Multi-step Prediction of Pathological Tremor With Adaptive Neuro Fuzzy Inference System (ANFIS)

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Abstract- In this paper, to overcome the inevitable phase delay due to pre-filtering techniques and electromechanical delay in the procedure of pathological tremor compensation, a machine learning technique based on fuzzy logic and neural networks (adaptive neuro fuzzy inference system (ANFIS)) is employed. Experimental evaluation on tremor data is performed with data acquired from eight patients. Results show that ANFIS provides good performance in comparison with existing methods.

I. Introduction

Pathological tremor is defined as an involuntary and approximately rhythmic oscillations of a body part [1]. Pathological is one of the serious disabling forms of tremors and often accompanies with aging. Although pathological tremor is not a life-threatening disorder, but it hampers the ability of individual to perform daily living activities like drinking water with a glass, unlock the door with a key etc. Further, the inability due to tremor leads to social embarrassment [1]. To compensate the functional disability (tremor) thereby to improve the quality of life, several pharmaceutical and surgical therapies are developed. The methods have their limitations and side effects. So, an effective treatment that can compensate tremor accurately yet to be developed.

Over the last decade, considerable research has been focussed on developing active pathological tremor compensation techniques in real-time [3], [4], [6], [7]. One such approach is compensating pathological tremor by stimulating the relevant muscle groups with appropriate electric pulses thru functional electrical stimulator (FES) [3]. For example, consider hand supination-pronation muscle group, if tremor is due to the supination muscle group necessary electric pulses will be provided to pronation muscle group to counteract the involuntary movement, and viceversa. To compensate the tremor, a wearable device named as WOTAS (wearable orthosis for tremor assessment and suppression) was developed by using a feedback controlled FES.

The efficacy of the wearable devices depends on the accurate and zero-phase delay filtering of tremulous motion from the whole motion. In the tremor compensation procedure with FES, a delay of approximately 80 ms was identified. The major source for the delay is electromechanical delay (EMD), defined as the delay between the onset of activation of muscle and the detection of movement [2]. As a result of several studies, the EMD was identified in the range of 50-60 ms [2]. The other source for delay is the pre-filtering stage which is used to separate the voluntary motion and tremulous motion from the whole sensed motion [7]. On a whole, a latency of 80 ms was inevitable in the procedure and this delay adversely affects the tremor compensation accuracy.

To overcome the phase delay limitation, multi-step prediction with harmonic method and Autoregressive method was proposed in [4]. The developed methods yield accurate prediction with periodic signals. Owing to the quasi-periodic nature of the tremor signals, prediction accuracy with the above methods is rather limited. To further enhance the prediction capabilities, in this work, we employed a machine learning technique, adaptive neuro fuzzy inference system (ANFIS). ANFIS has been recently popular as an effective method for time series prediction, function estimation, system identification and classification problems.

The goal of ANFIS is to find a model or mapping that will correctly associate the inputs (initial values) with the target (predicted values). The fuzzy inference system (FIS) is a knowledge representation where each fuzzy rule describes a local behaviour of the system. The network structure that implements FIS and employs hybrid-learning rules to train is called ANFIS. The paper is organized as follows: In section II, tremor data collection, delay in the procedure and the method employed are discussed. In the later section results obtained with ANFIS are presented. The last section presents the conclusions.

II. Methods

In this section, we first discuss about the collection of pathological tremor data. Later the detailed description regarding the delay associated in tremor compensation procedure and a brief description about ANFIS are presented.

