, i.e. velocity of the voluntary component of motion, and its derivative, (7). Prediction equation, is given by: $\mathbf{H}(k) = \begin{bmatrix}1 & 0\end{bmatrix}$.

$$\hat{\mathbf{x}}_{k,k-1} = \begin{bmatrix}1 & T_s \\ 0 & 1\end{bmatrix}\hat{\mathbf{x}}_{k-1,k-1} \tag{7}$$

As we aim at tracking voluntary motion, it is assumed that tremor is just sensor noise, thus the variance of the tremorous motion is employed to estimate the measurement covariance $\mathbf{R}(k) = \sigma_\omega^2 = 0.0643$ rad^2/s^{-2}. It is also hypothesized that process noise is related to voluntary motion velocity changes due to tremor. A piecewise constant white acceleration model, which assumes that voluntary motion undergoes constant and uncorrelated acceleration changes between samples, is considered, (8), [11]. σ_ν^2 is the variance of the random velocity component. The value of σ_ν^2 that defines process noise is sought within the $0.5\max_{\ddot{x}} \leq |\sigma_\nu| \leq \max_{\ddot{x}}$ interval as recommended in [11]. Calculation of the maximum acceleration yields $\max_{\ddot{x}} = 0.1042$ rad/s^{-3}. An example of application of the KF to voluntary motion estimation is shown in Fig. 2(b). Voluntary motion estimation yielded by the KF is less smooth than g–h filter estimation. This happens because the KF adapts in real–time its gain in order to minimize the a posteriori estimation error, whereas the CDF counts with a constant gain. On the contrary, the KF reacts faster to changes in voluntary motion. Its performance for different process noise covariances differs only in the filter transient. As expected, the KF provides almost exact results for the different measurement covariances, because it continuously adapts its gain to minimize the a posteriori error. Thus, small deviations among parameters are compensated by the filter itself. The only noticeable difference is the settling time at when the estimation begins. Values σ_ν^2=0.08 rad^{2}s^{-6} and σ_ω^2=0.0642 rad^{2}s^{-2} are selected as they provide almost the minimum KTE with low AEE.

$$\mathbf{Q} = \sigma_\nu^2 \begin{bmatrix} \frac{T_s^4}{4} & \frac{T_s^3}{2} \\ \frac{T_s^3}{2} & T_s^2 \end{bmatrix} \tag{8}$$

4) Filter selection and conclusions: Comparing the performance of the CDF and the KF for the above selected parameter(s), we observe that KTE values are very close. However, differences among AEE's are more significant. The lower figure for the KF is related to the fact that it yields a noisier estimation of voluntary motion as observed in Fig. 2(b). Moreover, computation of the power spectra demonstrates that KF estimation has a considerably large peak at tremor power, whereas this phenomenon is not observed for the CDF. Therefore, the CDF emerges as the optimal algorithm for voluntary movement estimation.

B. Tremor Tracking

As adaptive algorithms for real–time tremor modelling rely on a time varying Fourier representation of the process, input signals must not be corrupted by volitional movement, which will cause a bias on the adaptation. Moreover, algorithms built upon the least–mean–square (LMS) recursion [13], have inherent zero phase, which make them suitable for estimation of tremor parameters for our FES based wearable robot. In this section, we implement and evaluate two algorithms for tremor modelling, tune them, and compare their performance based on adequate figures of merit.

1) Metrics for Evaluation of Tremor Modelling: According to the goal of this paper, the absolute tremor estimation error (AEE) does not provide the most appropriate figure of merit, as it does not account for how the divergence affects the final result. Punctual overshoots, or a small phase difference between the real and estimated tremor can yield very large AEE's, shadowing a good overall performance, and making a given configuration appear as worse than a filter that provides a worse estimate, [14]. Thus, we have to first align the estimated tremor signal with the reference tremor, and afterwards, calculate the delay corrected estimation error. This figure of merit is called the Filtered Mean Square Error with Delay Correction, ($\mathrm{FMSE_d}$), [14], and is given by:

$$\mathrm{FMSE_d} = \sqrt{\left(s_k - t_{k-\hat{d}_k}\right)^2} \tag{9}$$

Where s_k represents the input tremor signal to be estimated, and $t_{k-\hat{d}_k}$ stands for the delay compensated tremor estimation. Instantaneous delay $\hat{d}_k$ is calculated by means of an adaptive algorithm that minimizes the mean square error function based on a LMS–like recursion.

