Biomedical Signal Processing and Control 5 (2010) 37–44

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Double adaptive bandlimited multiple Fourier linear combiner for real-time estimation/filtering of physiological tremor

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ARTICLE INFO

Article history:
Received 5 November 2008
Received in revised form 2 June 2009
Accepted 3 June 2009
Available online 10 July 2009

Keywords:
Adaptive filtering
Fourier linear combiner
Physiological tremor
Robotic compensation
Real-time tremor compensation

ABSTRACT

Tremor is the root cause for human imprecision during microsurgery. Accurate filtering of physiological tremor is extremely important for compensation in robotics assisted microsurgical instruments/procedures. A study on several surgeons tremor is conducted and the characteristics of the tremor are analyzed. A double adaptive bandlimited multiple Fourier linear combiner is designed to estimate the modulated signals with multiple frequency components for filtering and compensation of tremor in real-time. A separation procedure to separate the intended motion/drift from the tremor portion is developed. The proposed methods are compared with the existing weighted-frequency Fourier linear combiner (WFLC) algorithm on the tremor data of surgeons/subjects. Critical validation of the algorithm is performed, experiments are conducted for 1-degree of freedom (DOF) cancellation of tremor. Our experiments showed that our newly developed algorithm has a tremor compensation of at least 65% compared to 46% for the WFLC algorithm.

1. Introduction

Physiological hand tremor can be termed as involuntary human hand motion and can be approximated by a sinusoidal movement [1]. Physiological hand tremor exists in all human motion and lies in the band of 8–15 Hz with an amplitude of 100 μm in each principal axis [1–4]. In Ref. [5], it was shown that, the tremor corrupts the voluntary motion causing an unwanted disturbance or noise. This tremor leads to an intolerable imprecision of the surgical procedure which require a positioning accuracy of about 10 μm. For example, vitreoretinal surgeries require tip position accuracy close to 10 μm [6].

Active tremor compensation for robotics assisted surgical procedures has received significant attention [7–9]. The robotized approach is a technical challenge due to the compensation of tremor signals having frequencies of up to 14 Hz in real-time. In Ref. [7], a robotic handheld instrument to cancel physiological tremor of surgeon in vitreoretinal microsurgery was implemented.

Over the last decade, there has been significant development for tremor modeling and filtering [2,5,10–13]. Most of these techniques relied on low-pass filtering approaches to attenuate the tremor. Although linear filters are successful in compensating tremor, the inherent time delay [14] is a major drawback where zero-phase filtering is required. In Ref. [15], it was shown that delays small as 30 ms may degrade performance in human–machine control applications. Effective tremor compensation requires zero-phase lag in the filtering process so that the filtered tremor signal can be used to generate an opposing motion to tremor in real-time.

Adaptive noise cancelling is suited for tremor estimation as the filter can adapt to the changes in the frequency and amplitude of the tremor signal. An adaptive filter [16] adjusts its parameters online according to a learning algorithm. In general, the adaption process can be achieved using least mean square (LMS) optimization algorithm. Fourier linear combiner (FLC) [17,18] is an adaptive filter that forms a dynamic truncated Fourier series model of an input signal. The FLC operates by adaptively estimating the Fourier coefficients of the known frequency model according to the LMS algorithm. The FLC effectively estimates and cancels periodic interference of known frequency.

WFLC is an adaptive algorithm which models any quasi-periodic signal as a modulating sinusoid, and tracks its frequency, amplitude, and phase. WFLC incorporates frequency adaptation procedure into FLC. WFLC algorithm has been implemented in systems to cancel pathological tremor during computer input [19] and to counteract respiratory motion in percutaneous needle insertion [20]. Main drawback of WFLC lies in tracking signals with modulated frequencies, for e.g. subjects with essential tremor [21]. Any presence of high frequency components that are much higher than the tremor frequencies can adversely effect the frequency

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doi:10.1016/j.bspc.2009.06.001

adaptation in WFLC. This compels the use of pre-filtering (band-pass filter) which introduces delay into the filtering process of WFLC. A similar algorithm was developed in continuous time for rejection of sinusoidal signals with unknown frequencies [22]. In Ref. [23], a real-time algorithm to predict physiological tremor using an autoregressive (AR) model was developed.

WFLC algorithm in general adapts to a single frequency present in the incoming signal. For the case of tremor signal modulated by two frequencies close in spectral domain, the performance of WFLC will be degraded. To overcome the problems associated with modulated tremor, bandlimited multiple Fourier Linear Combiner (BMFLC) [24] that can track bandlimited modulated tremor signals was recently developed.

In this paper, we improve the BMFLC by incorporating an adaptive method for selection of frequency band in the analysis. By adaptive selection of the frequency band, the number of weights in the optimization process is reduced. Analysis on the microsurgeons and novice subjects tremor data is performed to study the characteristics of tremor during normal acts and microsurgery. Two different procedures are discussed for adaptive band selection based on the characteristics of the subject's tremor profile. The proposed estimation procedure is compared and tested in real-time with existing methods for 1-degree of freedom cancellation.

The rest of the paper is organized as follows: Section 2 studies the nature of the tremor frequencies and its band. Section 3 presents the main results on the design and analysis of double adaptive bandlimited multiple Fourier linear combiner. Section 4 presents experiment setup and demonstrates the effectiveness of the algorithm. Section 5 concludes the paper.

