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Online LS-SVM based Multi-step Prediction of Physiological Tremor for Surgical Robotics

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***Abstract*— Performance of robotics based hand-held surgical devices in real-time is mainly dependent on accurate filtering of physiological tremor. The presence of phase delay in sensors (hardware) and filtering (software) processes affects the cancellation accuracy. This paper focuses on developing an estimation algorithm to improve the estimation accuracy in the presence of phase delay for real-time implementations. Moving window based online training approach for least squares-support vector machines (LSSVM) is employed in this paper for tremor estimation. A study is conducted with tremor data recorded from the subjects to analyze the suitability of proposed approach for both single-step and multi-step prediction.**

I. Introduction

Physiological tremor has been the main cause for human imprecision in microsurgical procedures [1], [2]. For real-time tremor compensation in microsurgeries, hand-held robotics based instruments are developed, in [1]–[3], to retain the advantages possed by the human surgeons and to augment the tip position accuracy. To separate the tremulous motion from the sensed motion by accelerometers, bandpass filter was employed in [2], [3]. Moreover, this filtering stage is also required to compensate the unwanted numerical integration drift, noise and jerk [2]. To estimate the filtered tremor signal adaptive algorithms based on Fourier series [1], [2] (weighted frequency Fourier linear combiner (WFLC) and band limited multiple linear Fourier combiner (BMFLC)) were developed. Comparative performance of all adaptive tremor estimation methods can be found in [2].

In real-time implementation, this bandpass filtering stage introduces a phase delay of $20ms$. As the dominant frequency of physiological tremor is from $8-12$ Hz, this phase delay will adversely affect the real-time tremor estimation accuracy [3]. To overcome this phase delay, modifications to BMFLC and WFLC are proposed in [3]. However the methods are applicable to pre-filtered band-limited signals. To address this problem, we propose a method based on least- squares support vector machines (LS-SVM) to perform the multi-step prediction of physiological tremor.

LS-SVM generally has been employed for function estimation, system identification and prediction applications [4], [5]. The standard LS-SVM algorithm requires offline training with a fixed number of training samples. However offline training algorithms are not suitable for non-stationary time series prediction applications. To improve the performance of LS-SVM and to track the dynamic changes in tremor signal, online training for LS-SVM is proposed in this paper. In this paper, estimation of tremor signal is performed with online moving window LS-SVM (MWLSSVM). A study is conducted on tremor data of five subjects to review the suitability of the proposed approach for single-step and multi-step tremor prediction. Simulation results show that MWLSSVM improves the estimation accuracy in the presence of phase delay.

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II. Methods

In this section, we first present the basic formulation of standard LS-SVM. Later, the proposed online training approach for LS-SVM and tremor prediction with the proposed method are discussed.

A. Standard LS-SVM [5]

LS-SVM is the least squares version of support vector machines (SVM). In LS-SVM, Vapnik's $\epsilon-$ insensitive loss function has been replaced by a mean square error cost function [5]. Due to this reformulation, optimal solution with LS-SVM is obtained directly by solving a set of linear equations rather than a convex quadratic program. Moreover, computational complexity of LS-SVM is less compared to SVM because of this reformulation.

For N samples of training data $\{\boldsymbol{x}_i, y_i\}_{i=1}^{N}$ with $\boldsymbol{x}_i$ as input and y_i as the corresponding output, the regression model for LS-SVM is;

$$y = \mathbf{w}^T \varphi(\boldsymbol{x}) + b \tag{1}$$

where $\boldsymbol{x} \in \Re^n$, $y \in \Re$; $\mathbf{w}$ is the weight vector, $\varphi(\cdot)$ is the mapping of input to the higher dimensional feature space and b is the bias. In LS-SVM, the optimization problem for the function estimation is defined as follows:

$$\min_{\mathbf{w},b,e} J(\mathbf{w}, e) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{N} e_i^2 \tag{2}$$

subject to the constraints $y_i = \mathbf{w}^T\varphi(\boldsymbol{x}_i) + b + e_i;\ i = 1, 2, \cdots, N$. Where C is the user-defined regularization constant which balances the model's complexity and approximation accuracy and e_i is the estimation error.

