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Multi-step Prediction of Physiological Tremor for Robotics Applications

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***Abstract*— The performance of surgical robotic devices in real-time mainly depends on phase-delay in sensors and filtering process. A phase delay of $16-20$ ms is unavoidable in these robotics procedures due to the presence of hardware low pass filter in sensors and pre-filtering required in later stages of cancellation. To overcome this phase delay, we employ multi-step prediction with band limited multiple Fourier linear combiner (BMFLC) and Autoregressive (AR) methods. Results show that the overall accuracy is improved by 60% for tremor estimation compared to single-step prediction methods in the presence of phase delay. Experimental results with the proposed methods for 1-DOF tremor estimation highlight the improvement.**

I. INTRODUCTION

In recent past, with the aid of advanced robotic technology, hand-held robotic instruments were developed for tremor compensation in microsurgical procedures [1], [2], [3]. With these hand-held instruments, microsurgeries not only retain the advantages possessed my human surgeons but also the tip positioning accuracy. In these robotics assisted hand-held instruments, accelerometers form the core part for sensing the motion due to its small size and versatility [1]. Filtered tremulous motion from the sensed motion is used to generate the opposing motion to compensate the tremor in real-time, therefore filtering plays a vital role in the performance of these instruments.

To estimate the filtered tremor signal in real-time, adaptive algorithms based on Fourier series (weighted frequency Fourier linear combiner (WFLC) [3] and band limited multiple Fourier linear combiner (BMFLC)[4]) and Autoregressive (AR) method [5] were developed. Comparative performance of all adaptive tremor estimation methods can be found in [4]. In real-time tremor compensation due to the factors such as pre-filtering and cancellation of numerical integration drift, noise and jerk a delay of $16-20$ms will introduce into the procedures. As the tremor lies in the range of $8-12$ Hz this delay adversely effects the compensation efficiency. To overcome this phase delay modifications to BMFLC and WFLC are proposed in [6], however these methods are applicable to pre-filtered band-limited signals. To address this problem multi-step prediction based on BMFLC and AR methods are proposed in this paper.

Multi-step prediction is popular where time delay is inevitable or posteriori information is required [7]. Multi-step prediction has been successfully applied for several physiological motion predictions [8], [5]. In this paper, we analyze the suitability of multi-step prediction for real-time physiological tremor estimation. Two existing methods BMFLC and AR are modified to develop multi-step prediction methods. A study was conducted with tremor data of five surgeons and five novice subjects for various prediction lengths and various sampling frequencies. Several variants of these methods are reviewed to check the suitability for real-time tremor compensation. Experimental results for 1-DOF tremor estimation in the presence of delay show good improvement compared to earlier methods.

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II. METHODS

In this section, we first discuss about signal model employed followed by the procedure employed for multi-step prediction. Later the modifications proposed to the existing BMFLC and AR methods to perform multi-step prediction are discussed.

A. Signal model

The signal model employed for adaptive estimation is shown in Fig. 1(a). s_k represents the amplitude of the signal at kth sample. The model $\mathbf{x}_k$ together with the adaptive weights $\mathbf{w}_k$ represents the time-varying model for signal s_k, can be represented in the state-space form as

$$s_k = \mathbf{w}_k^T \mathbf{x}_k + e_k \quad (1)$$

$$\mathbf{w}_{k+1} = \mathbf{w}_k + \eta_k \quad (2)$$

where e_k and η_k are measurement noise and process noise respectively.

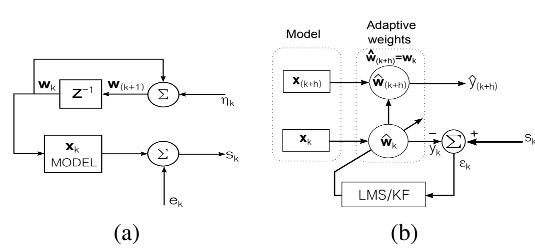


Fig. 1. (a) Signal model (b) Block diagram for multi-step prediction

When no priori information is available, the state dynamics can be best described by a random walk model (2) [9]. Adaptive algorithms like LMS [9] and KF [9] can be employed for adaptive estimation of state $\mathbf{w}_k$. The adaptive schemes for LMS and KF are provided in Table. I. Employing LMS or KF, the estimated output y_k and prediction error ϵ_k (shown in Fig. 1(b)) can be obtained as

