Modeling 3D Tremor Signals with a Quaternion Weighted Fourier Linear Combiner

Kabita Adhikari, *Student Member, IEEE*, Sivanagaraja Tatinati, *Student Member, IEEE*
Kalyana C. Veluvolu, *Senior Member, IEEE* and Kianoush Nazarpour, *Senior Member, IEEE*

***Abstract*— Physiological tremor is an involuntary and rhythmic movement of the body specially the hands. The vibrations in hand-held surgical instruments caused by physiological tremor can cause unacceptable imprecision in microsurgery. To rectify this problem, many adaptive filtering-based methods have been developed to model the tremor to remove it from the tip of microsurgery devices. The existing tremor modeling algorithms such as the weighted Fourier Linear Combiner (wFLC) algorithm and its extensions operate on the x, y, and z dimensions of the tremor signals independently. These algorithms are blind to the dynamic couplings between the three dimensions. We hypothesized that a system that takes these coupling information into account can model the tremor with more accuracy compared to the existing methods. Tremor data was recorded from five novice subjects and modeled with a novel quaternion weighted Fourier Linear Combiner (QwFLC). We compared the modeling performance of the proposed QwFLC with that of the conventional wFLC algorithm. Results showed that QwFLC improves the modeling performance by about 20% at the cost of higher computational complexity.**

I. INTRODUCTION

Physiological tremor is an unintentional oscillatory (roughly sinusoidal) movement of the body parts and is mainly observed in human hands [1–3]. The physiological hand tremor can be present in all healthy human beings and typically ranges between 8Hz to 12Hz [1]. Although it is not so much of problem for day to day task, it can cause major imprecisions in microsurgeries. The microsurgical procedures need surgeons to identify the tissues to be manipulated looking through a microscope and navigate the surgical tools in small volumes. Hence any oscillations due to such physiological tremor can cause unintended manipulations on the wrong place and result in tissue damage. For instance, it can cause the tip of the device to oscillate by 50μm in each axis where a positioning accuracy of 10μm is required [4].

A stand-alone steady robotic arm and robotic manipulators were often proposed for better steadiness and precision [5]. The direct surgery however holds the demand over tele-operated procedures as this involves direct correspondence between the surgeon's hand movement and his visual observation. In tele-operated procedures, there might be some time lag between the surgeon's decision and the action from the actuator. Robotic surgery also limits surgeons natural feel and lacks use of surgeon's dexterity which can lead to inadequate surgical performance [5]. Hence direct manual microsurgery is preferred due to direct sensorimotor control and superior feedback. These encourage scientists and engineers to create effective tremor compensation system in surgical hand held instruments for better precisions and greater surgical outcomes.

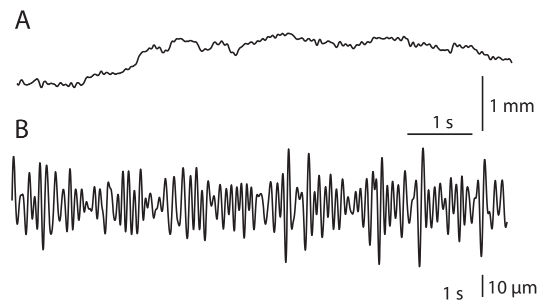

Fig. 1. A representative trace for the position of the tip of the microsurgical device in the x axis during holding the device still in a fixed position (A) and the physiological tremor calculated by bandpass filtering between 4Hz and 20Hz in (B).

Research shows that natural upper-limb movement is often a combination of regular sub movements between 1Hz to 4Hz [6]. The physiological tremor spectrum residing in a higher frequency band and hence the voluntary movement can easily be filtered out using a linear low-pass filter. In order to achieve the sharp cut-off to allow only voluntary movement through such filter needs larger number of taps. This introduces a delay in the process [7] and renders linear filter unsuitable for real-time microsurgery. Hand tremor is quasi-periodic signal which amplitude and frequency is time varying [2]. In Figure 1 a typical recording from hand whilst holding an instrumented device and associated physiological tremor signal are depicted

To attenuate the tremor at the tip of the hand-held device, the device should sense its own motion, distinguish between voluntary and tremulous movement, and then actuate the tip in equal but opposite direction with no time delay [2, 4]. The adaptive noise cancelling frameworks based on the least mean squares (LMS) algorithm have been extensively used to track the unknown frequency and amplitudes of the tremor from the primary motion (mixture of voluntary and tremulous hand motion). The estimated signal further deducted from the primary motion to extract only clean voluntary motion.

