Adhikari K, Tatinati S, Veluvolu KC, Chambers JA, Nazarpour K. [Real-time physiological tremor estimation using recursive singular spectrum analysis](#).

In: Proceedings of the 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 2017, Seogwipo, South Korea: IEEE.

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DOI link to article:

<https://doi.org/10.1109/EMBC.2017.8037538>

Date deposited:

30/01/2018

Real-time Physiological Tremor Estimation using Recursive Singular Spectrum Analysis

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Abstract—Physiological hand tremor causes undesirable vibration of hand-held surgical instruments which results in imprecisions and poor surgical outcomes. Existing tremor cancellation algorithms are based on detection of the tremulous component from the whole motion; then adding an anti-phase tremor signal to the whole motion to cancel it out. These techniques are based on adaptive filtering algorithms which need a reference signal that is highly correlated with the actual tremor signal. Hence, such adaptive approaches use a non-linear phase filter to pre-filter the tremor signal either offline or in real-time. However, pre-filtering causes unnecessary delays and non-linear phase distortions as the filter has frequency selective delays. Consequently, the anti-phase tremor signal cannot be generated accurately which results in poor tremor cancellation. In this paper, we present a new technique based on singular spectrum analysis (SSA) and its recursive version, that is, recursive singular spectrum analysis (RSSA). These algorithms decompose the whole motion into dominant voluntary components corresponding to larger eigenvalues and oscillatory tremor components having smaller eigenvalues. By selecting a group of specific decomposed signals based on their eigenvalues and spectral range, both voluntary and tremor signals can be reconstructed accurately. We test the SSA and RSSA algorithms using recorded tremor data from five novice subjects. This new approach shows the tremor signal can be estimated from the whole motion with an accuracy of up to 85% offline. In real-time, tolerating a delay of ≈ 72 ms, the tremor signal can be estimated with at least 70% accuracy. This delay is found to be one-tenth of the delay caused by a conventional linear-phase bandpass filter to achieve similar performance in real-time.

I. INTRODUCTION

Physiological tremor is an unintended rhythmic movement of body parts, which is mainly visible in hands while performing a task requiring high precision [1]. The physiological tremor is not an extreme form of tremor and is not related to any clinical conditions unlike pathological tremor. All healthy humans exhibit physiological tremor and its maximum amplitude can range from $50\mu\text{m}$ to $100\mu\text{m}$ in each of the xyz axes [2]. The physiological tremor frequency band can vary from person to person but it can have multiple dominant spectral peaks spread between 6Hz

to 14Hz [2]. The amplitude of the physiological tremor does not cause movement problem in daily life. However, microsurgical procedures require surgeons to manipulate tissues and nerves with microlevel positioning accuracy, e.g. $10\mu\text{m}$ [3]. Hence any unintended vibrations originated from physiological tremor can result in poor surgical outcomes causing undesirable nerve and tissue damage. The literature suggests that for real-time applications, tremor compensation of 70% would lead to acceptable results [2].

The voluntary motion is a combination of sub movements between 1Hz to 4Hz [4]. The spectral components of physiological tremor reside above 4Hz, which suggests a linear phase FIR bandpass filter can be used to filter out the tremor. However, to obtain a sharp roll-off, the filter order needs to be high, hence a delay of 1.5s-2s is inevitable. There is a general agreement among researchers that such a linear phase filter should be avoided due to the latency it adds to the system [5], [6].

To address this problem, Riviere [1] proposed a smart hand-held device which is capable of sensing its own motion, differentiating between voluntary and tremulous motion, and actuating the tip with the same amplitude, but opposite in direction, without any time delay. Adaptive noise cancellation algorithms were investigated to track an unknown tremor amplitude and spectrum from the whole motion. These adaptive approaches require a reference signal that is highly correlated with the tremor signal. Hence, the tremor signal is often pre-filtered using a non-linear phase IIR bandpass filter [1]. This non-linear phase filter causes frequency selective delay which distorts the tremor signal. Keeping all spectral components of the tremor 100% in phase is extremely important to preserve the shape of the reconstructed tremor signal; otherwise the system fails to accurately generate an anti-phase tremor signal yielding poor cancellation.