2. Tremor band

Several studies have indicated that the physiological tremor frequency is in the 8–15 Hz band having an rms-amplitude of 100 μm in *x*-, *y*- and *z*-direction [1,2,4]. The general assumption for tremor filtering and estimation is that tremor has a single dominant frequency [19,25]. In this section, we analyze the tremor profiles of various subjects to research on the tremor frequency range and its bandwidth.

2.1. Tremor recording M^2S^2

Tremor recordings are performed through the Micro-Motion Sensing System (M^2S^2) [26,27]. The M^2S^2consists of a pair of orthogonally placed position sensitive detectors (PSD) and an infra-red (IR) diode to tracks the 3D displacement of the tip of microsurgical instrument in real-time. The IR diode is used to illuminate the workspace. A ball is attached to the tip of an intraocular shaft to reflect IR rays onto the PSDs. Instrument tip position is then calculated from the centroid position of the light falling on the PSDs. The resolution, minimum accuracy and sampling rate of the M^2S^2 are 0.7 μm, 1.0 μm, and 250 Hz, respectively, [26].

2.2. Analysis on tremor band

The tremor data is recorded from 6 healthy subjects and 10 microsurgeons for analysis. Two types of tests are performed on the subjects: (1) stationary tests and (2) tracking tests. In the stationary tests, subjects are instructed to point the laser light at the center point of the platform. Tracking tests are path dependent tests and subjects trace the circumference of a circular path on the platform, with the speed that is realistic for surgical micro-manipulation tasks.

Figs. 1 and 2 shows the profiles of novice subject and surgeon, respectively, recorded on the M^2S^2. For simplicity, the tremor only in *z*-axis has been shown. The band of frequencies that are dominant in the tremor frequency range are identified, and this band is generally distributed by few frequencies defined as bandwidth. Dominant frequencies refer to the components with amplitude of minimum 10% of maximal amplitude. The tremor bandwidth of novice subject is about 2 Hz, (i.e., 10–12 Hz) and surgeon is about 3 Hz (i.e., 7–10 Hz). The tremor frequency of the surgeons and various healthy subjects involved in our experiments showed that the there existed a bandwidth of 2–3 Hz. For surgeons, the mean (± standard deviation) for the band and bandwidth are $[9.33(\pm 0.6) - 11.6(\pm 0.65)]$ Hz and $2.4(\pm\ 0.51)$ Hz, respectively. For the novice subjects, the mean (± standard deviation)for the band and bandwidth are $[7.6(\pm 0.42) - 10.3(\pm 0.44)]$ Hz and $2.7(\pm$ $0.44)$ Hz, respectively.

The tremor frequency of the surgeons is about 2 Hz lower than for the novice subjects. The bandwidth of the surgeons is by 0.3 Hz smaller than for the novice subjects and the tremor amplitude of surgeons is about a factor 5 lower than for the novices. The surgeons are able to control their tremor under test (and operation) conditions.

Our experiments showed that typically several dominant tremor frequencies are present. The measured bandwidth was 3–4 Hz. In contrast to our findings for healthy persons, Parkinson's

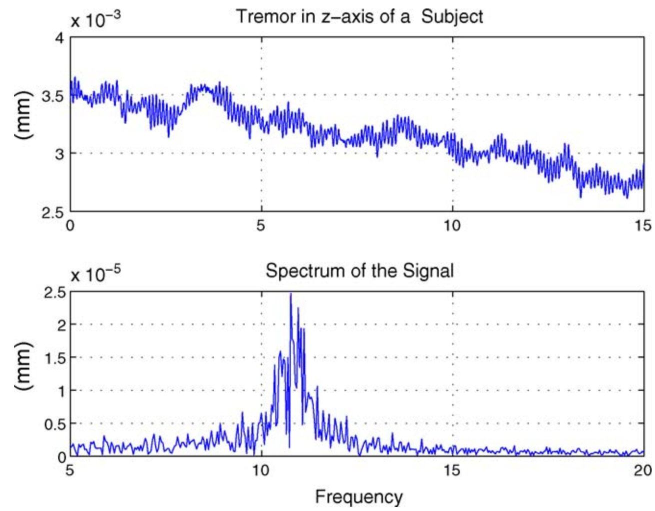

Fig. 1. Tremor of a novice subject.

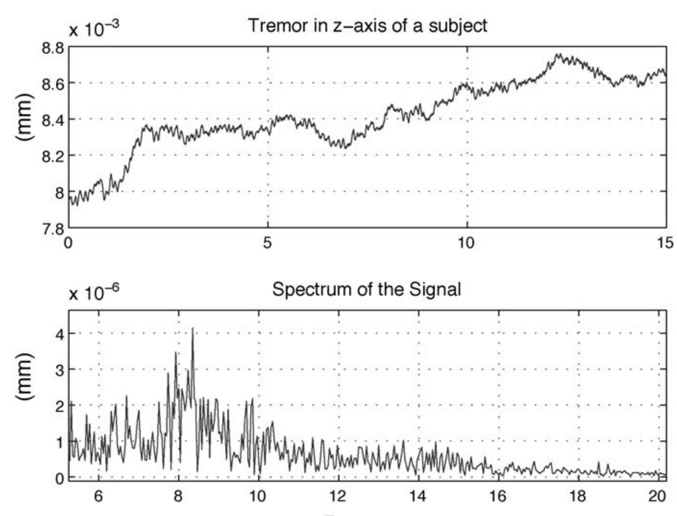

Fig. 2. Tremor of a surgeon.

tremor has one single peak in the spectrum [21]. To generalize our observation, we consider tremor frequencies between 6 and 13 Hz and that several frequencies occur in this band for the algorithm development.

