Adhikari K, Tatinati S, Veluvolu KC, Nazarpour K. Improvement in modelling of physiological tremor by inclusion of grip force in quaternion weighted Fourier linear combiner. *In: 2nd IET International Conference on Intelligent Signal Processing*. 2015, London: IET.

DOI link to article:

http://dx.doi.org/10.1049/cp.2015.1782

Date deposited:

31/01/2018

Improvement in modelling of physiological tremor by inclusion of grip force in quaternion weighted Fourier linear combiner

***K. Adhikari*[1], *S. Tatinati*[2], *K. C. Veluvolu*,[2] *and K. Nazarpour*[1,3,†]**

[1] *School of Electrical and Electronic Engineering, Newcastle University, Newcastle NE1 7RU, UK*
[2] *College of IT Engineering, Kyungpook National University, Daegu, Korea*
[3] *Institute of Neuroscience, Newcastle University, Newcastle NE2 4HH, UK.*
[†] *Email for correspondence: {Kabita.adhikari, Kianoush.Nazarpour}@Newcastle.ac.uk*

Keywords: Physiological tremor, quaternion algebra, weighted Fourier linear combiner

Abstract

Physiological tremor is an involuntary oscillatory movement of body parts particularly exhibited in hands. The unintended vibrations due to tremor causes tip of the microsurgical tools to fluctuate unnecessarily causing unacceptable imprecisions in micro-surgeries. All the existing algorithms such as weighted Fourier Linear Combiner (wFLC), and its extensions, treat three x, y and z axes of tremor as three independent channels. However our correlation and coherence analysis showed that there is significant coupling between tremor channels. More importantly grip force by which a surgeon holds a surgical device also shows significant coupling with three tremor channels, which has never been investigated before. We first modelled the tremor in 3 dimensions (3-D) using quaternion algebra, and found 27% improvement which we have presented in our previous work. In this paper, we show modelling tremor in 4 dimensions by incorporating grip force and three tremor channels further exploits the cross-channel coupling information which is naturally inherent between force and xyz tremor channels. Using quaternion algebra we extract this coupling information to improve the tremor modelling performance. We show that estimation performance of tremor improves by 45% using 4-D model instead 3-D, yielding overall improvement of 65% from 1-D to 4-D.

1 Introduction

Physiological tremor is unintentional oscillatory movement of the body parts which is mainly exhibited in human hands [1]. Unlike pathological tremor which is mainly caused due to severe clinical conditions, the physiological tremor can be present in all healthy human beings. It is quasi-periodic with roughly sinusoidal nature. Its frequency of oscillation can vary from 6Hz-14Hz with dominating frequency components lying between 8Hz-12Hz [1,2]. The amplitude of physiological hand tremor ranges from 50μm to 100μm in each xyz axes. Being low in amplitude, the physiological tremor is not so much of a problem for performing daily tasks [2]. However, tasks which requires high precision such as microsurgeries where micro-manipulation of tissues and nerves is required, the hand tremor becomes a major problem. For an example in vitro-retinal surgery position accuracy of 10μm is required, [3] but tremor can lead tip of microsurgical device to oscillate up to 100μm. This causes undesirable actuation artifact of the wrong cite resulting tissues and nerve damage. Hence the physiological tremor restricts a number of qualified surgeons, as a result teleoperation and steady-hand robotic surgical options are often proposed [4]. Although direct hand surgery is still preferred over teleoperated and steady hand robotic surgery, due to natural feel, fast correspondence between surgeon's hand movement and visual observation and its lower cost [1, 5]. Hence the complete suppression of physiological tremor from the fully hand held microsurgical instrument has been a research interest among scientists from last few decades. Such effective tremor suppressing system in hand held device would