Singular spectrum analysis (SSA) is a well-established technique for time series analysis [7]. It decomposes a time series into a number of interpretable components, such as a slowly varying trend, some cycles with different periods and even the structureless noise. It is based on the singular value decomposition (SVD) of a covariance matrix constructed from the time series. Being a non-parametric model, the SSA algorithm can be applied in a wide range of time series analysis applications such as in economics and financial mathematics, oceanography, social science, and bio-engineering [7]. Motivated by this and to overcome the latency and phase distortion caused by digital filters, we investigated the basic SSA and recursive singular spectrum

The work of KA is supported by Newcastle University. The work of K. Nazarpour is supported by EPSRC (EP/M025977/1 and EP/M025594/1).

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analysis (RSSA) algorithms on hand tremor data recorded from five novice subjects.

In this paper, we present a brief overview of the SSA and RSSA techniques in the next section, followed by the results obtained from offline and real-time SSA in Section III. Finally, we present conclusions and future work in Sections IV and V, respectively.

II. SINGULAR SPECTRUM ANALYSIS (SSA)

The basic SSA method consists of two main stages, decomposition and reconstruction, each of which has two sub-stages, namely *Decomposition* and *Eigentriple grouping*.

A. Decomposition

The decomposition stage involves an embedding followed by a SVD.

1) *Embedding*: Firstly, the one-dimensional time series $\mathbf{x} = (x_1, x_2, \dots, x_N)$ is mapped into multi-dimensional series of lagged vectors, $\mathbf{X} = [X_1, X_2, \dots, X_K]$. Each vector is of length L , hence for a time series of length N , the total number of L lagged vectors is $K = N - L + 1$. The parameter L is called window length and can range between $2 \leq L \leq N - 1$. The matrix $\mathbf{X}$ forms a L -lagged trajectory matrix whose elements in ascending diagonals are equal. This is a Hankel matrix $\mathbf{X}$ [7].

$$\begin{aligned} \mathbf{X} &= [X_1 : X_2 : \dots : X_K] \\ &= \begin{bmatrix} x_1 & x_2 & \dots & x_K \\ x_2 & x_3 & \dots & x_{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_L & x_{L+1} & \dots & x_N \end{bmatrix}_{L \times K} \end{aligned} \quad (1)$$

2) *Singular value decomposition (SVD)*: The SVD transformation of the sample covariance matrix $\mathbf{S} = \mathbf{X}\mathbf{X}^T$ is performed so that $\mathbf{S}$ can be expressed as $\mathbf{S} = \mathbf{U}\mathbf{\Lambda}\mathbf{V}^T$. The eigenvalues $[\lambda_1, \lambda_2, \dots, \lambda_L]$ are sorted in descending order and the orthonormal eigenvectors $\mathbf{U} = [U_1, U_2, \dots, U_L]$ corresponding to those eigenvalues are sorted similarly. The second set of eigenvectors (factor vectors) $\mathbf{V}$ is then calculated using $V_i = \mathbf{X}^T U_i / \sqrt{\lambda_i}$ where $(i = 1, 2, \dots, L)$. Hence, the trajectory matrix $\mathbf{X}$ can now be expressed as L matrices.

$$\mathbf{X} = \mathbf{X}_1 + \mathbf{X}_2 + \dots + \mathbf{X}_L, \quad (2)$$

where $\mathbf{X}_i = \sqrt{\lambda_i} U_i V_i$ where $(\sqrt{\lambda_i} U_i V_i)$ is the i_{th} eigentriple group, which forms an elementary matrix $\mathbf{X}_i$.

B. Reconstruction

At this stage, the signal is reconstructed from the selected elementary matrices, using two steps 1) *Eigentriple grouping* and 2) *Diagonal averaging*.

1) *Eigentriple grouping*: Depending on whether the signal of interest is a slow varying trend or oscillatory signal of certain periods, the elementary matrices are respectively grouped together. Normally, the first few eigentriples with high eigenvalues represent the dominant component of the signal and the last few just noise. Hence, former elementary

matrices corresponding to the higher eigentriple can be grouped together to extract important information. Mathematically,

$$\mathbf{X}_I = \mathbf{X}_{I_1} + \mathbf{X}_{I_2} + \dots + \mathbf{X}_{I_m}. \quad (3)$$

where $\mathbf{X}_I$ is the trajectory matrix of the desired signal, and the matrices on the right-hand side of (3) are its constituent elementary matrices.

$$\mathbf{X}_I = \begin{bmatrix} \hat{x}_{11} & \hat{x}_{12} & \dots & \hat{x}_{1K} \\ \hat{x}_{21} & \hat{x}_{22} & \dots & \hat{x}_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{x}_{L1} & \hat{x}_{L2} & \dots & \hat{x}_{LK} \end{bmatrix}_{L \times K} \quad (4)$$

This process of grouping sets of eigentriples $I_1, \dots, I_m$ is called eigentriple grouping.