3. Double adaptive bandlimited multiple Fourier linear combiner

Presence of multiple peaks in the FFT spectrum is the result of modulation of multiple frequency components in tremor. The range of frequencies and the bandwidth for subjects are analyzed in the previous section. Existing methods FLC, WFLC algorithms in general adapts to a single frequency present in the incoming signal. For the case of tremor signal modulated by multiple frequencies close in spectral domain, the performance of WFLC will be degraded [21]. Even the presence of two or three frequencies closely spaced in spectral domain can adversely affect the performance of WFLC. For e.g. 8.2 and 8.4 Hz signals produces a modulated wave containing both the frequencies. For this case, the frequency adaption process of the WFLC never stabilizes and an accurate estimation of the tremor signal cannot be attained as demonstrated in Ref. [24]. Any presence of high frequency noise can change the adaption process as the frequency weights are modified with the dominant frequency in the input signal.

To overcome the problems associated with WFLC, a new algorithm bandlimited multiple Fourier linear combiner (BMFLC) which comprises of several Fourier Linear Combiner's was developed [24,28]. The algorithm can track a band of frequencies or modulated signals of combined frequencies in real-time. The band of frequencies of BMFLC are chosen a priori. BMFLC chooses the whole tremor band as the band and bandwidth are not known exactly. This increases the number of weights and thus increases susceptibility to noise, which in turn reduces the accuracy.

Our focus in this paper is to develop an adaptive band selection procedure that tunes to according to the patients tremor profile. In this section, we improve the performance of BMFLC by adaptively choosing the frequency band rather than a fixed band. As the frequency band varies with the subject, the algorithm tunes itself to a optimum band thereby decreasing the number of weights in BMFLC. Due to the difference in tremor profiles of subjects, two techniques for optimum band selection are discussed.

Based on our research study in earlier section, without loss of generality, we consider the tremor signal to be distributed in the band of $[f_0 - f]$. Then the frequency band of interest is divided into 'L' finite number of divisions as shown in Fig. 3. For the estimation of the unknown tremor signal, we then choose a series comprising of sine and cosine components to form bandlimited multiple Fourier linear combiner at time instant 'k':

$$y_k = \sum_{r=0}^{L}\left[a_r \sin\left(2\pi\left(f_0 + \frac{r}{G}\right)k\right) + b_r \cos\left(2\pi\left(f_0 + \frac{r}{G}\right)k\right)\right] \tag{1}$$

where number of divisions L is given by $L = (f - f_0)G$, and G denotes the step size as shown in Fig. 3). f_0, f represents the frequency band under consideration. a_r, b_r represent the adaptive weights in the series. The series only considers 'n' fundamental frequencies in the band. With increase in G (i.e., the decrease in step size $1/G$ (in Fig. 3)), the divisions becomes smaller and the accuracy in estimation can be increased. The adaptive selection of the fundamental frequencies will be discussed in the later part of this section.

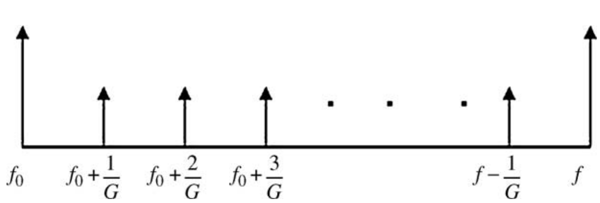

Fig. 3. Bandlimited multiple-FLC.

We adopt the LMS algorithm [16] to adapt the weights a_r, b_r to the incoming unknown signal. The algorithm can be stated as follows:

$$x_{rk} = \begin{cases} \sin\left(2\pi\left(f_0 + \frac{r-1}{G}\right)k\right), & 1 \le r \le L \\ \cos\left(2\pi\left(f_0 + \frac{(r-L)-1}{G}\right)k\right), & L+1 \le r \le 2L \end{cases} \tag{2}$$

$$\epsilon_k = s_k - \mathbf{w}_k^T \mathbf{x}_k \tag{3}$$

$$\mathbf{w}_{k+1} = \mathbf{w}_k + 2\mu \mathbf{x}_k \epsilon_k \tag{4}$$

where $\mathbf{w}_k = [w_{1k}, \ldots, w_{2M_k}]^T$ and $\mathbf{x}_k = [x_{1_k}, \ldots, x_{2M_k}]^T$ are the adaptive weight vector and reference input vector, respectively. s_k is the input signal and μ and is an adaptive gain parameter. Comparing with the FLC algorithm, we remove the harmonics, and we have multiple frequency components spaced closely in the spectral domain. The architecture is shown in Fig. 4. Due to the LMS algorithm, the corresponding weights adapt to the change in frequency of the incoming signal. The adaptive gain parameter μ can be chosen to have fast convergence without loosing stability. If the change in frequency is small, we can increase G to meet the required accuracy. In this way, the proposed algorithm accurately estimates tremor motion in the pre-defined band f_0 to f. This algorithm serves as a band-pass filter with passband f_0 and f. Based on our study, a frequency spacing of 0.1 Hz will give good estimation accuracy.