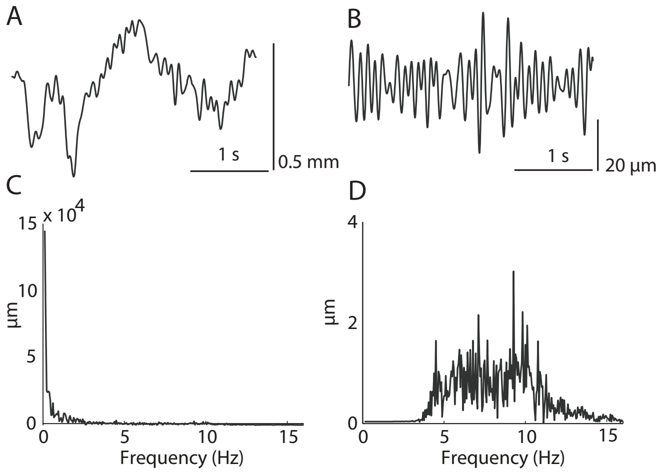

Fig. 1: A position of the tip of the microsurgical device in the x axis while holding the device still in a fixed position (A), the physiological tremor calculated by bandpass filtering between 5Hz and 20Hz (B). FFT of the voluntary motion (C) and FFT of the associated tremor (D)

result high precision with accurate micro-manipulation, hence less tissue damage, smaller incision, and better surgical outcomes [1].

The voluntary movement of upper-limb is a combination of regular sub movements with frequency of movement residing below 4Hz [6]. Hence there is clear distinction in frequency spectrum between tremulous and voluntary movement, which motivated early researchers to filter out voluntary movement with a linear low-pass filter. However the performance of the linear filter depends on sharpness of the cut-off, which in turn depends on the order of the filter. The larger filter length introduces delay in the filtering system at the cost of filtering performance [7], which deteriorates the performance of the real-time tremor cancelling systems. Physiological tremor is a non-stationary signal: its amplitude and frequency varies continuously with time. Hence adaptive noise cancelling system is best-suited for tremor compensation.

Figure 1 shows primary motion (voluntary + tremor) recording of a hand while holding an instrumented device, filtered out tremor signal exhibited during the process and Fast Fourier transform (FFT) of voluntary and tremulous signals.

Riviere and Thakor [2] proposed a model of an intelligent instrumented device to attenuate the tremor from the tip of a hand-held micro-surgical tool. This systems first senses its own motion, then learns the varying amplitude and frequency of the tremor to generate equal but opposite tip motion which effectively subtracts the tremulous motion, only allowing the tip to actuate according to the voluntary motion. Their adaptive model was based on the least mean square (LMS) algorithm, and was called weighted Fourier Linear Combiner (wFLC). Due to quasi-periodic and roughly sinusoidal characteristic of the tremor, they proposed that the tremor can be modelled by dynamic truncated Fourier series [2]. Such Fourier series is dynamic meaning its frequency components and amplitudes are formed by dynamic filter weights, which adapts to varying tremor with speed of convergence controlled by the filter learning rates. However in order to learn to adapt the tremor accurately; such adaptive algorithm requires a reference signal which should be highly correlated with the tremor. Hence the pre-filtering of the primary motion was essential in order to extract the original tremor as a reference signal. This algorithm has be been most effective to date and it has been also implemented and extended for tremor estimation and prediction by other researchers already [8].

All the existing adaptive algorithms such as wFLC and its extensions are blind to inherent dynamic coupling present in x, y, and z tremor channels. Through our correlation and coherence analysis we found that x, y, and z tremor channels are not independent time series and there exists a *subject-specific* and *task-specific* coupling between axes. Hence we hypothesized that adaptive algorithm which exploits such cross-channel coupling information could lead to better estimation accuracy.

Quaternion adaptive filtering techniques based on LMS (QLMS) has been recently shown useful for various real world data [9].The quaternion algebra preserve natural representation of 3-D or 4-D data and takes into account available coupled information within channels. It was shown that QLMS incorporates both pseudo-covariance and covariance of multidimensional data while adapting new filter parameters [9]. Hence it can improve modelling or prediction compared to 1-D or complex-valued LMS [9]. Due to such advantages quaternion operation has been highly popular over the last decade in many areas, e.g. image processing [10] and wind modelling [11]. Motivating by this, we extended the existing wFLC into three dimensions and called it QwFLC-3D which yielded 27% improvement in tremor modeling [12]. We further looked at the coherence between the grip force (force exerted by hand while holding a device) and three xyz tremor channels and found significant coherence between them. Based on this we further extended our QwFLC-3D into QwFLC-4D to incorporate coupling between xyz tremor channels and grip force.