The corresponding Lagrangian function for optimization problem is defined as

$$L(\mathbf{w}, b, e; \alpha) = J(\mathbf{w}, e) - \sum_{i=1}^{N} \alpha_i \mathbf{w}^T\varphi(\boldsymbol{x}_i) + b + e_i - n_i \tag{3}$$

with the Lagrangian multipliers $\alpha_i \in \Re, i = 1, 2, \cdots, N$.

After eliminating e_i and $\mathbf{w}$ from the Karush-Kuhun-Tucker (KKT) [5] conditions for optimality obtained from (3), the solution is obtained as

$$\delta_N = \Psi_N^{-1}\ \mathbf{y}_N \tag{4}$$

where $\delta_N = [b, \alpha_1, \cdots, \alpha_N]^T$, $\Psi_N = \begin{bmatrix} 0 & \overrightarrow{\mathbf{1}}^T \\ \overrightarrow{\mathbf{1}}^T & \mathbf{\Omega} + \mathbf{C}^{-1}\boldsymbol{I} \end{bmatrix}$, $\overrightarrow{\mathbf{1}} = [1, 1, \cdots, 1]^T$, $\mathbf{y} = [y_1, y_2, \cdots, y_N]^T$ and $\mathbf{\Omega}$ follows Mercer's condition [5], $\Omega_{ij} = K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \varphi(\boldsymbol{x}_i)^T\varphi(\boldsymbol{x}_j)\ i, j = 1, 2, \cdots, N$, here $K(\cdot,\cdot)$ is the Kernel function. In this work RBF Kernel function is employed, $K(\boldsymbol{x}, \boldsymbol{x}_i) = exp\left\{-\frac{||\boldsymbol{x}-\boldsymbol{x}_i||^2}{\sigma^2}\right\}$.

From (1) and (4), the prediction model with LS-SVM is obtained as

$$\hat{y}(k+T) = \sum_{i=1}^{N} \alpha_i K(\boldsymbol{x}_i, \boldsymbol{x}_k) + b;\ \ k = N+1, \cdots, l. \tag{5}$$

where b and α are from δ_N, equ. (4) and l is the length of test signal.

The performance of LS-SVM relies on the correlation between the characteristics of training signal and the testing signal. High correlation yields high accuracy. As tremor signal is non-stationary in nature, the correlation factor is very less. In order to make effective estimation with LS-SVM, training set has to be updated at every iteration. Moreover, this incrementing of training set for every sample is computationally expensive. Several online training algorithms for SVMs have been previously proposed in [4], [6]. In this paper, we employed a similar online training approach for LS-SVM, [4], [6]. Further, few modifications are proposed for the online training of standard LS-SVM in order to make it suitable for real-time applications by reducing the computational complexity.

B. Moving window LS-SVM (MWLSSVM)

For online training of LS-SVM, whenever a new sample arrives, the trained offline LS-SVM is updated by incrementing the training set with the new sample and there by discarding the oldest sample in the training set as shown in Fig. 1. To decrease the computational complexity, incremental algorithm is employed to increment the training set and decremental algorithm to discard the oldest sample. This moving window training approach allows LS-SVM to track the non-stationary dynamics in the tremor signal more effectively.The incremental and decremental algorithms employed for MWLSSVM are discussed below:

1) Incremental algorithm: Let $(\boldsymbol{x}_{N+1}, y_{N+1})$ be a new data pair, then incremental algorithm updates the trained LS-SVM (of N data pairs) by adding the new data pair and then computes the inverse of the matrix in (4), for $N+1$ data pairs (Ψ_{N+1}), without explicitly calculating the inverse of matrix. From (4), the solution for the optimal conditions with the incremented training set ($N+1$ data pairs) is given by

$$\delta_{N+1} = \Psi_{N+1}^{-1}\ \mathbf{y}_{N+1} \tag{6}$$

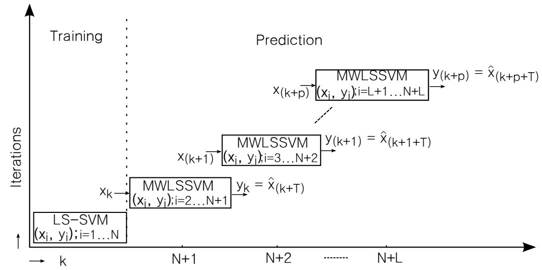


Fig. 1. Block diagram representation for tremor prediction with MWLSSVM

where $\delta_{N+1} = [b, \alpha_1, \cdots, \alpha_N, \alpha_{N+1}]^T$, $\Psi_{N+1} = \begin{bmatrix} \Psi_N & \mathbf{a} \\ \mathbf{a}^T & c \end{bmatrix}$, $\mathbf{a} = [1; K(\boldsymbol{x}_1; \boldsymbol{x}_{N+1}); \cdots; K(\boldsymbol{x}_N, \boldsymbol{x}_{N+1})]$, $c = C^{-1} + K(\boldsymbol{x}_{N+1}, \boldsymbol{x}_{N+1})$ and $\mathbf{y}_{N+1} = [\mathbf{y}_N\ \ \hat{y}_{k+T}]^T$.