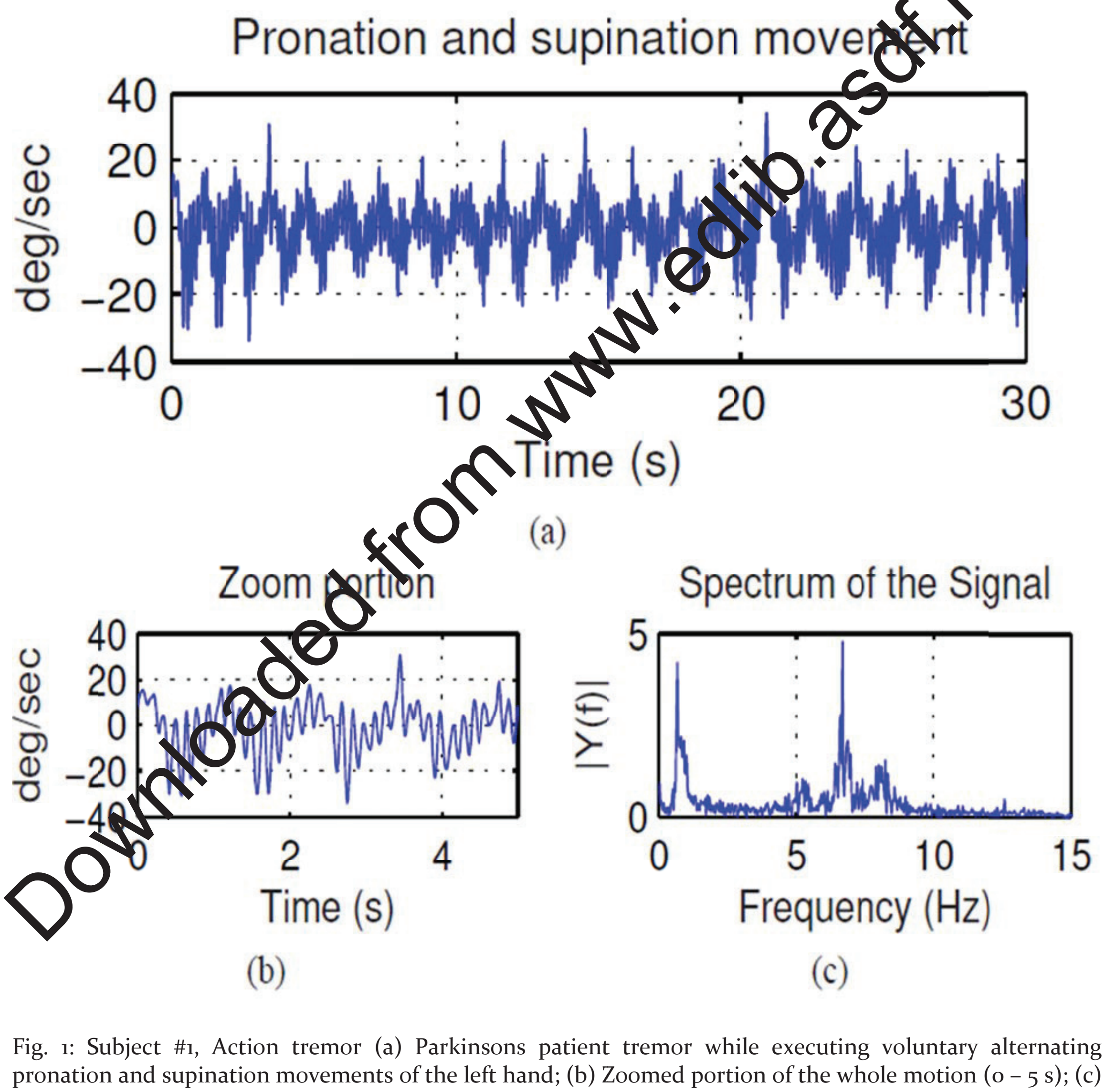

Fig. 1: Subject #1, Action tremor (a) Parkinsons patient tremor while executing voluntary alternating pronation and supination movements of the left hand; (b) Zoomed portion of the whole motion (0 – 5 s); (c) FFT of the whole motion

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A. Pathological Tremor data

Tremor is acquired with a portable Motus system comprises a gyroscope placed on the patient's wrist without objecting free flow of any motion [8]. All the subjects sign the informed consent forms approved by the Ethics Committee of local hospital. The sampling rate employed is 100 deg/sec. The collected pathological tremor data set contains postural tremor, parkinsonian tremor and essential tremor. In this work for analysis, four subjects' action tremor (tremulous motion collected while performing a voluntary motion) and four subjects postural tremor are employed. For an illustration, action tremor collected from a parkinsonian patient while voluntarily performing pronation and supination movement with left hand as shown in Fig. 1. FFT of the signal is also shown in Fig. 1(c).