2) Weighted Frequency Fourier Linear Combiner: The Weighted Frequency Fourier Combiner (WFLC) is the most spread algorithm for tremor modelling. The WFLC consists in an extension of the classical Fourier Linear Combiner (FLC) [13] to track tremor frequency based on the LMS method. As a consequence, the WFLC is capable of adapting in real-time its amplitude, frequency and phase, [6].

$$x_{r_k} = \begin{cases} \sin\left(r \sum_{t=1}^{k} \omega_{0_t}\right), & 1 \le r \le M \\ \cos\left(r \sum_{t=1}^{k} \omega_{0_t}\right), & M+1 \le r \le 2M \end{cases} \tag{10}$$

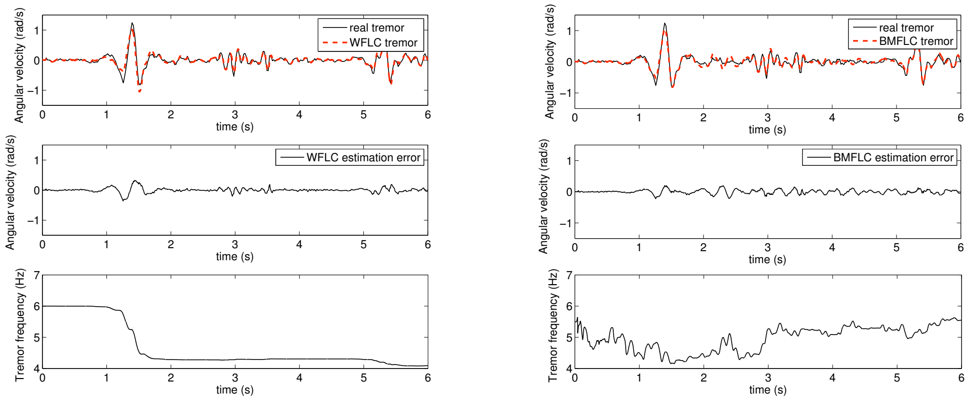
$$\varepsilon_k = s_k - \mathbf{W}_k^{\mathrm{T}} \mathbf{X}_k - \mu_b \tag{11}$$

$$\omega_{0_{k+1}} = \omega_{0_k} + 2\mu_0 \varepsilon_k \sum_{r=1}^{M} r \left(w_{r_k} x_{M+r_k} - w_{M+r_k} x_{r_k}\right) \tag{12}$$

$$\mathbf{W}_{k+1} = \mathbf{W}_k + 2\mu_1 \varepsilon_k \mathbf{X}_k \tag{13}$$

The WFLC is formulated in Equations (10) to (13). Equation (10) represents the frequency varying sinusoidal terms of the Fourier series, whereas (11) defines the error that the LMS minimizes. Equation (12) depicts the frequency adaptation, and (13) the amplitude weights adaptation. The WFLC has four parameters to tune: the amplitude and frequency gains, μ_0 and μ_1, the number of harmonics, M and a bias weight μ_b that can be included to minimize the error of lower frequency components, [6]. Normally the number of harmonics is set to 1, i.e. $M = 1$, [4], [6]. The other parameters were adjusted in an iterative manner: first, using as input signal a series of synthetic signals produced to simulate tremor, and afterwards fine–tuned with the recorded signals. Fig. 3(a) shows the performance of the WFLC with a tremor recording of patient 01. The findings agree with those reported in the literature. First, tremor frequency varies between tasks or even repetitions of the same task, but remains quite constant during one trial, overall after the oscillation reaches the steady state. Also tremor amplitude is more prone to change as WFLC tremor tracking demonstrates. Evaluation of the WFLC yields the smallest value of $\mathrm{FMSE_d}$ when parameters are set to: $\mu_0 = 5 \cdot 10^{-4}$, $\mu_1 = 2 \cdot 10^{-2}$ and $\mu_b = 1 \cdot 10^{-2}$, pointing out that the inclusion of a bias weight μ_b to compensate for low frequency components of error enhances the performance of the filter. The low AEE (average around 0.6 rad/s) proves the good performance of the WFLC for amplitude tracking. Fig. 4 shows tremor frequency estimation. Robust estimation is observed, as WFLC output agrees with the spectrograms.