In this paper we present our novel QwFLC-4D model which we extended from our QwFLC-3D model [12]. We test the performance of this QwFLC-4D against QwFLC-3D and QwFLC-1D using hand data recorded from five novice subjects performing a pointing task (detailed in method section).

2 Methods

A brief description of the acquisition and experimental protocols is presented in this section. We then review the FLC and wFLC algorithms and present the proposed QwFLC-4D algorithm. Finally we describe performance analysis method we used to analyse the results.

2.1 Experimental Setup

Tremor recordings were performed with a Micro Motion Sensing System [13]. The system used a pair of orthogonally placed position sensitive detectors to track 3-D displacement of the tip of an instrumented stylus in a $10 \times 10 \times 10mm^3$ workspace. The stylus had a similar mass characteristics to a typical surgical forceps. A force sensor (FSG15N1A, Honeywell Sensing and Control, USA) was also mounted on this stylus to quantify the grip force that ranged from 0N to 15N. The force data was digitized with a data acquisition card (PD-MF-16-150, United Electronic Industries, Inc, USA) at 16 bits resolution. An IR diode illuminated the workspace, and 3D displacement of a small white ball which was placed at the stylus tip, was calculated by the centroid position of the reflected infra-red rays onto the position sensitive detectors. The position and force data were both digitized at 250 samples per seconds. Hand tremor recordings were performed from 5 healthy novice subjects while performing a *pointing task*. Subjects were asked to take a comfortable seating position and rest their wrist on a platform. They were asked to hold the stylus between their index finger and thumb, and were asked to point the laser light at the center of the workspace for 30s.

2.2 Fourier Linear Combiner

In 1994, Vaz *et al.* [14] proposed that any periodic or semi-periodic biological signal s of known fundamental frequency ω_0 can be represented by dynamic truncated Fourier series $\hat{s}$. This dynamic series is combination of sine and cosine signals which amplitude (Fourier coefficients) are formed by adaptive weights.

$$\hat{s_t} = \sum_{h=1}^{H}[w_{h,t}\sin(h\omega_0 t) + w_{h+H,t}\cos(h\omega_0 t)] \quad (1)$$

where t denotes the time, H is the number of harmonics in the model $\hat{s}$. The filter weights are then adjusted adaptively as, $\mathbf{w}_t = [w_{1,t}, w_{2,t}, \cdots, w_{2H,t}]^T$. In general physiological tremor consists of more than one unknown frequency which is also time varying and subject dependent; hence this FLC method is not realistic for real-time tremor estimation.

2.3 Weighted Fourier Linear Combiner

Extending Vaz's work, Riviere [2] proposed a method to model multiple tremor frequencies by running sum of fundamental frequency. FLC with fixed ω_0 is extended to its time-varying form $\omega_{0,t}$ The modelled signal is mathematically formulated as

$$m_{h,t} = \begin{cases} \sin(h\sum_{t=0}^{t}\omega_{0,t}) & 1 \le h \le H \\ \cos((h-H)\sum_{t=0}^{t}\omega_{0,t}) & H+1 \le r \le 2H \end{cases} \quad (2)$$

$$\omega_{0,t+1} = \omega_{0,t} + \mu_\omega e_t \sum_{h=1}^{H} h(w_{h,t}m_{h+H,t} - w_{h+H,t}m_{h,t}) \quad (3)$$

The second set of adaptive weights $\mathbf{w}_t$ is adjusted again by another adaptive system to track the tremor amplitude, given by $\mathbf{w}_{t+1} = \mathbf{w}_t + 2\mu_{\mathbf{w}} e_t \mathbf{m}_t$, where the adaptation error e_t is given by

$$e_t = s_t - \hat{s}_t = s_t - \mathbf{w}_t^T \mathbf{m}_t \quad (4)$$

where s_t and $\hat{s_t}$ are the original tremor signal and the modelled tremor signal. μ_ω and $\mu_{\mathbf{w}}$ are the learning rates of two adaptive systems which determine speed of convergence to the tremor frequency and amplitude and $\mathbf{m}_t$ is a vector of $2H$ elements: $m_{h,t}$.