B. Latency in Tremor Compensation Procedure With FES

The phase delay in wearable devices with FES is due to the two sources: pre-filtering stage and EMD. In pre-filtering stage, to filter the tremulous motion from whole sensed motion, a Butterworth low-pass filter/Butterworth band-pass filter was employed. From the phase response, a average delay of 300 ms was identified for fifth order Butterworth low-pass filter, where as with fifth order butterworth band-pass filter with pass band 2-20 Hz a delay of 20ms was identified [7]. In the presence of either delays the prediction accuracy was adversely effected. EMD, in general a delay of 80§20 ms exists between peak muscle force and the apparent peak in EMG [2]. In [2], a delay of 40-60 ms was identified between surface EMG and force acquired form the flexion and extension muscle group in forearm.

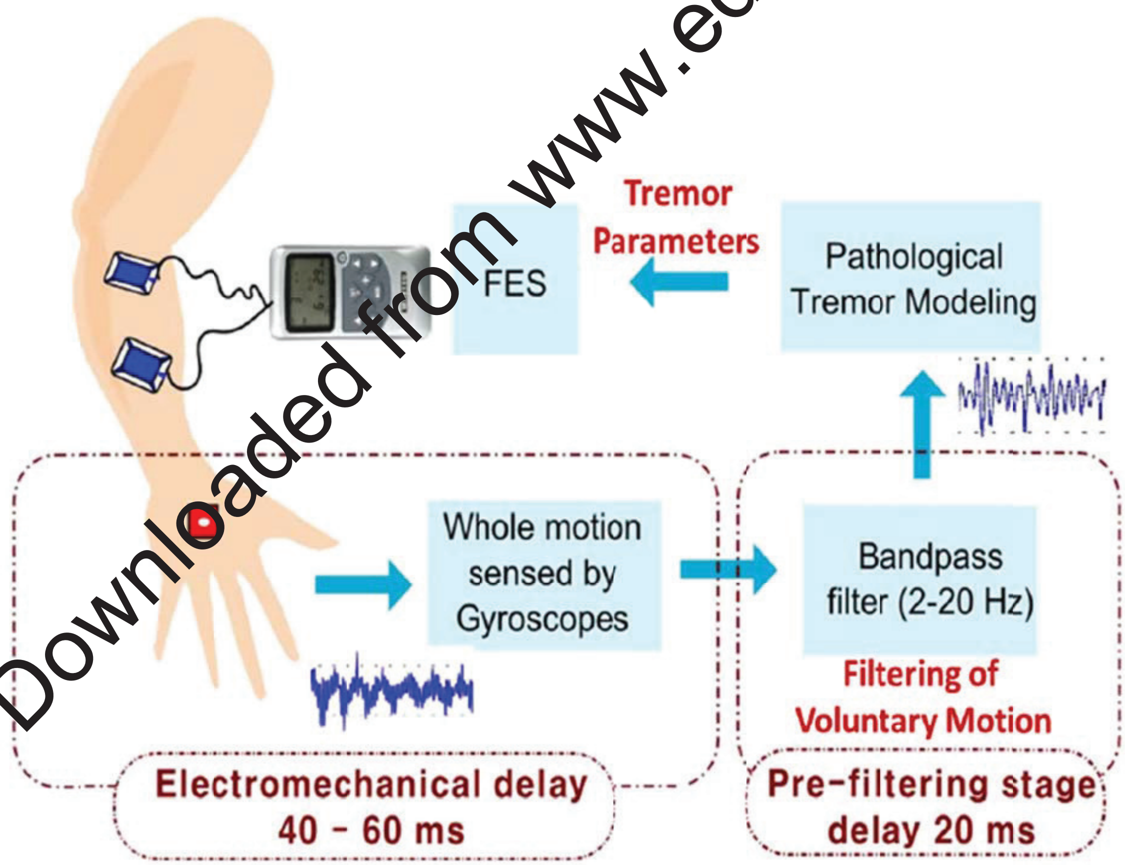

Fig. 2: Delay in tremor suppression procedure with FES

Thus a total delay of 60-80 ms is inevitable in the procedure, as shown in Fig. 2. With the sampling frequency, 100Hz, for a signal with frequency ranges from 6-12 Hz, the delay of 6 to 8 samples corresponds to about 90± phase difference. With this phase difference tremor suppression ability is drastically decreased. To overcome this delay, multi-step prediction based on ANFIS is developed in this paper.