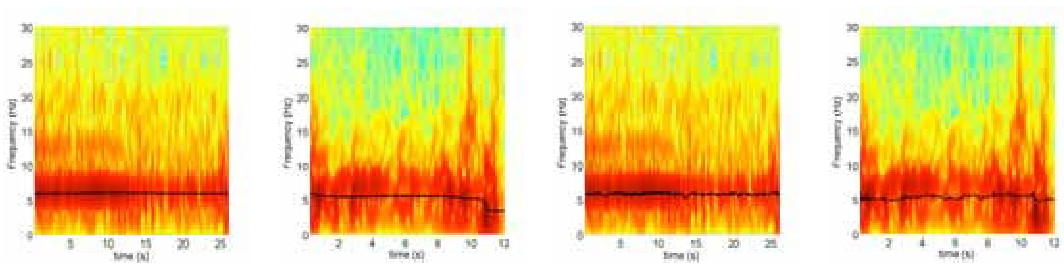
3) Bandlimited Multiple Frequency Fourier Linear Combiner: The Band Limited Multiple Fourier Linear Combiner (BMFLC) is a more recent extension of the FLC. It emerged to compensate for the limitations of the WFLC to track physiological tremor when two or more frequencies are present or when frequency variations are very fast, because both phenomena make the WFLC performance degrade, [7]. The BMFLC consists of a bank of FLCs that can track the input signal based on multiple frequency components, [7]. A frequency interval is thus defined with the upper and lower



(a) WFLC tremor estimation

(b) BMFLC tremor estimation

Fig. 3. WFLC (a) and BMFLC (b) estimation of tremor recorded during a finger to nose test performed by patient 01. The upper plot shows the input signal and the filter estimation, the estimation error is plotted below. Lower panels present frequency adaptation.



(a) AO, WFLC estimation.

(b) WG, WFLC estimation.

(c) AO, BMFLC estimation.

(d) WG, BMFLC estimation.

Fig. 4. WFLC (a, b) and BMFLC (c, d) estimation of tremor frequency (solid line) compared with power spectra (colored surface) for two tasks performed by patient 01: keeping the arms outstretched (AO), and pouring water from a bottle into a glass (WG).

frequency of the FLCs bank, ω_0 and ω_f. The number of FLCs to be placed in between is defined by parameter G.

$$x_{r_k} = \begin{cases} \sin\left(\omega_0 + \left(\omega_f - \omega_0\right) \frac{r-1}{G+1} k\right), & 1 \leq r \leq M \\ \cos\left(\omega_0 + \left(\omega_f - \omega_0\right) \frac{r-1}{G+1} k\right), & M+1 \leq r \leq 2M \end{cases} \tag{14}$$

$$\varepsilon_k = s_k - \mathbf{W}_k^{\mathrm{T}} \mathbf{X}_k - \mu_b \tag{15}$$

$$\mathbf{W}_{k+1} = \mathbf{W}_k + 2\mu\varepsilon_k \mathbf{X}_k \tag{16}$$

The BMFLC is formulated in Equations (14) to (16). The sinusoidal terms of BMFLC tremor model are included in (14), whereas Equation (16) represents the amplitude weights update based on the LMS recursion of error, (15). Again, the BMFLC has a series of parameters to be adjusted. First, the lower and upper frequencies of the FLCs bank, ω_0 and ω_f, and the number of FLCs to be placed in between, G, need to be selected. Afterwards, the harmonics of each FLC, M, and its adaptive amplitude gain, μ, are defined. A bias weight μ_b to minimize the low frequency drift of the LMS recursion is also included. Although the BMFLC does not aim at frequency tracking, an equation to calculate the current frequency of the signal based on the contribution of each FLC to the instantaneous signal estimate can be derived. For a first order Fourier series (M=1) it becomes:

$$\omega_k = \sum_{r=0}^{G+2} \frac{\left(a_r^2 + b_r^2\right) \omega_r}{\sum_{r=0}^{G+2} \left(a_r^2 + b_r^2\right)} \tag{17}$$