Although such an adaptive system is an ideal choice, for it to function accurately, a reference signal that is correlated with the true tremor needs to be fed to the filter. Hence, the tremor signal is pre-filtered with digital filters prior to the adaptive tracking system [1]. Due to quasi-periodic characteristics, tremor was modeled with a truncated Fourier series representation that tracks the unknown amplitude and frequency of non-stationary tremor. The method was called weighted Fourier linear combiner [1]. A second set of the adaptive weights are repeatedly updated to approximate a single frequency or multiple frequencies in tremor signal with a running sum.

The existing mathematical frameworks such as weighted Fourier linear combiner (wFLC) and its extensions treat the 3-d tremor signals as three independent one-dimensional signals. Through correlation analysis, we have found the 3 dimensions are not independent time series and there exists a subject-specific and dynamic coupling between channels. Hence we hypothesized a hyper-complex adaptive system which takes this cross-channel coupling information into account can improve the modeling performance.

In this paper, we present a novel quaternion wFLC algorithm to enable simultaneous modeling of tremor in the xyz dimensions. We call it quaternion weighted Fourier linear combiner (QwFLC). We briefly overview the existing wFLC algorithm and development of proposed QwFLC. We test the QwFLC and wFLC algorithms with tremor recordings of 5 healthy subjects; and compare the results obtained from both algorithms.

II. Methods

A. Fourier Linear Combiner (FLC)

With the FLC, Vaz *et al.* [8] demonstrated that any periodic or quasi-periodic signal s of known main frequency ω_0 can be estimated $\hat{s}$ by adaptively combining sine and cosine waves (1). FLC uses a truncated Fourier series representation with its adaptive coefficients $\mathbf{w}_k = \left[w_{1_k}, w_{1_k}, \cdots, w_{2M_k}\right]^T$ with

$$\hat{s} = \sum_{r=1}^{M} [w_{r_k} \sin(r\omega_0 k) + w_{r+M_k} \cos(r\omega_0 k)] \qquad (1)$$

where k denotes the time, M is the order of the Fourier series representing the measured signal s and $\{.\}^T$ denotes the vector transpose operation. By doing so, the FLC adapts to the original signal amplitude and phase accurately. However, FLC is not directly applicable to the case when s is the tremor signal as exact tremor frequency is unknown and is subject-specific and time-varying. Therefore the wFLC algorithm was proposed [1].

B. Weighted Fourier Linear Combiner

wFLC can track single or multiple tremor frequencies by modeling it as a running sum of an initial reference frequency. This is done by replacing fixed ω_0 with ω_{0_k} that the tracks spectrum of the tremor. The learning rates μ_0 and μ_1 govern the step size of the frequency and the amplitude and phase updates, eventually determining the speed of convergence. Mathematically,

$$\hat{s}_{r,k} = \begin{cases} \sin(r \sum_{t=0}^{k} \omega_{0_t}) & 1 \leq r \leq M \\ \cos((r-M) \sum_{t=0}^{k} \omega_{0_t}) & 1 \leq r \leq M \end{cases}, \qquad (2)$$

$$\omega_{0_{k+1}} = \omega_{0_k} + \mu_0 \epsilon_k \sum_{r=1}^{M} r(w_{r_k} \hat{s}_{M+r_k} - w_{M+r_k} \hat{s}_{r_k}) \qquad (3)$$

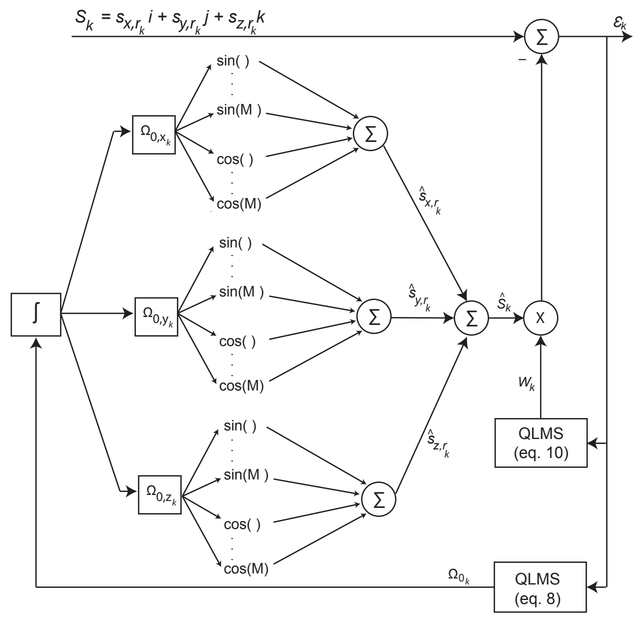

Fig. 2. The block diagram of the QwFLC algorithm. Symbol $\int$ denotes the integration operation and Σ and $\times$ represent quaternion summation and vector multiplication, respectively.