C. Adaptive Neruo Fuzzy Inference System (ANFIS)

A neuro-Fuzzy system is inspired from the supervisory human brain's feed forward activities therefore this intelligent hybrid system enjoys both the metrics of neural system and fuzzy logic approaches.

A brief description of ANFIS is provided below. For detailed description of the algorithm and its implementation refer to [5].

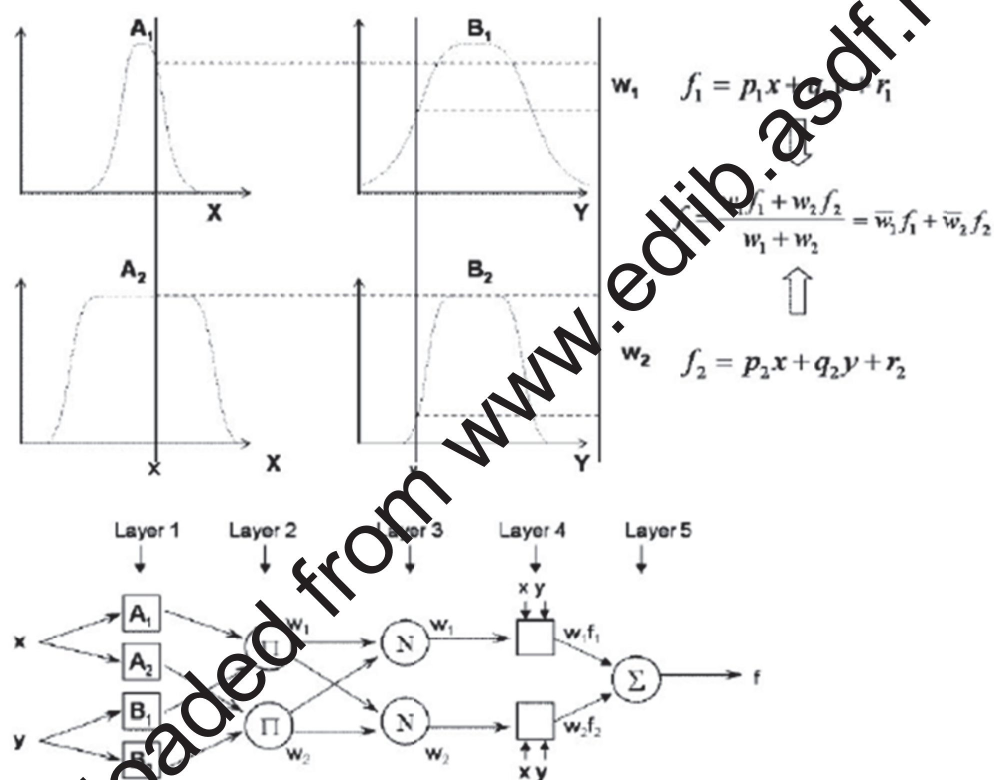

Fig. 3: Sugeno type fuzzy model illustration and ANFIS architecture [5]

In general, ANFIS structure follows the takagi-sugeno fuzzy sets with set of rules (combination of numerical and linguistic variables) and multi-layers (5 layers), as shown in Fig. 3. In this connected structure, the input nodes represents the training values and output nodes represents predicted values, and in the hidden layers nodes functioning as membership functions (MF's) and rules. All nodes in different layers of ANFIS are either fixed or adaptive, as shown in Fig. 3 [5]. Different layers and their corresponding nodes can be described as below:

- Layer 1: All nodes in this layer are adaptive. Further, parameters in this layer are named as premise parameters.

