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Bandlimited Multiple Fourier Linear Combiner for Real-time Tremor Compensation

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***Abstract*— Surgical accuracy of the hand-held instruments depends on the active compensation of disturbance and tremor. Physiological tremor is one of the main causes for imprecision in micro-surgery procedures. One of the popular tremor compensation methods is based on weighted-frequency Fourier linear combiner (WFLC) algorithm, that can adapt to the changes in frequency as well as amplitude of the tremor signal. WLFC estimates the dominant frequency and the amplitude. For the case of tremor with frequency variation or comprising of two or three frequencies close in spectral domain, the WFLC performance is degraded. In this paper, we present a bandlimited multiple Fourier linear combiner that can track the modulated signals with multiple frequency components. We also discuss the tremor sensing with accelerometers. Using the proposed algorithm the drift caused by the accelerometers is also eliminated. The proposed filter is tested in real-time for 1-DOF cancellation of tremor.**

I. Introduction

Physiological hand tremor can be termed as involuntary human hand motion and can be approximated by a sinusoidal movement [1]. Physiological hand tremor lies in the band of 8-12 Hz and has an amplitude of $50\mu m$ in each principal axis, has resulted in imprecision in surgical procedures of the surgeons, where the requirement of positioning accuracy of $100\mu m$ is required.

Robotized approach for active compensation of physiological tremor presents a different class of technical challenge because of the higher frequency band. In [2], a robotic handheld instrument to cancel physiological tremor of surgeon in vitreoretinal microsurgery was implemented. The handheld instrument, Micron [3] was further developed to sense itself the tremor and compensate in real-time. The tip of the micron will be unaffected by the tremor motion of the surgeon. Real-time filtering of tremulous motion component is done via a weighted-frequency Fourier linear combiner (WFLC) algorithm. The WFLC algorithm has also been implemented in systems to cancel pathological tremor during computer input [4] and to counteract respiratory motion in percutaneous needle insertion [5]. Besides Riviere's group, Zhang and Chu [6] also propose a realtime algorithm to predict physiological tremor using yet another AR model.

In essence, the key technical challenge of the active compensation approach is the uphill task of overcoming causality. The error compensation control loop has to be executed in real-time, i.e. the system has to sense the motion of interest, distinguish between voluntary and undesired components, and take the appropriate action (hardware or software) to nullify the erroneous part, all in one sampling cycle. This approach will only work when there is a distinctive frequency separation between the desired and unwanted motion. For example, dominant frequency of physiological hand tremor lies in the band of 8-12 Hz while hand movement of surgeon during microsurgery is almost always less than 0.5 Hz.

This paper presents a new method that performs zero phase filtering to extract the tremor signal. 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 this aspect, we propose a new bandlimited multiple-FLC to track multiple frequency components in the incoming signal. In the present paper, we first discuss the development of FLC and WFLC algorithms followed by the proposed algorithm. Simulation results are performed to compare the performance characteristics of WFLC and the proposed algorithm. In the later part of the paper, tremor sensing by accelerometers is discussed with the real-time implementation of the proposed algorithm for cancellation of the tremor.

II. Estimation of Tremor

There are many successful applications of linear filters for tremor cancelling. However, due to inherent time-delay [7] associated with the filtering process, their application to active tremor remained a challenging. 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 canceling is well suited for tremor estimation as the filter can adapt to the changes in the frequency and amplitude of the tremor signal. An adaptive filter [8] adjusts its parameters online according to a learning algorithm. In general, the adaption process can be achieved using least mean square (LMS). In the following subsections, we discuss the adaptive filter algorithms based on fourier series [9], [10] that can achieve zero-phase filtering. In the next section, we design a new algorithm to overcome some of the issues involved with the existence techniques.

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A. FLC [9], [11]

The Fourier linear combiner (FLC) estimates the quasiperiodic signal of known frequency by adapting the amplitude and phase of a reference signal generated artificially by a dynamic truncated Fourier series model

$$y_k = \sum_{r=1}^{M} [a_r \sin(r\omega_0 k) + b_r \cos(r\omega_0 k)] \tag{1}$$

in which the adaptive filter weights are the Fourier coefficients. The least mean square (LMS) algorithm [8] is used to update the weights. The FLC can be written as follows:

$$x_{rk} = \begin{cases} \sin(r\omega_0 k), & 1 \leq r \leq M \\ \cos((r-M)\omega_0 k), & M+1 \leq r \leq 2M \end{cases} \tag{2}$$

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

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

where $\mathbf{w}_k = \begin{bmatrix} w_{1k} & \cdots & w_{2M_k} \end{bmatrix}^T$ and $\mathbf{x}_k = \begin{bmatrix} x_{1_k} & \cdots & x_{2M_k} \end{bmatrix}^T$ are the adaptive weight vector and reference input vector respectively. s_k is the input signal, M is the number of harmonics in the model, μ and is an adaptive gain parameter. The FLC is inherentently zero phase [9], and has an infinite null [8]. The algorithm can be viewed as an adaptive notch filter with the width of the notch being directly proportional to μ.