2.4 Quaternion Weighted Fourier Linear Combiner

In [12] we have explained how we modelled 3 xyz tremor channels in 3-D quaternion form and showed the proposed new model improves the estimation performance. Extending our work from there, using same quaternion algebra we further extend our algorithm into 4-D as shown in Figure 2.

Vectorically combining force $s_{f,t}$ as real and three xyz tremor channels $s_{x,t}, s_{y,t}$, and $s_{z,t}$ as imaginary components, we formed a quaternion signal $\mathcal{S}_t$ at a time t given by

$$\mathcal{S}_t = s_{f,t} + s_{x,t}i + s_{y,t}j + s_{z,t}k \quad (5)$$

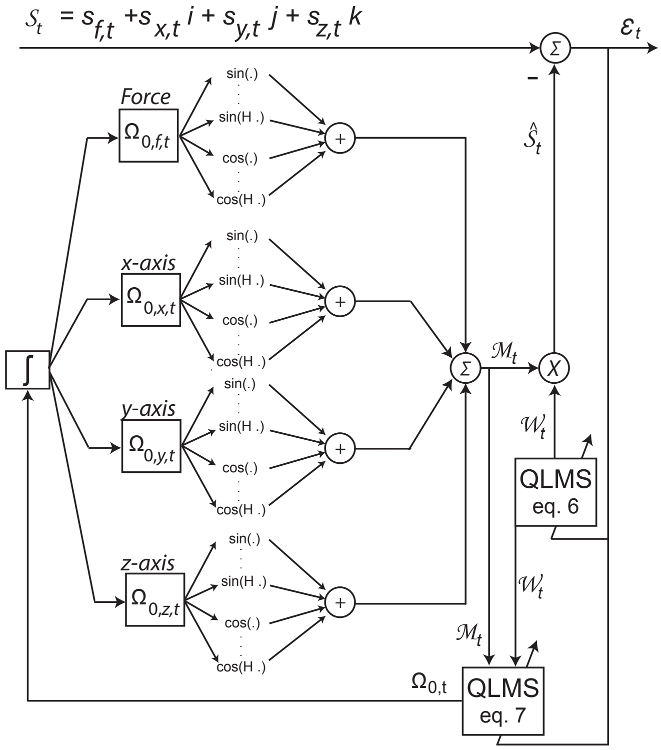

Fig. 2: A block diagram for the QwFLC algorithm. Symbol $\int$ denotes the integration operation.

In this quaternion model, each previous parameter of wFLC, $\mathbf{w}$, $\mathbf{m}_t$, $\omega_{0,t}$ and e_t are now transformed into quaternion form $\mathcal{W}$, $\mathcal{M}$, $\Omega_{0,t}$ and $\mathcal{E}_t$ respectively. Quaternions $\mathcal{W}_t$ and $\Omega_{0,t}$ are updated using two separate QLMS blocks given by equation 6 and 7 below,

$$\mathcal{W}_{t+1} = \mathcal{W}_t + \mu_{\mathcal{W}}(2\mathcal{E}_t\mathcal{M}_t^* - \mathcal{M}_t^*\mathcal{E}_t^*) \quad (6)$$

The frequency update equation in the quaternion domain will be

$$\Omega_{0,t+1} = \Omega_{0,t} + \mu_\Omega(2\mathcal{E}_t\mathcal{G}^* - \mathcal{G}^*\mathcal{E}_t^*), \quad (7)$$

where $\mathcal{G} = \sum_{h=1}^{H} h(\mathcal{W}_{h,t}\mathcal{M}_{h,t+H} - \mathcal{W}_{h,t+H}\mathcal{M}_{h,t})$ and the quaternion adaptation error is $\mathcal{E}_t = \mathcal{S}_t - \mathcal{W}_t^T\mathcal{M}_t$.

The learning rates of two QLMS algorithms $\mu_{\mathcal{W}}$ and μ_Ω are fixed across all channels for simplicity. The detailed quaternion derivations can be found in [9].