Our study showed that every subject has his own tremor profile, see Section 2. If we select a large signal bandwidth (6–14 Hz) which would cover the tremor of all subjects, the number of parameters in the model cannot be handled in real-time anymore. This large bandwidth would include an unnecessarily number of weights as each subject has a tremor bandwidth of 1–3 Hz, shown in Section 2. To address our observation, we adaptively choose the signal bandwidth $f_0 - f$ by selecting dominate frequency weights. The weights are selected by the following two procedures. The first

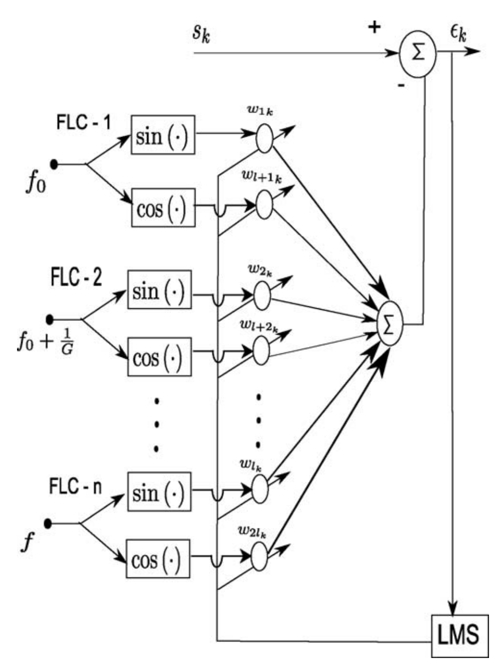

Fig. 4. Bandlimited multiple-FLC architecture.

procedure adopts a threshold to select weights and thereby reducing the number of weights. Our experiments showed good results by using a threshold of 10% of the maximal weight. Weights which are below this threshold are set to zero and are removed from the optimization process. The second procedure uses a fixed band pass having the maximal spectral value as central frequency.

3.1. Adaptive weight selection by thresholding

In this procedure, we use a threshold limit to identify the weights that are active. After time instant T, we compute the absolute of mean of weights to determine the significant weights. We then consider the weights that are less than the 10% of the maximum weights to be insignificant and modify the corresponding entries of weights to be zero. After the completion of the modification for all the weights, the algorithm is updated accordingly. The flow chart is shown in Fig. 5.

The band of frequencies adjusts to the dominant components within the signal. The adapting period can be a few seconds and the band adjusts to the optimal range. In practice, 3–5 s of data of a subject is adequate to finalize the band.

The above procedure is more feasible than dominant frequency procedure because of the presence of multiple dominant frequencies in surgeons tremor. This procedure will identify the multiple dominant frequency components within the band. By choosing an appropriate time window of 3–5 s for analysis, the dominant weights within the time window are analyzed and the weights that are not active are discarded for future estimation.

3.2. Adaptive weight selection by dominant frequency

Subjects with Parkinson's tremor are likely to have dominant frequency with a tremor bandwidth of 2–3 Hz. In this procedure, we first identify the dominant weight and its corresponding frequency after a given time T. We then choose a bandwidth of 3–4 Hz with the dominant frequency as the center frequency for the band. This procedure eliminates the unwanted/redundant weights for ease of analysis. As small time window is chosen for processing and compensation in real-time, the computation and delay associated with the implementation are extremely important for real-time cancellation of tremor. Although, accuracy of the estimation is slightly effected, the implementation will be faster and stable if there are less weights.

The procedure can be itemized as follows:

- Compute the mean of the absolute of the weights.
- Identify the dominant frequency (for e.g. f_d).
- Choose the bandwidth for BMFLC as $f_d - 2$ to $f_d + 2$.

As most subjects tends to display a bandwidth within a range of 3–4 Hz as discussed in Section 2, the bandwidth for adaptive selection of weights are chosen to be $f_d - 2$ to $f_d + 2$ around the dominant frequency f_d.

One can choose the adaptive time T to be 2–3 s to adjust to the band. The weights profile of the novice subject with tremor profile in Fig. 1 with bandwidth 6–14 Hz is shown in Fig. 6. It is clear that the weights corresponding to the band 10–12 Hz are dominant. After the dominant frequency (11 Hz) is identified, the band is adjusted and the weights profile with bandwidth 9–13 Hz is shown in Fig. 7. The number of weights is reduced from 160 to 80 by the Double Adaptive BMFLC. The adaptive BMFLC algorithm bandwidth is therefore 9–13 Hz. A narrow band eliminates the noise effects present outside the band.

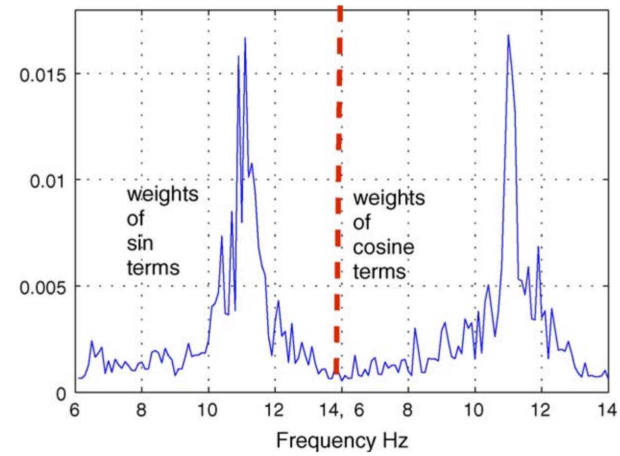

Fig. 6. Novice subject: mean of the absolute weights with bandwidth 6–14 Hz.