Incremental algorithm updates Ψ_{N+1}^{-1} from Ψ_N^{-1} without explicit computation of the matrix inverse. The mathematical proof for calculating the augmented matrix is well documented in [7] and the main result is reproduced here:

$$\Psi_{N+1}^{-1} = \begin{bmatrix} \Psi_N^{-1} & \mathbf{0}^T \\ \mathbf{0} & 0 \end{bmatrix} + [c - \mathbf{a}^T\Psi_N^{-1}\mathbf{a}]^{-1} \begin{bmatrix} \Psi_N^{-1}\mathbf{a} \\ -1 \end{bmatrix} [\mathbf{a}^T\Psi_N^{-1}\ -1] \tag{7}$$

where Ψ_N^{-1} is obtained from trained LS-SVM, c and $\mathbf{a}$ are obtained from (6). The updated Lagrangian multipliers (α_{N+1}) and bias (b) due to the addition of new data pair are also calculated from (6).

2) Decremental algorithm: With this algorithm, the out-of-date information is removed from the training data pairs and this maintains a constant number of data pairs to perform multi-step prediction. Similar to the case of incremental algorithm, to avoid matrix inversion, Ψ_N^{-1} is updated from Ψ_{N+1}^{-1}, here Ψ_N^{-1} is the inversion of matrix Ψ_{N+1} without kth row and kth column.

Let $(\boldsymbol{x}_k, y_k)$ be the data pair to remove from the $N+1$ data pairs. Without explicitly calculating the matrix inversion for the N data pairs, the update rule was obtained in [6] as

$$\Psi_{ij} = \Psi_{ij} - \frac{\Psi_{ik}\Psi_{kj}}{\Psi_{kk}} \tag{8}$$

where $i, j = 1, \cdots, N$; $i, j \neq k$, Ψ_{ij} stands for ith row and jth column of Ψ_{N+1}^{-1}

From (4), the corresponding Lagrangian multipliers and bias values are computed for the updated N data pairs. With the updated Lagrangian multipliers and bias, prediction is performed with (5).

C. Multi-step prediction of tremor with MWLSSVM

To perform multi-step prediction of physiological tremor with MWLSSVM, consider N samples of tremor data to form a training set i.e, $\{\boldsymbol{x}_i, y_i\}_{i=1}^{N}$; where $\boldsymbol{x}_i$ represents tremor signal $x(k)$ and past n samples of $x(k)$ i.e. $\boldsymbol{x}_i = [x(k), x(k-1), \cdots, x(k-n)]$ and y_i is T samples ahead value for $\boldsymbol{x}_i$ i.e. $y_i = x(k+T)$.Algorithmic representation for the procedure employed for predicting tremor by updating the training set at each instant of time with MWLSSVM is provided in Algorithm 1.

Initialize: Number of training sets (N), Constant (C), Kernel variance (σ^2) and Number of samples ahead prediction (T)
Offline training: Solve (4), store Ψ_N^{-1}.
while *when a new sample arrives* **do**
  Incremental algorithm:
  increment the trained LS-SVM training set;
  compute Ψ_{N+1}^{-1} with (6);
  Decremental algorithm:
  discard the oldest sample in training set;
  compute new Ψ_N^{-1} from (8);
  Prediction:
  update the parameters, Lagrangian multipliers and bias from (4);
  perform tremor prediction with (5);
end

Algorithm 1: MWLSSVM for tremor prediction

III. Results

In this section, we first discuss about the physiological tremor data collection. Later, performance analysis of MWLSSVM for single-step tremor prediction and multi-step prediction is discussed.