2.5 Performance Analysis

To quantify the modelling performance of the proposed new algorithm against QwFLC-3D and wFLC-1D, we compute root means square error (RMSE) between the actual and estimated tremor:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{L}(\mathcal{X}_{org,i} - \mathcal{X}_{mod,i})^2}{L}}. \quad (8)$$

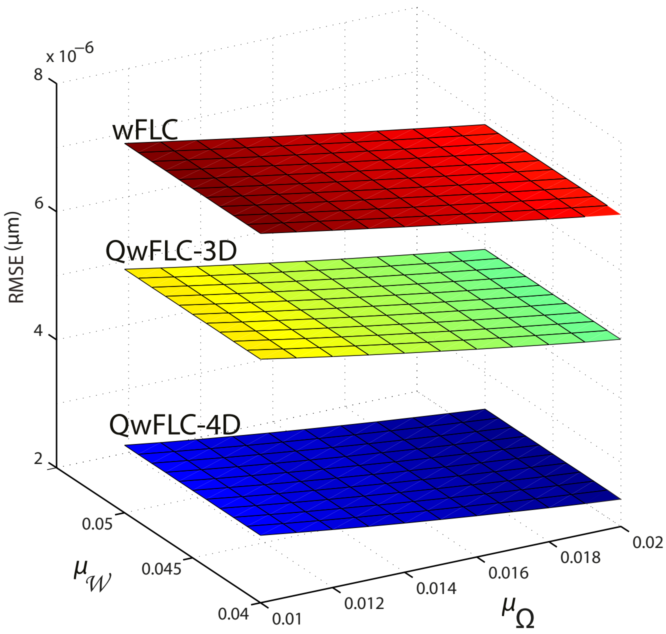

Fig. 3: Average RMSE performance comparison between QwFLC-4D, QwFLC-3D, and wFLC-1D algorithms varying $\mu_{\mathcal{W}}$ and μ_{Ω} values.

Where $\mathcal{X}_{org,i}$ and $\mathcal{X}_{mod,i}$ represent the i-th sample of the observed and modelled quaternion signals and L denotes data length.

3 Results

We quantified the modelling performance of three algorithms computing the average RMSE across x, y and z channels for all five subjects. In order to rigorously verify the performance of the algorithms against range of filter parameters, we varied $\mu_{\mathcal{W}}$ and μ_{Ω} and computed the RMSE in each of those values. Figure 3 shows the RMSE surface plots of three algorithms, showing the lowest RMSE obtained using QwFLC-4D, the error rises further using QwFLC-3D with wFLC-1D yielding the highest error. From Figure 3 we found the reduction of estimation error is in average 27% using QwFLC-3D instead wFLC-1D, the error further drops down by 45% in average by using QwFLC-4D instead QwFLC-3D. Hence overall improvement in the estimation performance is 65% from 1-D to 4-D. This result strongly justifies our hypothesis that inclusion of grip force in modelling enhances our previous 3-D model, and hence the estimation performance. Hence the inclusion of this extra channel of grip force facilitates to exploit the additional coupling information between the force and tremor channels. Using quaternion modelling to incorporate all tremor channels plus force preserves the inherent inter-channels information, which leads to improved estimation performance.

4 Discussion and Conclusions

We investigated the time-domain correlation and frequency-domain coherence between tremor channels and force, and found significant subject-specific interactions. Based on this we hypothesized that inclusion of grip force by which a surgeon holds a device into quaternion tremor modelling can yield better performance. We then extended our earlier QwFLC-3D model into QwFLC-4D by incorporating hand grip force as real component of quaternion algebra and three xyz tremor channels as imaginary components. We tested our new algorithm with recordings from five novice subjects while they performed the pointing task. We showed that exploitation of such cross-channel information between force and tremor enhances estimation performance significantly.

Although QwFLC-4D outperforms conventional wFLC-1D, computational complexity offered by QwFLC-4D is $\mathcal{O}(82H)$ compared to $\mathcal{O}(27H/2)$ offered by $3\times$wFLC, where H is the filter length. Hence the complexity of our algorithm is 6 times higher compared to conventional wFLC.