- Layer 2: All nodes in this layer are labelled as ¦ and are fixed. The output obtained from this layer is the product of all the inputs. Further, the firing strength of each rule is represented by each node in this layer.
- Layer 3: Like layer 2, each node in this layer is also fixed and labelled as *N*. In this layer, I th node computes the ratio of firing strengths of ith rules. Thereby, the outputs of this layer are named as normalized firing strengths.
- Layer 4: In this layer, all nodes are adaptive. The parameters corresponds to all nodes in the layer are referred as consequent parameters.
- Layer 5: This layer contains only one node and that node is also fixed and labelled as P. The node computes the overall output of the system by summations of all inputs to the node.

The parameters of ANFIS are optimized with combination of gradient descent and least squares method. Least-squares method is employed to update the parameters iteratively in the forward pass until layer 4. The gradient descent method is to update the premise parameters with the obtained error signal in backward pass. The error measure to train the above-mentioned ANFIS is *E* = P*n* *k*=1(*fk* − ^ *fk*)2 where *fk* and ^ *fk* are the k th desired and estimated output, respectively, and n is the total number of pairs (inputs outputs) of data in the training set.Due to the implication of two update algorithms, the convergence of is faster and reduce the search space dimensions due to back propagation algorithm. The overall output can be expressed as a linear combination of the consequent parameters, as shown
in Fig. 3.

D. Multistep prediction of pathological tremor with ANFIS

The procedure employed to perform multi-step prediction with ANFIS is shown in Fig. 4. To perform multi-step prediction, a two-dimensional matrix of dimensions 100025 (each row being referred to as an epoch) was constructed as shown in (1). Data points in each row were chosen to be six steps apart and each epoch contained one data points:

$$\begin{bmatrix} s(t-24) & s(t-18) & s(t-12) & s(t-6) & s(t) \\ s(t-18) & s(t-12) & s(t-6) & s(t) & s(t+6) \\ \cdots & & & & \end{bmatrix} \quad (1)$$

ANFIS was trained with the first 500 epochs. With the training epochs, weights of neural network and the membership functions will be optimized for accurate prediction (with cost function as minimum mean square error). The optimized parameters obtained with the training epochs are employed for the testing epochs to perform the multi-step prediction.

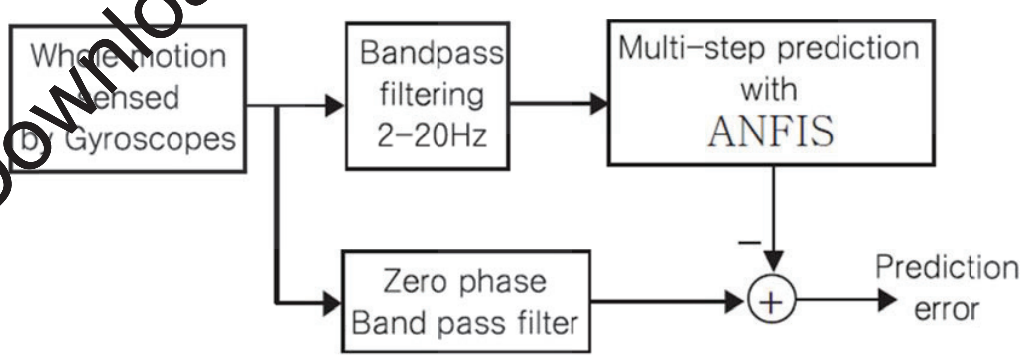

Fig. 4: Multistep prediction of pathological tremor with ANFIS

III. Results

In this section, we analyze the multi-step ahead tremor prediction performance with ANFIS thru simulations. To quantify the performance, we employ %*Accuracy*, defined as:

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

where $RMS(s) = \sqrt{(\sum_{k=1}^{k=m}(s_k)^2/m)},$ m is the number of samples, sk is the input signal at instant k and e is the prediction error.