$$\mathbf{w}_{k+1} = \mathbf{w}_k + 2\mu_1 e_k \hat{s}_k \qquad (4)$$

where

$$e_k = s_k - \mathbf{w}_k^T \hat{s}_k. \qquad (5)$$

C. Quaternion weighted Fourier Linear Combiner

Our analysis showed that the tremor signal exhibits a subject-specific coupling between dimension. The wFLC algorithm is blind to this and does not benefit from any cross-channel information. We exploited quaternion algebra, modeled the 3-d tremor as a quaternion vector and developed the QwFLC algorithm. Figure 2 depicts the block diagram of the proposed algorithm.

We first combined the 3 individual *xyz* tremor components s_{r_k} to form a pure quaternion signal $\hat{\mathcal{S}}_k$ (which approximates $\mathcal{S}_k$):

$$\hat{\mathcal{S}}_k = \hat{s}_{x,r_k} i + \hat{s}_{y,r_k} j + \hat{s}_{z,r_k} k \qquad (6)$$

where i, j, and k are unit vectors representing the Cartesian coordinates. Then, all wFLC formulae were recast in the quaternion domain where all vectors are quaternion pure vectors, for instance the adaptive filter weight $\mathcal{W}$ and the error $\mathcal{E}$. Hence the formulae for the QwFLC algorithm are:

$$\mathcal{E}_k = \mathcal{S}_k - \mathcal{W}_k^T \hat{\mathcal{S}}_k \qquad (7)$$

and

$$\mathit{\Omega}_{0_{k+1}} = \mathit{\Omega}_{0_k} + \mu_0(2\mathcal{E}_k \mathcal{G}^* - \mathcal{G}^* \mathcal{E}_k^*) \qquad (8)$$

where

$$\mathcal{G} = \sum_{r=1}^{M} r(\mathcal{W}_{r_k} \hat{\mathcal{S}}_{M+r_k} - \mathcal{W}_{M+r_k} \hat{\mathcal{S}}_{r_k}) \qquad (9)$$

and

$$\mathcal{W}_{k+1} = \mathcal{W}_k + \mu_1(2\mathcal{E}_k \hat{\mathcal{S}}_k^* - \hat{\mathcal{S}}_k^* \mathcal{E}_k^*), \qquad (10)$$

where $\{.\}^*$ denotes the vector conjugate transpose operation.

This expansion have been enabled by the recent work of Cheong-Took and Mandic in [11] where quaternion LMS (QLMS) was proposed and analytical derivations were presented. The QLMS algorithm incorporates both the pseudo-covariance and the covariance while updating the filter weights and hence the extra terms in equations (8) and (9) e.g. $\mathcal{E}_k\mathcal{G}^*$. This property provides improvements in the estimation compared to uni-dimensional and complex-valued LMS.

In this formalism we kept μ_0 and μ_1 fixed across all channels. However, it is straightforward to augment the QwFLC to have channel-specific learning rates.

D. Performance Analysis

To quantify the modeling performance of both algorithms we computed the normalized root mean square error (nRMSE) defined by

$$nRMSE = \sqrt{\frac{\sum_{i=1}^{L}(X_{obs} - X_{est})^2}{\sum_{i=1}^{L} {X_{obs}}^2}} \tag{11}$$

where X_{obs} and X_{est} represent the observed and modeled tremor signal and L denotes that length of the signal.

E. Experimental Setup

Tremor recordings were performed with the Micro Motion Sensing System [3]. The resolution, minimum accuracy and sampling rate of the recording system were 0.7 μm, 98%, and 250 Hz [4]. Hand tremor recordings were performed for stationary hand positions from 5 healthy subjects. Subjects had their wrists rested on a comfortable seating position. They were asked to hold an instrumented stylus between their index finger and thumb, and were instructed to point the laser light at the center of the platform for 5 seconds. The stylus simulated a microsurgical tool. The experiment was approved by local ethics committee.

In order to generate appropriate reference for adaptive system we pre-filtered the tremor using a digital filter of pass-band 4Hz–20Hz. This filtered out voluntary motion below 4Hz. The output of the band-pass filter was provided as a reference to the adaptive system for tremor modeling.

III. Results

Figure 3 depicts a typical modeling result. We have shown the tremor recorded in the x axis and its predictions using the QwFLC and wFLC algorithms. A closer look at the figure confirms that the QwFLC can model the tremor more accurately. In addition we calculated the cross-correlation between the original signal and its predictions with the two algorithm (Figure 3B). It can be seen that the time lag between the original tremor signal and the QwFLC prediction is smaller (by 1 lag) than that between the original signal and wFLC prediction. Note that 1 time lag accounts for $4ms$ (sampling rate: 250 Hz).