The performance analysis of all methods are discussed with tremor data of 5 subjects with 4 trials/subject. To quantify the performance, we employ the root mean square (RMS) defined as $RMS(s) = \sqrt{(\sum_{k=1}^{k=m}(s_k)^2/m)}$, where m is the number of samples and s_k is the input signal at instant k. Based on RMS, $\%Accuracy$ is defined as

$$\%Accuracy = \frac{RMS(s) - RMS(e)}{RMS(s)} \times 100;$$

where e is the prediction error between the actual signal and the predicted signal.

A. Physiological Tremor Data

Physiological tremor data of 5 subjects, 4 trials data per subject is considered for analysis in this paper. Two tasks (tracking and tracking) are performed by the subjects. Sampling rate of 250 Hz is employed. For more information on data collection, protcol and conditions, see [8].

B. Parameter Selection for MWLSSVM

Performance of MWLSSVM mainly relies on the initialization of parameters: number of training samples (N), variance in RBF kernel (σ) and the constant (C). To identify the optimal values to initialize these parameters, a study was conducted on tremor data over a range of parameters to attain minimum RMS.

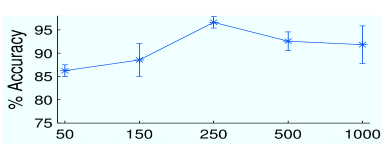
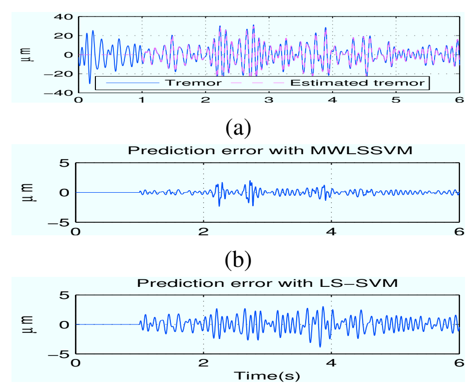


Fig. 2. Selecting the optimal value of N for tremor modeling.

Selection of optimal number of samples (N), required for offline training is crucial for accurate prediction. For identification, the estimation accuracy obtained with MWLSSVM for various number of training samples is shown in Fig. 2. Results show that $N = 250$ is the optimal number of training samples required for tremor prediction with MWLSSVM. To find the optimal values to initialize C, σ and n, we conducted a study on estimation accuracy over a range for all parameters for constant $N = 250$. The identified parameters are provided in Table. II. Further, these values remained constant with very less variation for different values of N.

1) Single-step prediction with MWLSSVM: To perform single step prediction with MWLSSVM, the 1 sec (N=250) data of Subject #3(tracing task) is used for training the LS-SVM. The proposed approach is employed for single-step prediction from 1 sec onwards. Actual tremor and estimated signal with MWLSSVM is shown in Fig. 3(a). The prediction error is shown in Fig. 3(b). For comparison, LS-SVM method is employed for prediction and the estimation error obtained is shown in Fig. 3(c). The average estimation accuracy obtained for single-step prediction with MWLSSVM for 5 subjects tremor data over all trials is $96.62 \pm 1.24\%$.



(c)

Fig. 3. (a) Tremor signal (Subject #3, tracing task) along with estimated signal by MWLSSVM; (b) Prediction error with MWLSSVM; (c) Prediction error with Standard LS-SVM.

Recently, in [2], a comparative study was conducted on all existing adaptive tremor estimation methods. In order to validate our proposed approach, we compared the estimation accuracy of MWLSSVM with BMFLC-KF [2], WFLC-KF [2] and LS-SVM. Results are tabulated in Table. I. MWLSSVM shows good estimation performance.

TABLE I
Comparison with Existing Methods

S.No.	Method	% Accuracy
1	WFLC-KF	92.43 ± 0.64
2	BMFLC-KF	99.97 ± 0.02
3	LS-SVM*	94.54 ± 2.56
4	MWLSSVM	96.62 ± 1.24

**Initialization for LS-SVM is same as MWLSSVM*

2) Multi-step prediction: In general, to filter the tremor data from the sensed motion (voluntary and tremor motion), 5th order Butterworth filter with pass band 7-14 Hz is employed in surgical robotic devices [1], [3]. This filtering stage introduces a delay of approximately $20ms$ in tremor compensation procedure. In the presence of this frequency dependent delay, estimation accuracy drops to $8 \pm 1\%$. For illustration, the prediction error obtained with MWLSSVM for single step prediction in the presence of phase delay is shown in Fig. 5(b). In order to improve the estimation accuracy in the presence of phase delay, multi-step prediction of tremor with MWLSSVM is performed.