B. WFLC [4], [10]

As FLC only operates at a fixed frequency, the goal of WFLC algorithm is to adapt to periodic signal of unknown frequency and amplitude. The WFLC algorithm extends the FLC algorithm to also adapt to the time-varying reference signal frequency, using a modification of the LMS algorithm. The algorithm can be given as

$$x_{rk} = \begin{cases} \sin\left(r \sum_{t=0}^{k} \omega_{0_t}\right), & 1 \leq r \leq M \\ \cos\left((r-M) \sum_{t=0}^{k} \omega_{0_t}\right), & M+1 \leq r \leq 2M \end{cases} \tag{5}$$

$$\begin{aligned} \epsilon_k &= s_k - \mathbf{w}_k^T \mathbf{x}_k \\ \omega_{0_{k+1}} &= \omega_{0_k} + 2\mu_0 \epsilon_k \sum_{r=1}^{M} r\left(\omega_{r_k} x_{M+r_k} - \omega_{M+r_k} x_{r_k}\right) \\ \mathbf{w}_{k+1} &= \mathbf{w}_k + 2\mu \mathbf{x}_k \epsilon_k \end{aligned} \tag{6}$$

Input signal amplitude and phase are estimated by the adaptive vector $\mathbf{w}_k$ similar to FLC, whereas ω_{0_k} estimates the unknown frequency of the input signal. μ and μ_0 are adaptive gain parameters that govern the adaptation process of frequency and amplitude respectively. In usual practice, the combination of WFLC and FLC is employed for tremor filtering. Using the frequency information from the WFLC reference vector $\mathbf{x}_k$, a second set $\hat{\mathbf{w}}_k$ of amplitude weights operates on a raw signal s_k to track the amplitude of the signal as follows [10]:

$$\begin{aligned} \hat{\epsilon}_k &= s_k - \hat{\mathbf{w}}_k^T \mathbf{x}_k \\ \hat{\mathbf{w}}_{k+1} &= \hat{\mathbf{w}}_k + 2\hat{\mu} \mathbf{x}_k \hat{\epsilon}_k \end{aligned}$$

where $\hat{\mathbf{w}}_k = \begin{bmatrix} \hat{w}_{1k} & \cdots & \hat{w}_{2M_k} \end{bmatrix}^T$. The main advantage of WFLC is that it can adapt to changes in frequency of the signal. It is well known that the physiological tremor has a dominant frequency between 8-12 Hz.

If the frequency variations are fast enough, the performance of WFLC will be degraded. 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 Hz and 8.4 Hz signals produces a modulated wave containing both the frequencies. For this case, the frequency adaptation process of the WFLC can never be stabilized and accurate estimation of the tremor signal cannot be attained. Any presence of noise of high frequency can change the adaptation process of the algorithm. In this context, we design a new algorithm that can estimate a band of frequencies or modulated wave of combined frequencies.

III. Bandlimited Multiple-FLC

In this section, we present a new algorithm to estimate the tremor signal within a band of frequencies. Recent studies has suggested that the tremor to be in the range of 8-12 Hz. To estimate the signal of unknown frequency and amplitude, we choose a series of sine and cosine components to form bandlimited multiple-FLC. We first divide the frequency band of interest into finite number of divisions $L = (f - f_0)G$. Where $G(\geq 1) \in \mathcal{N}$ is the scaling number that decides the step-size of the series as shown in the Fig. 1 below. For estimation of the unknown signal,

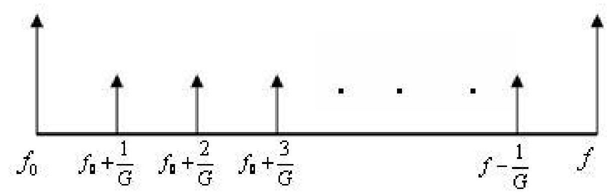

Fig. 1. Bandlimited Multiple-FLC

we then form the following series comprising of sine and cosine components:

$$y_k = \sum_{r=0}^{L} a_r \sin(2\pi(f_0 + \frac{r}{G})k) + b_r \cos(2\pi(f_0 + \frac{r}{G})k) \tag{7}$$

where $L = (f - f_0)G$. With increase in G, the divisions becomes smaller and the accuracy in estimation can be increased according to user requirement.