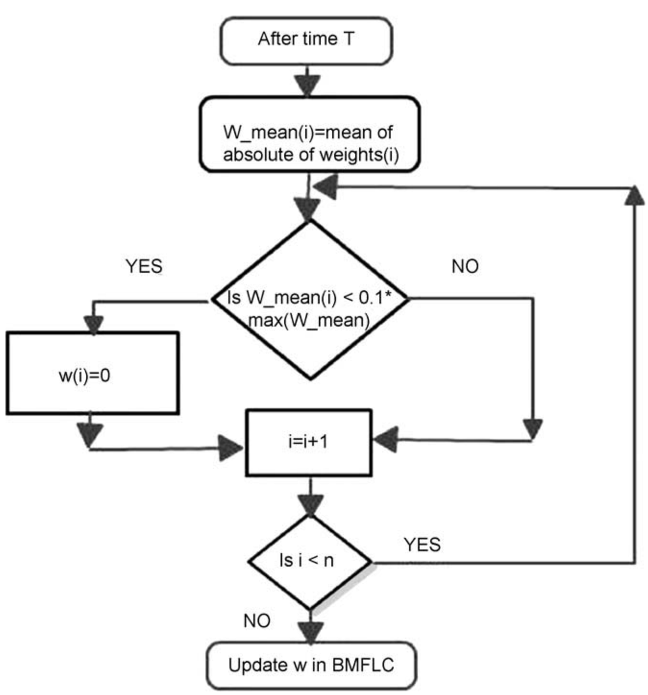

Fig. 5. Adaptive weight selection by thresholding.

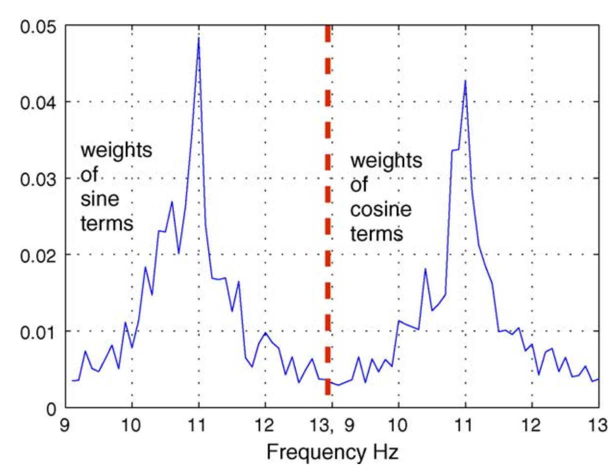

Fig. 7. Novice subject: weight selection algorithm applied, mean of the absolute weights with bandwidth 9–13 Hz.

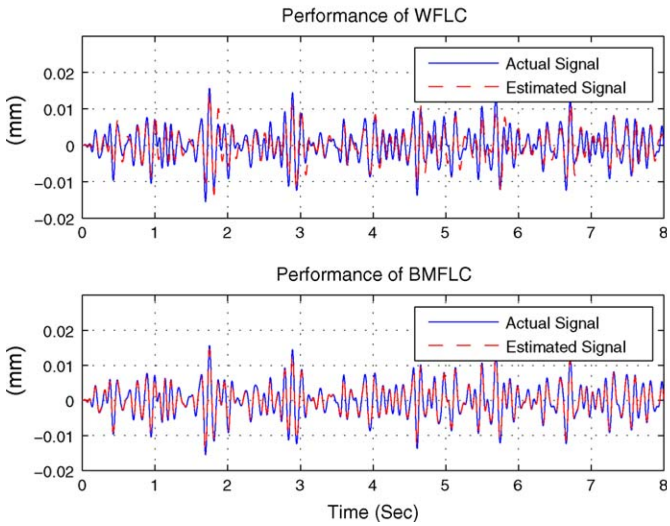

Fig. 8. Performance of WFLC and Double Adaptive BMFLC, Surgeon #1.

3.3. Performance analysis of the method on surgeon's tremor

In this section, we analyze the performance of the proposed algorithm for tremor estimation/filtering on the data recordings of the surgeons. The data recordings of the surgeons are bandpass filtered with pass band 6–14 Hz. The bandpass filtered signal is required for estimation using WFLC [25].

The tremor recording of surgeon #1 is shown in Fig. 8. The performance of WFLC, BMFLC and Double Adaptive BMFLC are analyzed with the data of microsurgeons. The performance of WFLC and Double Adaptive BMFLC are shown in Fig. 8, whereas the estimation errors are shown in Fig. 9. The proposed approach performs better than the WFLC method. The performance analysis on the tremor data of five microsurgeons is tabulated in Table 1. For subjects 1–3, the thresholding method is employed and for subjects 4–5, dominant frequency method is employed. The compensation (%) is computed as (Compensated Motion (RMS)/Tremor motion (RMS)) $\times 100$. The percentage of compensation of double adaptive BMFLC drops by 1–3% compared to BMFLC as narrow band is selected.

Although, BMFLC performs better than Double Adaptive BMFLC, the former is more stable and convenient for real-time implementation. The number of weights decreases drastically as the

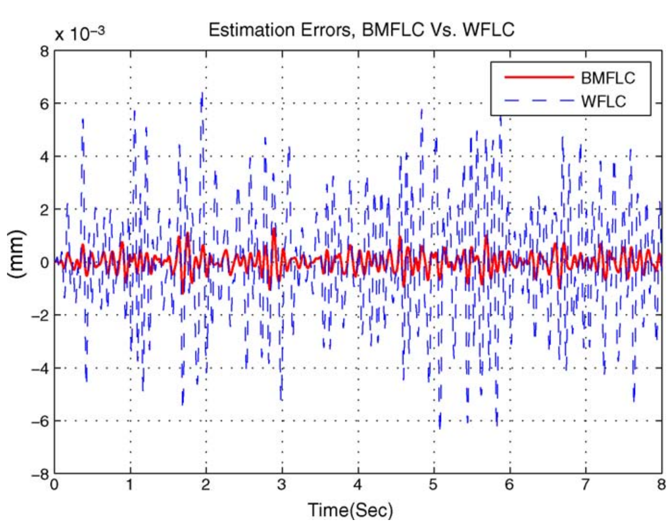

Fig. 9. Estimation errors, Surgeon #1.