$$y_k = \hat{\mathbf{w}}_k^T \mathbf{x}_k \quad (3)$$

$$\epsilon_k = s_k - y_k \quad (4)$$

In contrary to above, multi-step prediction requires prediction of the signal y_{h+k} several samples ahead (say h samples), based on its past observations $s_k, s_{k-1}...$ as shown in Fig. 1(b). Model is represented by the reference vector and the weights ($\hat{\mathbf{w}}_k$) represent the estimated adaptive parameters (states). Depending on the type of model (reference vector) employed, it may involve time-varying functions or constant reference inputs. With the reference vector ($\mathbf{x}_{k+h}$) accurately known at time instant $k+h$, the estimated parameters (weights) at the current sample ($\hat{\mathbf{w}}_k$) can be employed to obtain multi-step prediction for output y_{k+h} as

$$\hat{y}_{k+h} = \hat{\mathbf{w}}_k^T \mathbf{x}_{k+h} \tag{5}$$

TABLE I

ADAPTATION SCHEMES

LMS [9]	KF [9]
$\hat{\mathbf{w}}_{k+1} = \hat{\mathbf{w}}_k + 2\mu \mathbf{x}_k \epsilon_k$	$\hat{\mathbf{w}}_{k+1} = \hat{\mathbf{w}}_k + \mathbf{K}_k(s_k - \mathbf{x}_k^T \hat{\mathbf{w}}_k)$
$\epsilon_k = s_k - \mathbf{x}_k^T \hat{\mathbf{w}}_k$	$\mathbf{K}_k = \frac{\mathbf{P}_{k-1}\mathbf{x}_k^T}{\mathbf{x}_k^T \mathbf{P}_{k-1}\mathbf{x}_k + R}$
	$\mathbf{P}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{x}_k^T)\mathbf{P}_{k-1} + \mathbf{Q}$

B. Multi-step prediction with BMFLC (MS-BMFLC)

To estimate the tremor signal in the pre-defined band $[\omega_1 - \omega_n]$, a series comprising of sine and cosine components are combined to form BMFLC [4]:

$$y_k = \sum_{r=1}^{n} a_{rk} \sin(\omega_r k) + b_{rk} \cos(\omega_r k) \tag{6}$$

where y_k denotes the estimated signal at sampling instant k. a_{rk}, b_{rk} represents the adaptive weights corresponding to the frequency ω_r at instant k. $\Delta\omega$ represents the step size in the frequency band $[\omega_1 - \omega_n]$ division and $n = [\omega_1 - \omega_n]/\Delta\omega$. The series only considers 'n' fundamental frequencies in the band.

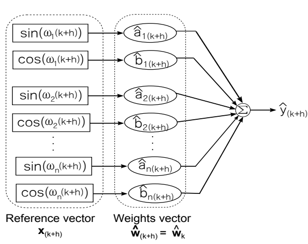


Fig. 2. Multi-step prediction with BMFLC

BMFLC can be represent in the state-space form (1)-(2), [4]. The model parameters of BMFLC used for the estimation of tremor are amplitude weights ($\mathbf{w}_k$) and the reference vector ($\mathbf{x}_k$). The block diagram representation for multi-step prediction with BMFLC is shown in Fig. 2. The amplitude of signal h samples ahead can be predicted as

$$\hat{y}_{(k+h)} = \mathbf{x}_{(k+h)}^T \hat{\mathbf{w}}_{k+h} \tag{7}$$

where

- $\hat{\mathbf{w}}_{k+h} = \mathbf{w}_k$ (amplitude weight vector (state vector) remains constant for k to $(k+h)$ samples)
- $\mathbf{x}_{(k+h)} = \left\{ \begin{array}{c} \left[\sin(\omega_1(k+h)) \cdots \sin(\omega_n(k+h)) \right]^T \\ \left[\cos(\omega_1(k+h)) \cdots \cos(\omega_n(k+h)) \right]^T \end{array} \right\}$

C. Multi-step prediction with AR model (MS-AR)

AR model is a type of random process which is popular for prediction of various types of natural phenomena. It is also one of the linear prediction methods designed to predict output of a system based on the previous outputs. AR model of order M can be represented as AR(M), described as

$$s_k = \sum_{i=1}^{M} w_i \; s_{k-i}$$

By denoting

$$\begin{aligned} \mathbf{w}_k &= \left[\begin{array}{cccc} -w_1 & -w_2 & \cdots & -w_M \end{array} \right]^T \\ \mathbf{x}_k &= \left[\begin{array}{cccc} s_{k-1} & s_{k-2} & \cdots & s_{k-M} \end{array} \right] \end{aligned}$$

the AR model can be represented in the state-space form (1)-(2). Adaptive algorithms both LMS and KF can be employed as discussed in earlier subsection.