2) *Diagonal averaging*: Once the trajectory matrix is computed as shown in (3) and (4), the desired sub-series are computed by diagonal averaging of the elementary matrix $\mathbf{X}_I$. Diagonal averaging is necessary as the reconstructed matrix, $\mathbf{X}_I$, is not a Hankel matrix. Hence averaging it cross diagonally leads to an accurate estimation of the sub-series of interest $\hat{\mathbf{x}}_N$ which can be expressed with

$$\hat{\mathbf{x}}_N = (\hat{x}_1, \hat{x}_2, \hat{x}_3 \dots \hat{x}_N) \quad (5)$$

where

$$\begin{cases} \hat{x}_1 = \hat{x}_{11} \\ \hat{x}_2 = (\hat{x}_{12} + \hat{x}_{21})/2 \\ \hat{x}_3 = (\hat{x}_{13} + \hat{x}_{22} + \hat{x}_{31})/3 \\ \dots \\ \hat{x}_N = \hat{x}_{LK} \end{cases}$$

C. Recursive singular spectrum analysis (RSSA)

In the basic SSA setting, the covariance matrix is formed using all of the data and then the SVD transformation is performed. In the real-time version, the covariance matrix is formed using the first $k-1$ number of samples as in the basic SSA algorithm. Once the k_{th} sample arrives, this covariance matrix is updated to form the weighted covariance matrix $\mathbf{S}_w(k)$ as in (6).

$$\mathbf{S}_w(k) = (1 - \gamma)\mathbf{S}_w(k-1) + \gamma X_K X_K^T, \quad (6)$$

where $\gamma = 1/k$ is the forgetting factor and X_K is the last column of matrix $\mathbf{X}$ as shown in (1).

Then the SVD and eigentriple grouping are performed on $\mathbf{S}_w(k)$ to obtain the k_{th} sample of the desired sub-series [8]. As shown in (4) and (5), the k_{th} sample is the last element of the Hankelized matrix $\mathbf{X}_I$; hence there is no need to diagonal average the matrix to reconstruct this element, as $x_k = \hat{x}_N = \hat{x}_{LK}$.

D. Performance Analysis

To measure the performance of SSA and RSSA we calculate tremor estimation accuracy in percentage: Accuracy(%). For validation we have pre-filtered (offline) the voluntary motion from the recorded whole motion using a 5th-order zero-lag Butterworth filter with a cut-off frequency of 5Hz. This forward-backward filtering technique obtains the voluntary

motion without any phase delay hence it serves as a ground truth for performance validation. This filtering technique is only feasible offline and cannot be implemented in real-time applications. The actual tremor signal is then obtained by deducting this pre-filtered voluntary motion from the whole motion. The Accuracy(%) becomes,

$$Accuracy(\%) = \frac{RMS(x_k) - RMS(e_k)}{RMS(x_k)} \times 100\%, \quad (7)$$

where $RMS(x_k) = \sqrt{\frac{1}{N} \sum_{k=1}^N x_k^2}$, and $RMS(e_k) = \sqrt{\frac{1}{N} \sum_{k=1}^N (x_k - \hat{x}_k)^2}$.

The variables x_k , $\hat{x}_k$ and e_k represent the actual tremor signal, estimated tremor signal and the error between the actual and estimated tremor signal respectively.

E. Experimental Setup

Tremor recordings were taken at 250Hz using the Micro Motion Sensing System (M²S²). The system has an integrated microsensing system containing two orthogonally-placed position sensitive detectors [9]. The subjects were asked to hold an instrumented stylus (similar to microsurgical forceps) between their index and thumb fingers. They were seated facing to the 19" 2-D flat LCD TV monitor where two two dots were displayed for visual feedback. One was a fixed white dot and another an orange dot which moved according to the tool tip position held by the subjects. The subjects had to overlap the orange dot with the white for 30s [9]. The 3-D position of the hand movement was measured by the 3-D (x, y and z) displacement of a small white ball, that was placed at the tip of the stylus. The position was calculated by the reflected infra-red rays onto the detectors. For more details please refer to [10]–[12].