Our quaternion modeling provided significant performance improvement. We however use a linear band pass filter in order to generate the reference signal. The delay induced by this filter is approximately 20ms. For real-time applications we have to consider hardware delay in sensors and actuators which is about 4ms [8]. This delay can largely deteriorate tremor estimation and cancellation. One approach to overcome this issue is to implement a predictive mechanism.

Acknowledgements

The work of K. Adhikari is supported by Newcastle University. K. C. Veluvolu is supported by the Basic Science Research Program, National Research Foundation of Korea (NRF), Ministry of Education, Science and Technology (2014R1A1A2A10056145). The work of K. Nazarpour is supported by EPSRC (EP/M025977/1 and EP/M025594/1).

References

[1] C. N. Riviere, R. S. Rader, and N. V. Thakor, "Adaptive cancelling of physiological tremor for improved precision in microsurgery," *IEEE Trans. Biomed. Eng.*, vol. 45, no. 7, pp. 839–46, 1998.

[2] C. N. Riviere and N. V. Thakor, "Modeling and canceling tremor in human-machine interfaces," *IEEE Eng. Med. Biol. Mag.*, vol. 56, no. 3, pp. 29–36, 1996.

[3] S. Tatinati, K. C. Veluvolu, S. Hong, W. T. Latt, and W. T. Ang, "Real-time tremor modeling with auto-regressive model and Kalman filter for surgical robotics applications," *IEEE Sens. J.*, vol. 13, no. 12, pp. 4977–85, 2013.

[4] C. N. Riviere, J. Gangloff, and M. d. Mathelin, "Robotic compensation of biological motion to enhance surgical

accuracy," *Proc. IEEE*, vol. 94, no. 9, pp. 1705–1716, 2006.

[5] Y. S. Kwoh, J. Hou, E. A. Jonckheer, and S. Hayati, "A robot with improved absolute positioning accuracy for ct guided stereotactic brain surgery," *IEEE Trans. Biomed. Eng.*, vol. 35, no. 2, pp. 153–160, 1988.

[6] T. H. Hall, F. de Carvalho, and A. Jackson, "A common structure underlies low-frequency cortical dynamics in movement, sleep, and sedation," *Neuron*, vol. 83, no. 5, pp. 1185–1199, 2014.

[7] A. V. Oppenheim and R. W. Schaefer, *Discrete-Time Signal Processing*. Prentice-Hall, Bergen Country, NJ, USA, 2001.

[8] S. Tatinati, K. Veluvolu, and W. T. Ang, "Multistep prediction of physiological tremor based on machine learning for robotics assisted microsurgery," *IEEE Trans. Cybern.*, vol. 45, no. 2, pp. 328–339, 2015.

[9] C. Cheong Took and D. P. Mandic, "The quaternion LMS algorithm for adaptive filtering of hypercomplex processes," *IEEE Trans. Sig. Process.*, vol. 57, no. 4, pp. 1316–1327, 2009.

[10] B. Chen, Q. Liu, X. Sun, X. Li, and H. Shu, "Removing Gaussian noise for colour images by quaternion representation and optimisation of weights in non-local means filter," *IET Sig. Process.*, vol. 8, no. 10, pp. 591–600, 2014.

[11] N. Ur Rehman and D. P. Mandic, "Empirical mode decomposition for trivariate signals," *IEEE Trans. Sig. Process.*, vol. 58, no. 3, pp. 1059–1068, 2010.

[12] K. Adhikari, S. Tatinati, K. C. Veluvolu, and K. Nazarpour, "Modeling 3d tremor signals with a quaternion weighted Fourier linear combiner," in *Neural Engineering (NER), 2015 7th Int IEEE/EMBS Conf*, pp. 799–802, April 2015.

[13] E. L. Su, W. T. Latt, W. T. Ang, T. C. Lim, C. L. Teo, and E. Burdet, "Micromanipulation accuracy in pointing and tracing investigated with a contact-free measurement system," in *IEEE Engineering in Medicine and Biology Society, Annual Int Conf*, pp. 3960–3963, 2009.

[14] C. Vaz, X. Kong, and N. V. Thakor, "An adaptive estimation of periodic signals using a Fourier linear combiner," *IEEE Trans. Sig. Process.*, vol. 42, no. 1, pp. 1–10, 1994.