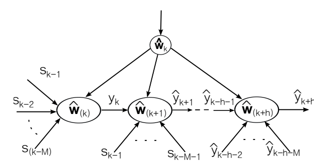


Fig. 3. Multi-step prediction with AR method

AR model prediction is dependent on the delayed input vector $\mathbf{x}_k$ and amplitude weights $\mathbf{w}_k$. Multi-step prediction scheme with AR model is shown in Fig. 3. The amplitude of the signal predicted at h samples ahead using AR model can be obtained as

$$\hat{y}_{(k+h)} = \hat{\mathbf{x}}_{(k+h)}^T \hat{\mathbf{w}}_{k+h} \tag{8}$$

where

- $\hat{\mathbf{w}}_{k+h} = \mathbf{w}_k$ (the amplitude weight vector remains constant for k to $(k+h)$ samples)
- $\hat{\mathbf{x}}_{(k+l)} = \left[\begin{array}{cccc} \hat{y}_{k-(l+1)} & \hat{y}_{k-(l+2)} & \cdots & \hat{y}_{k-(l+M)} \end{array} \right]$; $l = 1, 2, \cdots, h$. (the input vector $\hat{\mathbf{x}}_k$ is updated iteratively)

III. RESULTS

A. Physiological Tremor Data

Physiological tremor data of 5 healthy subjects and 5 surgeons, 6 trials data per subject is considered for analysis in this paper. Pointing and tracing tasks are performed by subjects. Sampling rate of 500 Hz is employed. For information about data collection, protocol and conditions see [10].

B. Latency in tremor compensation

Accelerometers are employed to sense the motion as shown in the experimental setup in Fig. 7. It contains an on-board lowpass filter, the hardware filter time constant calculated from the step-response is approximately $3ms$. As shown in Fig. 7, to separate the tremulous motion from the sensed motion by acclerometers and to remove the unwanted integration drift and noise [4], a fifth order Butterworth filter with pass-band $2-20$ Hz is employed. This filtering stage is the main source for phase delay in real-time. For illustration, phase delay due to fifth order Butterworth bandpass filter with pass band $2-20$ Hz is shown in Fig. 4. As dominant frequency of tremor lies within the range of $8-12$ Hz, an average $12-16ms$ phase delay exists in real-time. Thus, a total of $16-20ms$ phase delay is unavoidable due to hardware and software filtering as shown in Fig. 7.

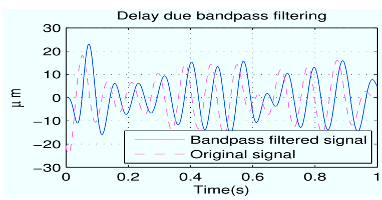


Fig. 4. Delay due to fifth order Butterworth bandpass filter.

C. Simulation Results

In this subsection, we present performance analysis of all methods thru simulations for the data of 10 subjects. We also include WFLC-LMS/KF methods [3], [11] for comparison. To accurately analyze the performance in the presence of delay, we induce a known delay into the process as shown in Fig. 5. A zero-phase bandpass filter is employed to remove the voluntary motion. We then analyze the comparative performance of all methods for various prediction lengths and various sampling rates.

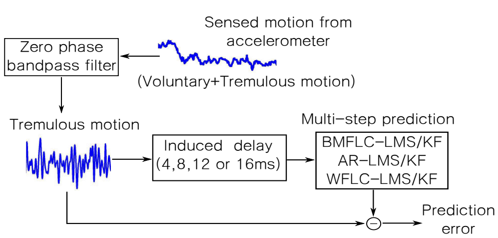


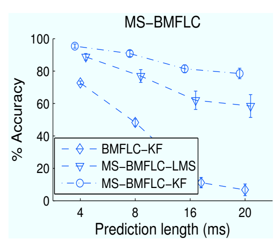
Fig. 5. Performance analysis

1) Parameter selection: For adaptive estimation algorithms, parameter selection and initialization can affect the estimation accuracy. Parameter selection for BMFLC and WFLC based methods is well documented. For more information, see [3], [11], [4]. For AR model, to identify the optimal values for AR order and the initial filter coefficients, a study was conducted on collected tremor data, results identify AR(3) as the optimal order and $\mathbf{w}_0 = \{-2.88, -0.94, 2.83\}$ to initialize the filter coefficients. Parameters and initialization for all methods are tabulated in Table. II.