Table 1
Performance of WFLC, BMFLC and Double Adaptive BMFLC.

Surgeon #	WFLC, compensation (%)	BMFLC, compensation (%)	Double Adaptive BMFLC, compensation (%) (method employed)
Surgeon 1	58.4	92.5	90.5 (Threshold)
Surgeon 2	50.5	93.2	91.2 (Threshold)
Surgeon 3	59.5	91.5	90.2 (Threshold)
Surgeon 4	43.5	84.2	79.4 (Dominant Freq.)
Surgeon 5	68.5	97.5	94.2 (Dominant Freq.)

Double Adaptive BMFLC chooses a very narrow band after its estimation. As a trade off, the estimation accuracy drops by 1–3%, and that is not a major concern as the final compensation is targeted to be in the range of 60–70%.

3.4. Separation of tremor motion from intended motion

Separation of tremor from the intentional motion is extremely important in the real-time compensation. In general, pre-filtering is required in WFLC, to separate the intentional component/drift (low frequency component) from the tremor signal. Pre-filtering inherently introduces delay and the accuracy of the estimation will be effected.

To overcome this problem, a bias weight [16] with adaptive gain is introduced to separate the intended motion/drift (low frequency component) from the tremor signal without the need of any pre-filtering. The algorithm can be modified by adding an extra term $a_0 > 0$ to track the intentional component in the LMS algorithm as follows:

$$x_{rk} = \begin{cases} \sin\left(2\pi\left(f_0 + \dfrac{r-1}{G}\right)k\right), & 1 \le r \le L \\ \cos\left(2\pi\left(f_0 + \dfrac{(r-L)-1}{G}\right)k\right), & L+1 \le r \le 2L \\ a_0, & r = 2L+1 \end{cases} \tag{5}$$

$$\epsilon_k = s_k - \mathbf{w}_k^T \mathbf{x}_k \tag{6}$$

$$\mathbf{w}_{k+1} = \mathbf{w}_k + 2\mu \mathbf{x}_k \epsilon_k \tag{7}$$

Since, the high frequency components track their respective frequencies, the weight vector corresponding to a_0 will give the required intentional component of the motion. Therefore, we can

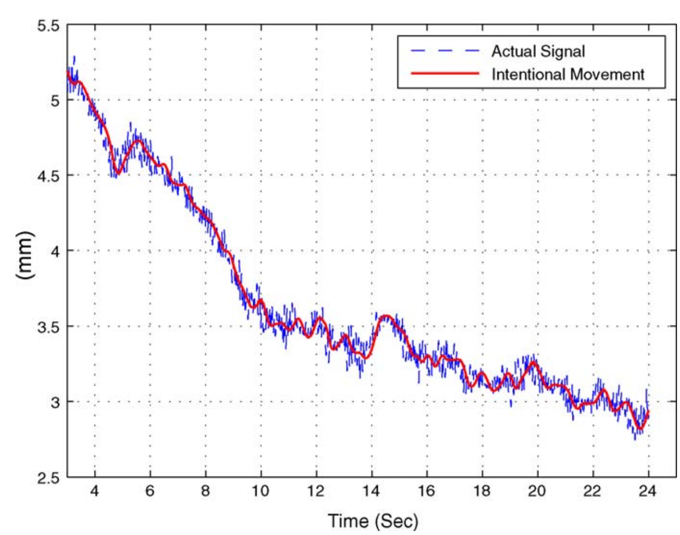

Fig. 10. Actual and intended motion.

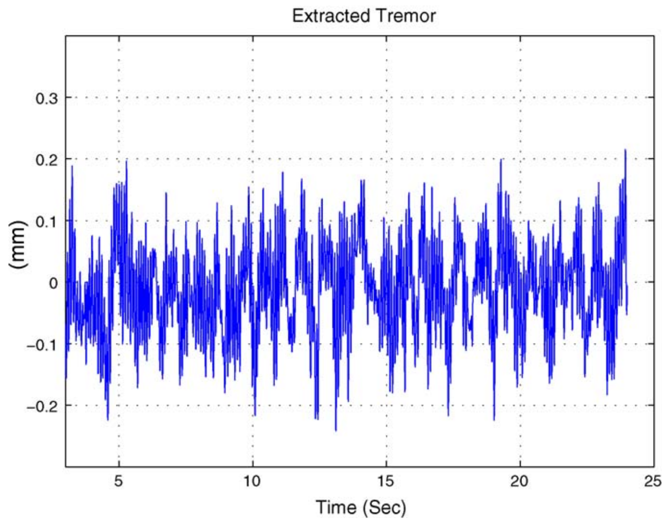

Fig. 11. Extracted tremor motion.