As for WFLC, the BMFLC was first tested with synthetic tremor signals in order to tune its parameters and test its performance. Fig. 3(b) shows the results obtained with a tremor recording from patient 01. Tremor tracking performance is comparable to that obtained with the WFLC, Fig. 3(a), although frequency estimation provides poorer results as it changes more abruptly than in reality. Fig. 4 shows the performance of the BMFLC as frequency estimator, proving that BMFLC based frequency estimation also provides good qualitative results, although the estimated frequency is less smooth than for the WFLC. This is due to the fact that tremor frequency is calculated as the instantaneous contribution of each FLC to tremor amplitude estimation. The performance of the BMFLC as mesured by the $\mathrm{FMSE_d}$ improves as the amplitude gain increases. Moreover, inclusion of a bias weight μ_b does not modify the performance of the algorithm. Thus, the best performance of the BMFLC depends only on the amplitude gain μ, and is optimized when $\mu = 4 \cdot 10^{-2}$. Higher amplitude gains made the filter become unstable during tremor transients.

4) Algorithm selection and conclusions: The BMFLC provides a more accurate tremor model than the WFLC, as the $\mathrm{FMSE_d}$ is smaller for all tasks, being always around 0.02 rad/s. Moreover, looking at the transient response, the BMFLC also adaptats faster, as its AEE is always smaller, showing a more dramatic improvement in the "more dynamic" tasks, i.e. the finger to nose and glass of water tests. Looking at frequency estimation, Fig. 4, demonstrates that both algorithms provide robust tremor frequency estimation, although WFLC yields a smoother estimate. However, we could implement a low pass filter to overcome this drawback. According to this, the BMFLC is chosen as the optimal tremor modelling algorithm in the context of this work.

IV. Discussion

The objective of TREMOR project is to develop a smart wearable robot that suppresses tremor letting the user perform his (hers) ADLs. Thus, generating accurate tremor models is mandatory to achieve selective tremor compensation. As pathological tremors are time varying oscillations, they can be fully parameterized by their instantaneous amplitude and frequency. This paper focuses on the design of a two-stage tremor modelling algorithm to achieve accurate and robust tremor characterization. To do so, adequate figures of merit are employed, first, for tuning of filter parameters, and afterwards, for algorithm selection. Algorithm evaluation yields that the Critically Dampened Filter (CDF) constitutes the optimal volitional movement estimator, as it provides short delay and smooth response. This has a series of implications in the nature of the estimated signal. First, analysis of the recorded data agrees with the literature: there exists a clear separation in frequency between tremorous and volitional movements, and accelerations when performing ADLs are almost constant, which is consistent with previous findings that demonstrate that fluctuations on acceleration worsen accuracy of upper limb movements, overall in the elder, [15]. Regarding the implementation of tremor modelling algorithms, the fact that the BMFLC outperforms the WFLC implies that (at least) for the recorded patients, tremor characteristics change more rapidly than in the case of physiological tremor. As a matter of fact, observation of WFLC and BMFLC results yields that tremor frequency during the same task keeps relatively constant, although it varies among patients and pathologies, [9], but amplitude changes are considerably more frequent and unpredictable. As the BMFLC counts with multiple harmonics at close frequencies it can adapt quickly to these variations, whereas the WFLC will try to adapt its only harmonic to this change, which seems likely to take more time. Regarding the overall performance of the algorithm, we observe that it worsens for more "dynamic tasks", i.e. those that imply performing more abrupt voluntary movements, such as the finger to nose test. This is due to the fact that voluntary movement estimation degrades due to the presence of more transitory periods, but also does tremor estimation, as tremor seems more prone to change dramatically during kinetic tasks. In fact, assessment of how different tasks impact the same types of tremor remains as a topic of future research.

V. Conclusions

This work presents a two–stage algorithm for real–time estimation of instantaneous tremor parameters in the context of robotic suppression of tremors. The core of the method is to isolate tremorous movement from concomitant volitional motion, in order to provide an adaptive algorithm with an uncorrupted estimation of tremor. In a second stage, tremor amplitude and frequency are estimated from this isolated tremor signal. Voluntary movement estimation is carried out with a Critically Dampened Filter, a special type of g–h filter, which provides good transient response and smooth estimation. Next, the Bandlimited Multiple Fourier Linear Combiner tracks tremor characteristics. As the input signal is not contaminated with undesired components (voluntary motion in this case), the algorithm yields accurate and robust tremor amplitude and frequency estimation. Average tremor estimation error is less than 0.141 rad/s (less than 10 % of the peak to peak value), and frequency estimation coincides with the results provided by spectrograms.

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