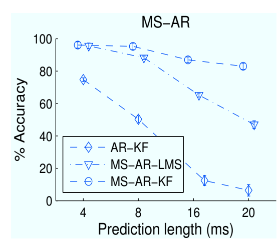
TABLE II
METHODS & PARAMETERS

Method	Model parameters and initial conditions
WFLC-LMS [3]	$\mu_0 = 1.10^{-5}$; $\mu = 5.10^{-4}$; $f_0 = 7$ Hz;
WFLC-KF [11]	$M = 1$; $R = 0.01$; $\mathbf{Q} = 0.01 \times \mathbf{I}$; $\mathbf{P}_0 = 0.01 \times \mathbf{I}$;
BMFLC-LMS [4]	$\omega_1 = 2\pi \times 7$; $\omega_n = 2\pi \times 14$; $\Delta\omega = 0.1$; $\mu = 0.01$;
BMFLC-KF [4]	$R = 0.01$; $\mathbf{Q} = 0.01 \times \mathbf{I}$; $\mathbf{P}_0 = 0.01 \times \mathbf{I}$;
AR-LMS	$\mu = 0.5$; $M = 3$; $\mathbf{w}_0 = [-2.88, 2.83, -0.94]$;
AR-KF	$R = 0.001$; $\mathbf{Q} = 0.01 \times \mathbf{I}$; $\mathbf{P}_0 = 0.001 \times \mathbf{I}$;

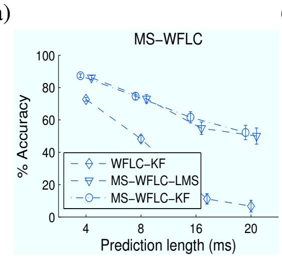
2) Performance analysis: We choose various prediction lengths ($4ms$ (2 samples), $8ms$, $16ms$ & $20ms$ (10 samples)) for the tremor signal to analyze the performance of all methods. The statistical results (mean and variance) obtained for all the methods are shown in Fig. 6. Results for different prediction lengths ($4ms$, $8ms$, $16ms$ and $2ms$) are shown together with single-step prediction for comparison. For all prediction lengths, KF based methods outperform its LMS counterparts. For single-step prediction methods $\%Accuracy$ decreases as prediction length increases. With the proposed method, a good estimation accuracy can be obtained for higher prediction lengths as shown in Fig. 6. For e.g. the estimation accuracy obtained with AR-KF is $8 \pm 3\%$ for 20 ms ahead prediction, whereas with MS-AR-KF the estimation accuracy increases to $81 \pm 2\%$ and with MS-BMFLC-KF it is $78 \pm 1\%$. MS-AR-KF and MS-BMFLC-KF performs better than MS-WFLC-KF for higher prediction lengths. This clearly highlights the robustness and suitability of the proposed methods for tremor prediction.



(a)



(b)



(c)

Fig. 6. Multi-step prediction for various prediction lengths: (a) BMFLC (b) AR (c) WFLC; representation is standard deviation around mean

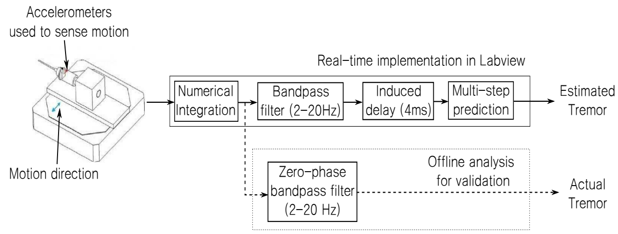


Fig. 7. Experimental procedure

D. Experimental Validation

In this section, we present the experimental results for MS-AR-KF and MS-AR-LMS methods. Since BMFLC was evaluated experimentally earlier [6] and as the performance was similar to AR based methods, we only evaluate AR methods experimentally in this section. The procedure employed for experimental validation is shown in Fig. 7. The nanopositioning stage is driven in one axis to replicate the tremor motion from the subject as shown in Fig. 7. Phase delay of 4ms is induced into the process to include the accelerometer low-pass filter delay. Butterworth filter with pass band 2-20 Hz introduces a delay of about 14-16 ms. In contrast to earlier section, a time varying delay of 16-20 ms is now present in the process. To counter this delay, a 20 ms ahead prediction is performed with MS-AR-LMS and MS-AR-KF. To obtain the ground truth for performance validation, we employ zero-phase bandpass filter in offline, since a zero-phase linear filter implementation is impractical in real-time.