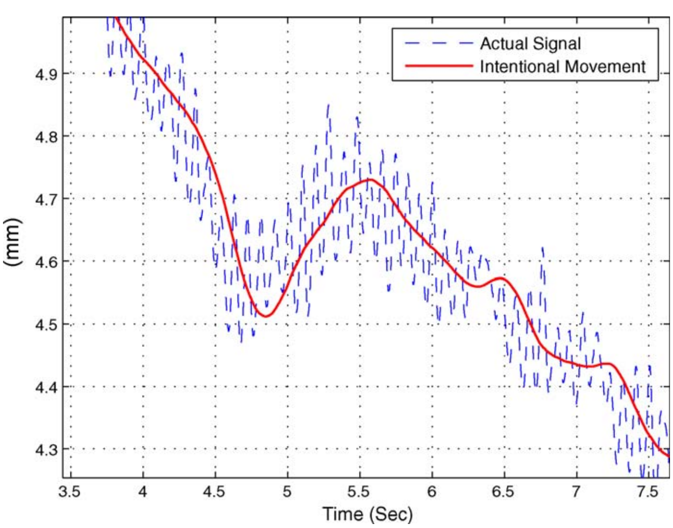

Fig. 12. Actual and intended motion.

obtain the components as

$$I(k) = \frac{\mathbf{w}_k(2L+1,:)}{a_0} \tag{8}$$

$$T(k) = \hat{S}(k) - I(k) \tag{9}$$

where $\hat{S}(k)$ is the estimated signal with (5) and (6). $I(k)$ and $T(k)$ represents the intentional and the tremor portions of the signal at the kth instant, respectively.

We have applied the proposed method on the tremor data of a subject, to estimate the intentional and actual tremor. The subject was told to hold the instrument stationary and it caused a drift in the tremor recordings. The results are shown in Figs. 10 and 11. The filtering algorithm clearly separates the tremor motion from the intended motion/drift. For clarity, a small portion of Fig. 10 is shown in Fig. 12.

4. Experimental setup and real-time implementation

4.1. Tremor sensing using accelerometer

An accelerometer board (DE-ACCM2G, Dimension Engineering), containing ADXL322 dual axis accelerometer and dual rail to rail operational amplifier buffers is employed for the experiment. The ADXL322 accelerometer chip has an output impedance of 32 k Ω, which is too high to connect directly to a data acquisition (DAQ) card (PD2-MF-150, United Electronic Industries (UEI)). The onboard buffers reduce output impedance to a lower value suitable for the DAQ card. QNX real-time operating system is used to acquire the accelerometer output data in real-time. The sampling rate of the DAQ card (PD2-MF-150, United Electronic Industries (UEI)) is set to be 120 kHz. The sampled data are temporarily stored in the onboard memory (FIFO) of the DAQ card until the card is signalled (interrupted) to send data to the user program. The interruption is carried out using "pdimmediate update" library function provided by UEI. Interruption is performed at every 0.5 ms and its timing period is created through a QNX timer. Therefore, the acquired data is made available to user program at a rate of 2 kHz (1/0.5 ms). The 60 samples (120 k/2000) in each interruption time are averaged to get one sample inorder to remove unwanted high frequency noise in the measurements. We modeled the accelerometer by a quadratic function using least square fit. The accelerometer is moved up and down at a frequency of 8 Hz with known amplitude using a nanopositioning system P-561.3CD from Physik Instrumente (PI). The peak to peak of the motion is 100 μm. For more information on experimental setup, readers may refer to Refs. [26,27].

4.2. Position sensing from acceleration

The main purpose of this research is to develop smart surgical device such as Micron [25,8] with accelerometers to sense the tremor and cancel in real-time during microsurgery. The cancellation of tremor is performed through piezoelectric actuators in displacement domain. As the input to the piezoelectric actuators is required in displacement domain, the algorithm needs to provide the accurate estimate of displacement. As accelerometers only provide the acceleration measurement, numerical integration is generally performed to obtain the position information. Due to the presence of noise and dc bias, the integration drift grows quadratically over time after double integration [29]. The drift is unavoidable, and the its presence corrupts the position information.

To overcome the drift, we applied our proposed algorithm in the acceleration domain to obtain the acceleration of the tremor signal. In Eq. (1), as the frequency of the components remain constant, we can apply double integration to obtain:

$$\int\int y_k = -\sum_{r=0}^{L}\left[\frac{a_r}{(2\pi(f_0+(r/G)))^2}\sin\left(2\pi\left(f_0+\frac{r}{G}\right)k\right) + \frac{b_r}{(2\pi(f_0+(r/G)))^2}\cos\left(2\pi\left(f_0+\frac{r}{G}\right)k\right)\right] \tag{10}$$

As the BMFLC algorithm provides the weight vectors of all the sine and cosine components in acceleration domain, the numerical integration shown above (10) can be easily implemented to obtain the non-drifting position information.

4.3. Tremor compensation

As shown in Fig. 13, the disturbance motion is sensed by the accelerometer inertial measurement unit (IMU). We use Eq. (10), to obtain the non-drifting position measurement from the acceleration data. The tremor disturbance is provided by a nanopositioning system P-561.3CD from Physik Instrumente (PI). The displacement readings after the compensation through the piezoelectric-driven mechanism are obtained through position sensitive devices

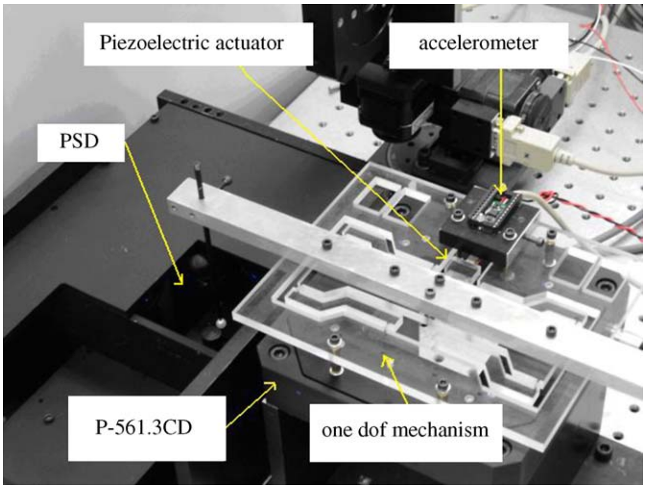

Fig. 13. Experimental setup.

developed by Ref. [26]. The M^2S^2system is used to measure the displacement information after the compensation.