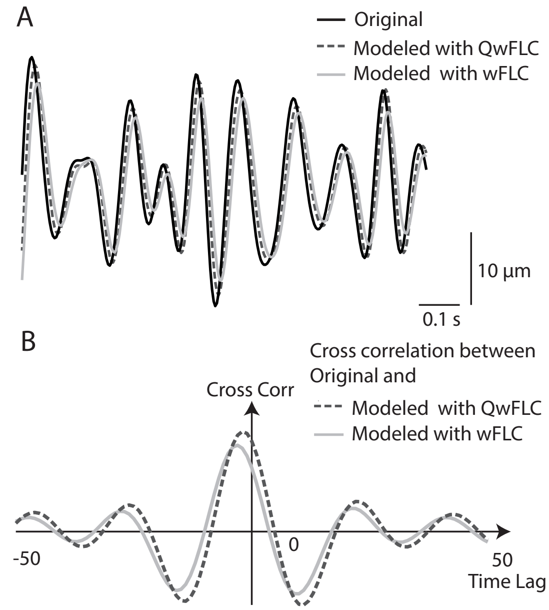

Fig. 3. A representative trace for the position of the tip of the microsurgical device in the x axis during holding the stylus still in a fixed position (A) and the estimated cross-correlation between the original tremor signals and QwFLC and wFLC outputs in (B).

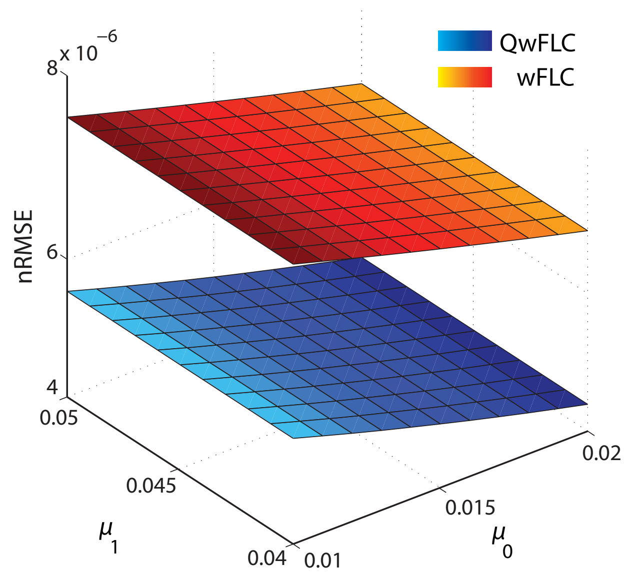

Fig. 4. Performance comparison between the QwFLC and wFLC algorithms in terms of the nRMSE parameter for different μ_0 and μ_1 values.

Figure 4 shows the average nRMSE results for all subjects across all (xyz) dimensions; the only difference being that in QwFLC the modeling was carried out in (xyz) concurrently and in wFLC analysis was performed independently for each channel and then the modeling errors in terms of the nRMSE (eq. 11) index were averaged. It is clear from Figure 4 that the QwFLC improves the modeling performance by about 20%.

IV. CONCLUDING REMARKS

A new adaptive algorithm, namely the QwFLC, was developed by extending the existing wFLC algorithm to include cross-channel couplings. As a proof of principle, the developed algorithm was applied to physiological tremor data recorded from healthy subjects holding still an instrumented stylus.

Preliminary analysis showed that not only QwFLC improves the estimation performance by about 20%, it can reduce the time lag between the predicted and actual tremor which is of significant importance in real-life application.

Future work will include analysis of data recorded from expert surgeons holding the stylus still as well the both groups move the pen to track an instructed trajectory. Another area of work could be taking into account the force by which the subjects held the stylus. The force data can be included in the calculation as the real part of the quaternion variable to model how 3-d tremor signal is modulated by force. Our working hypothesis is that as the force increases the tremor will decrease but that is subject-dependent, although that may can reveal a non-linear interaction.

In addition, the proposed QwFLC structure could be utilised in other applications such as, modelling of gait analysis [9] and modeling of respiratory body motions [10].

The use of QwFLC will entail a significantly larger computational load. Cheong and Mandic in [11] showed that the computational complexity of the basic QLMS is seven times that of the LMS. Future work will include a complete analysis of computational complexity of the developed algorithm and evaluating the feasibility of real-time implementation.

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