III. RESULTS

The window length L is the only parameter of the SSA algorithm which determines the accuracy of the decomposition of a signal. If a time series has a periodic component with an integer period, to achieve separability of that component, L should be chosen proportional to that period. Hence we performed SSA on 5 novice subjects' data across x, y , and z axes independently with L varying from 15 to 400.

Figure 1 shows the SSA performance peaks at $L = 20, 42, 67$, and 119 with estimation accuracy of 70.6%, 82.3%, 85%, 83.7% and 84.3%, respectively. The performance at $L = 42$, and 67 are comparable, but the computation time at $L = 67$ is $2.68 \times$ larger than that at $L = 42$. Hence, we chose $L = 42$ for testing of the basic SSA and RSSA algorithms. At $L = 42$, the average tremor estimation accuracy is above 70%, which is required for the tremor compensation.

Figure 2 shows how a basic SSA successfully decomposes the whole motion into slow varying voluntary motion, oscillating tremor signal with different periods and noise. The

Fig. 1. Tremor estimation Accuracy(%) across 5 subjects, averaged across the x, y and z axes.

Fig. 2. At $L = 42$, data decomposition of Novice subject 1 in the z -axis (vertical movement). A) Whole Motion B) Zero-phase filtered voluntary motion C) Zero-phase filtered tremor motion D-O) First twelve SSA decomposed components of whole motion.

plots D-O show the first twelve significant components, each reconstructed using an eigentriple set arranged in descending order corresponding to their eigenvalues. The rest of the components (after the first twelve components) correspond to low eigenvalues hence they represent the noise. Since the signals to be reconstructed are narrow-band with known frequency range, components are grouped automatically according to their frequencies, obtained using the Fourier transform. This process is repeated for all twelve components to determine whether they are to be grouped together as the voluntary motion (below 4Hz) or the tremulous motion (between 5Hz to 16Hz) or noise (above 16Hz). The dominant frequencies obtained for the first two components, D and E were below 4Hz hence they are grouped together to be voluntary motion B. The components F to J are grouped together to form the tremulous motion C and components after J are assumed to

Fig. 3. Tremor estimation Accuracy(%) for 5 subjects, averaged across the x , y and z axes at a delay of 22 samples, 20 samples, 18 samples, 16 samples and 14 samples. Error bars show deviation across three axes.

be noise.

To validate the performance of the SSA in real-time, we implemented the RSSA algorithm on the same data. Using the RSSA algorithm, we found that, performance drops significantly below the required limit of 70% if estimation is performed with no delay, however if a delay of a certain number of samples is tolerated, the required estimation performance can be achieved. Figure 3 shows estimation accuracy of $\geq 70\%$ can be achieved with a lag of 18 samples ($18 \times 4ms = 72ms$). The accuracy increases with further increase of the delay. The testing performed on several linear phase FIR bandpass filters showed the similar performance accuracy could be achieved, but the filter order needs to be as high as 700. Thus it contributes impractical delay between 1.5s-2s. Although a non-linear phase IIR filter performs filtering with less delay, in real-time its performance is very weak, below the benchmark in accuracy, due to its frequency selective delay.

IV. CONCLUSIONS

We have presented an investigation of the RSSA algorithm which shows it can be a promising method for physiological tremor estimation in real-time, improving upon previous adaptive filter-based approaches. Being a non-parametric and model free approach, RSSA is a suitable choice for tremor estimation; as the physiological tremor is a non-stationary signal and also it varies from person to person. The RSSA algorithm does not cause frequency selective delay unlike non-linear phase filters, hence the filtered out spectral components will be 100% in phase. This preserves the natural shape of the tremor signal, hence the tremor signal can be extracted accurately. Performance of the RSSA algorithm in real time was found to be comparable with a high performing linear phase FIR bandpass filter but with one-tenth of the delay.

V. FUTURE WORK

Future work will include implementing the RSSA algorithm on the data recorded from expert surgeons and

novice subjects performing other tasks, such as tracking an instructed trajectory path; and surgeons performing a pointing task to hold the stylus to point at the centre of the platform. This will further validate the performance of RSSA across a wide range of subjects. Other two main areas of investigation would include: investigating prediction algorithms to reduce the current delay offered by RSSA and extending the RSSA algorithm to multidimensional and quaternion RSSA, as our previous work shows processing tremor signal in the quaternion domain yields better results due to xyz cross-axis temporal dependency [12], [13].

ACKNOWLEDGMENT

The authors thank Dr Wei Tech Ang at Nanyang Technological University, Singapore for provision of data.

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