TABLE II

METHODS & PARAMETERS

Method	Model parameters and initial conditions
WFLC-KF	$f_0 = 7$ Hz; $\mu_0 = 1.10^{-5}$; $\mu_1 = 5.10^{-4}$; $M = 1$; $R = 0.01$;$\mathbf{Q} = 0.01 \times \mathbf{I}$; $\mathbf{P}_0 = 0.01 \times \mathbf{I}$;
BMFLC-KF	$\omega_1 - \omega_n = 7 - 14$ Hz; $\Delta\omega = 0.1$; $R = 0.01$; $\mathbf{Q} = 0.01 \times \mathbf{I}$; $\mathbf{P}_0 = 0.01 \times \mathbf{I}$;
MWLSSVM	$N = 250$; $C = 100$; $\sigma = 0.0001$; $n = 12$;

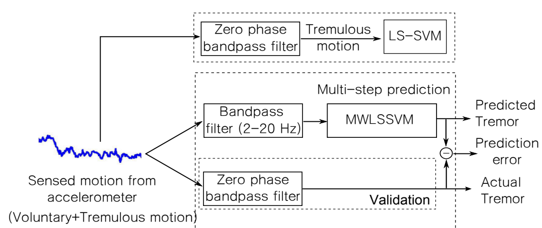


Fig. 4. Procedure employed for multi-step prediction with MWLSSVM.

The procedure employed to perform multi-step prediction with MWLSSVM is shown in Fig. 4. In the testing phase to analyze the performance of multi-step prediction with MWLSSVM, frequency dependent delay is introduced by employing a bandpass filter as shown in Fig. 4. As delay of 16-20ms is involved due to the pre-filtering, we performed multi-step prediction for 20 ms (5 samples). To quantify the performance, analysis is conducted on tremor data of 5 subjects with 4 trials/subject. The average estimation accuracy obtained is $60.1 \pm 6.85\%$. To validate the proposed method, we also present the performance analysis of MWLSSVM together with WFLC-KF [9] and standard LS-SVM in Table. III. For illustration, prediction error for all methods with 20ms of prediction is shown in Fig. 5Results show that proposed multi-step prediction method improves estimation accuracy by more than 50% compared to single-step prediction methods. Moreover, proposed method outperforms other existing multi-step tremor prediction methods.

TABLE III

MULTI-STEP PREDICTION PERFORMANCE ANALYSIS

S.No.	Method	% Accuracy
1	WFLC-KF [9]	42.54 ± 2.64
3	LS-SVM	52.32 ± 8.56
4	MWLSSVM	60.1 ± 6.85

IV. CONCLUSIONS

In this paper, multi-step prediction of tremor is employed to improve the estimation accuracy in the presence of phase delay. The effectiveness of the proposed technique MWLSSVM has been analyzed with tremor data of several subjects thru simulation results. An average estimation accuracy of 60% is obtained with the multi-step prediction with MWLSSVM for 20 ms ahead prediction.

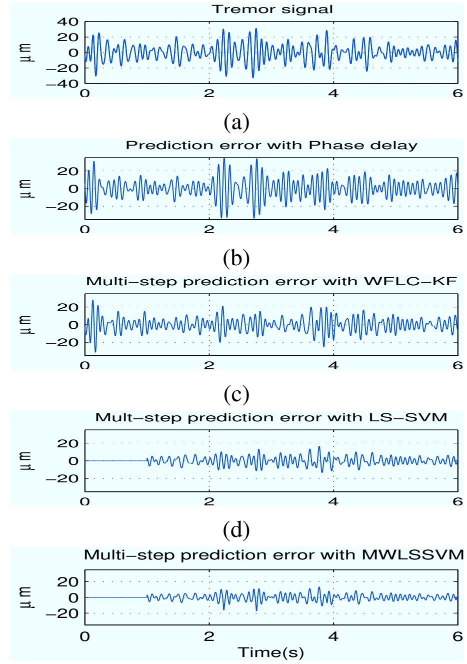


Fig. 5. Multi-step prediction error with prediction horizon of 20ms (5 samples) (a) Tremor signal (Subject #3, tracing task) ; (b) Single-step prediction error due to frequency dependent phase delay; (c-e) Multi-step prediction error with WFLC-KF, LS-SVM and MWLSSVM respectively.

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