Experiments are conducted with data of three subjects (S#1 (tracing task), S#2 (tracing task), S#4 (pointing task)) with two trials per subject. Parameters and initial conditions for real-time experiments are similar to simulation experiments. For illustration, results obtained with tremor data of subject #1 (tracing task) are shown in Fig. 8. The zero-phase bandpass filtered tremor signal is shown in Fig. 8(a). The % accuracies obtained with MS-AR-LMS and MS-AR-KF methods for three subjects and two trials are $53 \pm 4\%$ and $64 \pm 2\%$ respectively. Experimental results show that MS-AR-KF improves prediction accuracy by over 60% compared to single-step prediction.

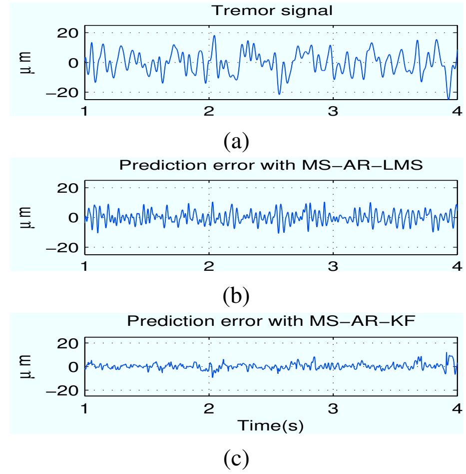


Fig. 8. Experimental results (a) Tremor signal (Subject #1, tracing task); (b) Prediction error with MS-AR-LMS; (c) Prediction error with MS-AR-KF

IV. Conclusions

In this paper to overcome the affect of phase delay in real-time tremor compensation, multi-step prediction with BMFLC and AR based methods is proposed. The proposed methods are validated thru simulation and experimental studies. Results show that both AR-KF and BMFLC-KF show similar performance and are more suitable for real-time tremor estimation. Future work will focus on real-time estimation of phase delay to further improve the multi-step prediction estimation.

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References

[1] W. T. Ang, C. N. Riviere, and P. K. Khosla, "An active hand-held instrument for enhanced microsurgical accuracy," *Medical Image Computing and Computer-Assisted Intervention*, vol. 1935, pp. 878–886, 2000.
[2] W. T. Latt, U. X. Tan, C. Y. Shee, C. N. Riviere, and W. T. Ang, "Compact sensing design of a handheld active tremor compenstaion instrument," *IEEE Sensors*, vol. 9, pp. 1864–1871, 2009.
[3] C. N. Riviere, W. T. Ang, and K. P. K., "Toward active tremor canceling in handheld microsurgical instruments," *IEEE Transactions on Robotics and Automation*, vol. 19, no. 5, pp. 793–800, October 2003.
[4] K. C. Veluvolu and W. T. Ang, "Estimation of physiological tremor from accelerometers for real-time applications," *Sensors*, vol. 11, pp. 3020–3036, 2011.
[5] A. P. L. Bo, P. Poignet, F. Widjaja, and W. T. Ang, "Online pathological tremor characterization using extended kalman filtering," in *IEEE EMBS conference, Vancouver, canada*, 2008.
[6] W. T. Latt, K. C. Veluvolu, and W. T. Ang, "Drift-free position estimation of periodic or quasi-periodic motion using inertial sensors," *Sensors*, vol. 11, pp. 5931–5951, May 2011.
[7] G. Favier and D. Dubois, "A review of k-step-ahead predictors," *Automatica*, vol. 26, pp. 75–84, 1990.
[8] S. G. Yuen, D. T. Kettler, P. M. Novotny, R. D. Plowes, and R. D. Howe, "Robotic motion compensation for beating heart intracardiac surgery," *The International Journal of Robotics Reseach*, vol. 28, pp. 1355–1372, 2009.
[9] S. Haykin, *Adaptive Filter Theory*. Prentice-Hall: Englewood Cliffs, 2001.
[10] L. M. S. Eileen, 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 *Proceedings of IEEE International Conference EMBS*, 2009.
[11] J. A. Gallego, E. Rocon, J. O. Roa, J. C. Moreno, and J. L. Pons, "Real-time estimation of pathological tremor parameters from gyroscope data," *Sensors*, vol. 10, pp. 2129–2149, 2010.