A. Performance Analysis

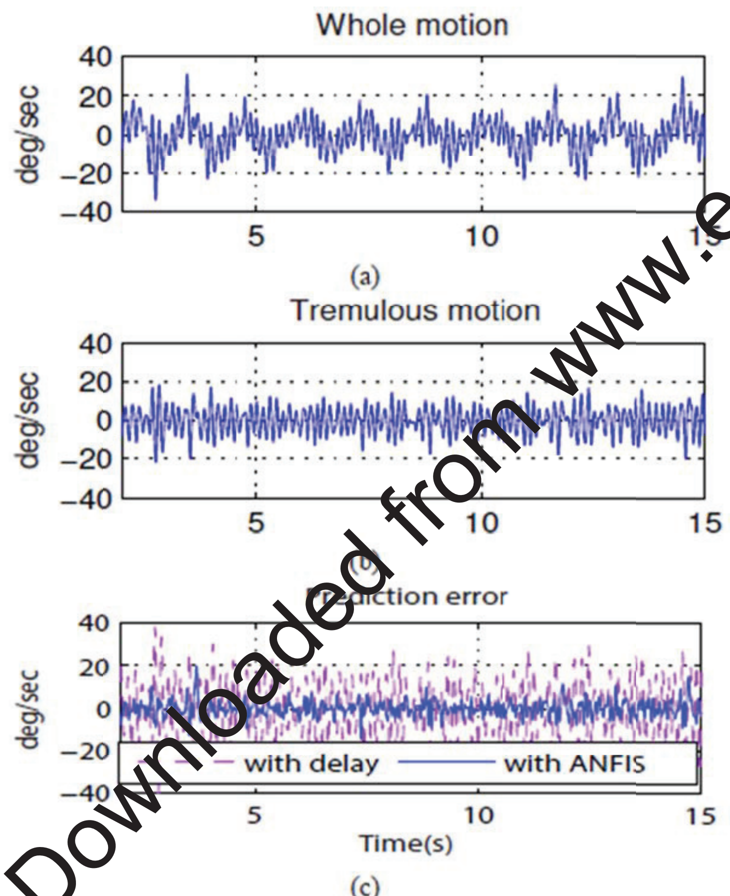

Fig. 5: Multistep prediction with ANFIS (a) Whole motion (Subject #1, action tremor); (b) Tremulous motion obtained after bandpass filtering ; (c) Prediction error obtained due to 80 ms delay together with multistep prediction error obtained with ANFIS

The procedure employed to perform multi-step prediction with ANFIS is shown in Fig. 4. First 500 samples of the collected tremor data was provided for offline training of ANFIS to obtain the optimized weights for neural network and membership functions. For multi-step prediction, the whole motion sensed with gyroscope is provided as an input to a fifth order Butterworth bandpass filter with pass band 2-20 Hz to filter the tremulous motion from the whole sensed motion. Further, multi-step prediction for 6 samples (60 ms) and 8 samples (80ms) is performed with LS-SVM to overcome the delay associated with bandpass filtering and EMD. To validate mult-istep prediction with ANFIS, filtered tremulous motion form a zero-phase bandpass filter with same specifications is employed, as shown in Fig. 4.

For illustration, the prediction error due to the delay of 80 ms and the prediction error obtained after performing multi-step prediction for the same delay for subject #1 are shown in Fig. 5. In Fig. 5 (a), the whole motion is shown, where as in Fig. 5 (b), filtered tremulous motion obtained after bandpass filtering is shown. In Fig. 5(c), prediction error obtained due to 80 ms is shown together with the multistep prediction error obtained with ANFIS for comparison. The prediction accuracy obtained for subject #1 is 49:21 § 1:21%. The average prediction accuracy obtained over all subjects and trials for 60 ms prediction length is 50 § 2% and 80 ms prediction length is 45:25 § 5%.

IV. Conclusions

In this paper, ANFIS is employed for multi-step prediction of pathological tremor to overcome the phased delay and to improve the performance. The performance of ANFIS was experimentally assessed with the tremor data collected from eight patients. An average prediciton accuracy of 50§2% is obtained with the multi-step prediction with ANFIS for 60 ms ahead prediction and an average accuracy of 45:25 § 5% is obtained for prediction length 80 ms.

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