We then adopt the LMS algorithm [8] to adapt the weights a_r, b_r to the incoming unknown signal. The algorithm can be stated as follows:

$$x_{rk} = \begin{cases} \sin(2\pi(f_0 + \frac{r-1}{G})k), & 1 \leq r \leq L \\ \cos(2\pi(f_0 + \frac{(r-L)-1}{G})k), & L+1 \leq r \leq 2L \end{cases} \tag{8}$$

$$\epsilon_k = s_k - \mathbf{w}_k^T \mathbf{x}_k \tag{9}$$

$$\mathbf{w}_{k+1} = \mathbf{w}_k + 2\mu \mathbf{x}_k \epsilon_k \tag{10}$$

Comparing with the FLC algorithm, we remove the harmonics, i.e. we have $M = 1$ with multiple frequency components spaced closely in the spectral domain. Due to

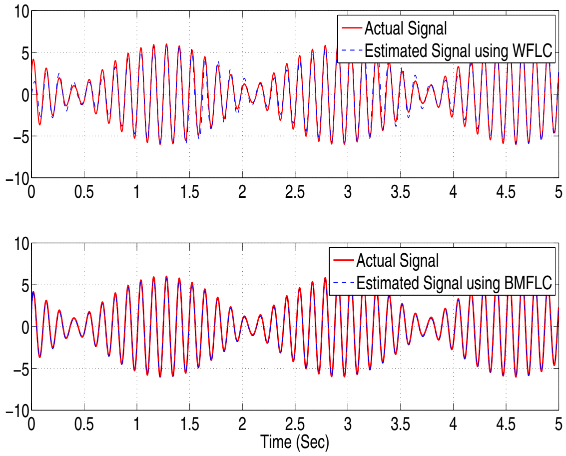

Fig. 2. Estimation Performance of WFLC and BMFLC

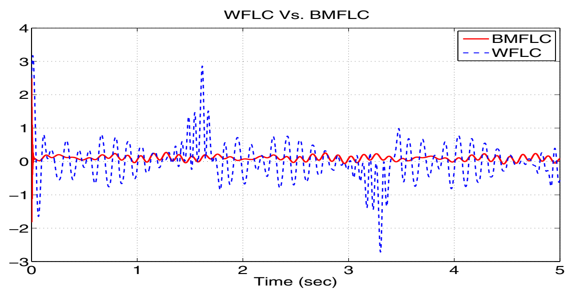

Fig. 3. Estimation errors

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. The proposed algorithm can track modulated signals of multiple frequencies in the given band of interest. If the change in frequency is small, we can increase G to meet the required accuracy. In this way, the proposed algorithm can clearly differentiate between the intended and tremor motion depending on the pre-defined band f_0 to f. This algorithm also serves as a band-pass filter.

Also, pre-filtering inherently introduces delay and the accuracy of the estimation will be affected. In the proposed algorithm, we do not require pre-filtering of the signal as required in WFLC algorithm.

A. Simulation Results & Discussion

In this section, we compare the performance of the WFLC with bandlimited multiple-FLC (BMFLC) algorithm. The following parameters are set for the WFLC algorithm: $\mu_0 = 0.017$, $\mu = 0.012$, $\hat{\mu} = 1 \times 10^{-5}$, $\omega_{0_1} = 0$. For the the proposed algorithm, the parameters are set to be $\mu = 0.01$, $G = 0.1$, $f_0 = 3$ and $f = 15$. The input signal is selected to be

$$s_k = 3.5\sin(2\pi f_1 t) + 2.5\cos(2\pi f_2 t)$$

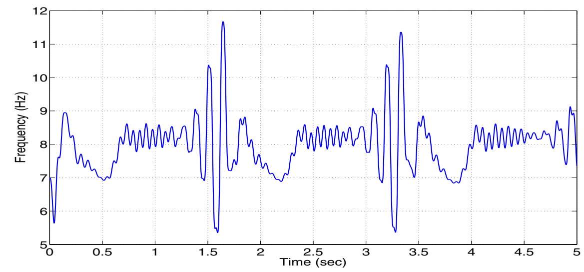

Fig. 4. Frequency adaptation in WFLC

For sake of illustration, simulation results for the case of $f_1 = 8$ and $f_2 = 8.6$ are shown in Fig. 2 - 4. Fig. 2 shows the estimation performance of WFLC and BMFLC, whereas Fig. 3 shows the estimation errors of both the algorithms. It is clear that BMFLC outforms the WFLC in the presence of two frequencies. Also the frequency weights do not converge due to the presence of two frequencies as depicted in Fig. 4. For various values of f_1 and f_2 the performance characteristics of the WFLC and BMFLC are evaluated and tabulated in the Table I below.