4.4. Results and discussion

In order to evaluate the real-time performance for the case of tremor, a known positive tremor signal of a subject recording is shown in Fig. 14 is given as input to the system.

The Double Adaptive BMFLC algorithm with $f_0 = 8$, $f = 14$, $G = 10$ and $\mu = 0.01$ is used for compensation in real-time QNX. The recorded tremor from accelerometers is converted to position information and the outcome of the experiment is shown in Fig. 14. The dotted-line shows the estimated tremor and error in compensation is shown in Fig. 15. Adaptive weight selection by dominant frequency is employed for the first 4 s on the tremor data and the bandwidth is chosen accordingly. The tremor motion was compensated by 65%. Without the double adaptive loop in the algorithm, the implementation with BMFLC [24] achieved 67% compensation. Most trails showed the settling time to be around 2–3 s. In real-time compensation, both the algorithms performed similar, whereas the implementation of the former was stable and much simpler. Minimizing the errors in sensing and reducing inevitable delays caused by capacitors will certainly improve the experimental performance.

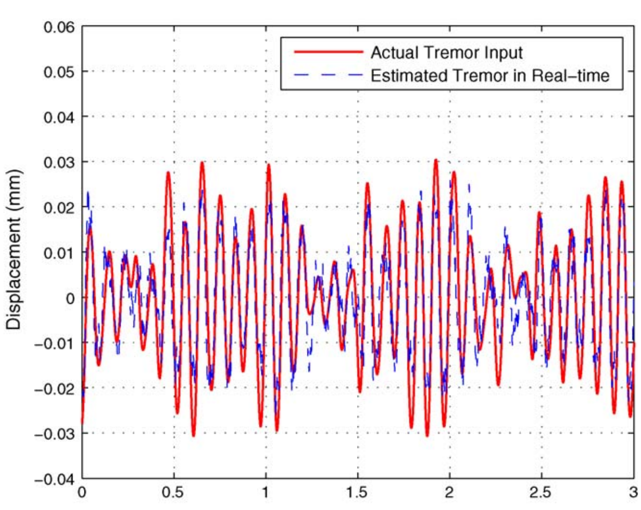

Fig. 14. Actual tremor and estimated tremor.

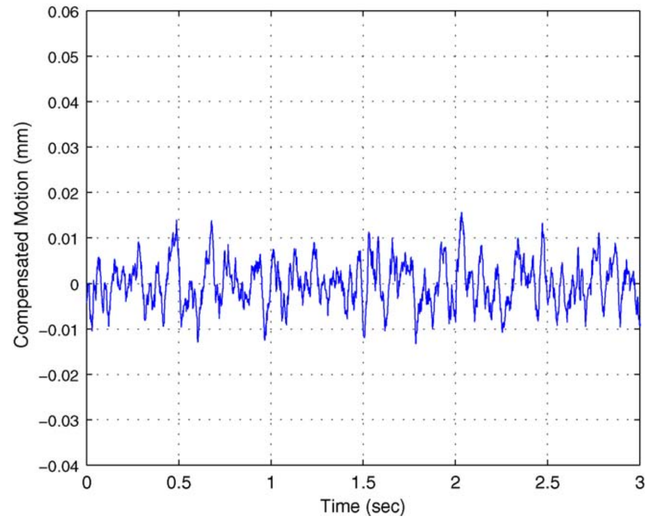

Fig. 15. Error in estimation.

To compare the performance, WFLC method was implemented in real-time QNX. The following parameters are chosen for WFLC [19]: $\mu_0 = 0.002$, $\hat{\mu} = 1 \times 10^{-5}$ and initial guess for the frequency ω_{0_1} is chosen to be 7 Hz. The tremor motion was compensated by 46%.

5. Conclusions and future work

In this paper, we have proposed new algorithms for estimation/filtering of tremor. The data recordings of the microsurgeons are used to demonstrate the effectiveness of the proposed Double Adaptive BMFLC algorithms. The proposed algorithms does not require the pre-filtering as required in WFLC algorithms. Comparative performance of the proposed methods with WFLC is studied. The intended motion and tremor motion has been separated for the real data of microsurgeons. Real-time implementation of a tremor signal and its compensation proves the effectiveness of the proposed method compared to existing approaches. The proposed algorithm has a tremor compensation of at least 65% compared to 46% for the WFLC algorithm.

As part of our continuing research in developing smart surgical device such as Micron [25,8] with accelerometers, the algorithms are developed for cancellation of tremor in real-time with accelerometers. In future, the sensing of 3-DOF accelerometers will provide the tip position of *x*, *y* and *z* separately. So, the BMFLC algorithm can be applied for the 3-axis separately and 3-DOF cancellation of tremor can be achieved.

Acknowledgement

We sincerely thank the microsurgeons of National University Hospital, Singapore for providing their time in recording the tremor.

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