Table I.

f_1	f_2	WFLC		BMFLC	
		$\hat{\epsilon}$ (RMS)	Compensation (%)	ϵ (RMS)	Compensation (%)
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

From the above table, as the frequency gap between f_1 and f_2 increases WFLC fails to adapt to the modulated signal. The proposed algorithm maintains a constant compensation irrespective of the frequency of the signals. But, when both the frequencies are equal $f_1 = f_2 = 8$, the WFLC performs better than the proposed algorithm.

IV. Experimental Setup & Real-time Implementation

A. 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. 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. 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 millisecond). The 60 samples (120k/2000)

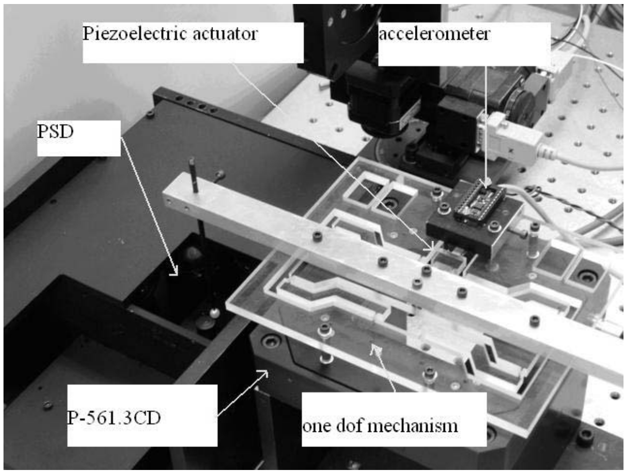

Fig. 5. Experimental setup

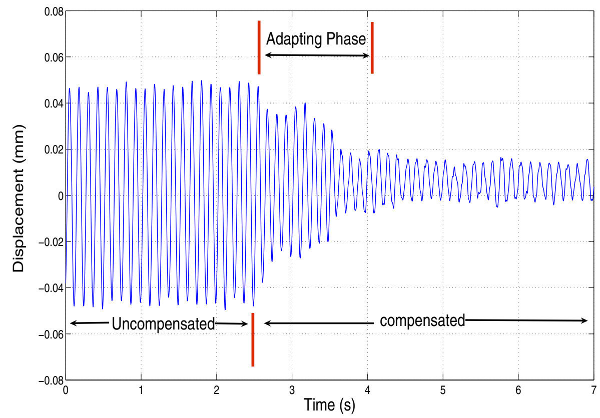

Fig. 6. Compensation with bandlimited multiple-FLC

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.

B. Drifting

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. The drift in general 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 (7), as the frequency of the components remain constant, we can apply double integration to obtain:

$$\int\int y_k = -\sum_{r=0}^{L}\Big[\frac{a_r}{(2\pi(f_0+\frac{r}{G}))^2}\sin(2\pi(f_0+\frac{r}{G})k) + \frac{b_r}{(2\pi(f_0+\frac{r}{G}))^2}\cos(2\pi(f_0+\frac{r}{G})k)\Big] \quad (11)$$

As the algorithm provides the weight vectors of all the sine and cosine components, the non-drifting position information can be obtained with (11).

C. Implementation & Results

As shown in the Fig. 5, the disturbance motion is sensed by the accelerometer inertial measurement unit (IMU). We use (11), 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 developed by [12]. A known positive disturbance of 8Hz of RMS tremor motion of 33.3 μm is given as input. Due to technical difficulties involved in nanopositioning system P-561.3CD, we were unable to test for a modulated input comprising of multiple frequencies. The proposed algorithm with $f_0 = 5$, $f = 15$, $G = 0.1$ and $\mu = 0.01$ is used for compensation in real-time QNX. The outcome of the experiment is shown in Fig. 6. The compensation is turned on after a time gap of 2.5 sec after the disturbance input is given. The algorithm adapted for a period of 1.5 sec and compensated the disturbance as shown in the Fig. 6. The RMS value of the motion after compensation drops to 8.8 μm by 73.57%.

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