Short Communication

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Prediction of the Wrist Joint Position During a Postural Tremor Using Neural Oscillators and an Adaptive Controller

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ABSTRACT

The prediction of the joint angle position, especially during tremor bursts, can be useful for detecting, tracking, and forecasting tremors. Thus, this research proposes a new model for predicting the wrist joint position during rhythmic bursts and inter-burst intervals. Since a tremor is an approximately rhythmic and roughly sinusoidal movement, neural oscillators have been selected to underlie the proposed model. Two neural oscillators were adopted. Electromyogram (EMG) signals were recorded from the extensor carpi radialis and flexor carpi radialis muscles concurrent with the joint angle signals of a stroke subject in an arm constant-posture. The output frequency of each oscillator was equal to the frequency corresponding to the maximum value of power spectrum related to the rhythmic wrist joint angle signals which had been recorded during a postural tremor. The phase shift between the outputs of the two oscillators was equal to the phase shift between the muscle activation of the wrist flexor and extensor muscles. The difference between the two oscillators' output signals was considered the main pattern. Along with a proportional compensator, an adaptive neural controller has adjusted the amplitude of the main pattern in such a way so as to minimize the wrist joint prediction error during a stroke patient's tremor burst and a healthy subject's generated artificial tremor. In regard to the range of wrist joint movement during the observed rhythmic motions, a calculated prediction error is deemed acceptable.

Key words: *Neural oscillator, predictive model, tremor burst, wrist joint angle position*

INTRODUCTION

A pathological tremor is defined as an involuntary oscillatory movement which often involves the upper body limbs.[1-3] The quality of life of people suffering from Parkinson, stroke, and other conditions can severely worsen due to such abnormal movements. Thus, a lot of researches in the recent years have been focused on treating tremors. So far, many treatment methods have been evaluated.[4-13] Among the various approaches which have been proposed to cope with such frustrating conditions, the assistive techniques offer an attractive alternative to traditional treatments such as surgery and deep brain stimulation.[9] Assistive techniques are based on the intervention of tremor suppression by devices which operate based on the application of mechanical loads to the affected limbs,[6] passive or active biomechanical loading working in parallel to the upper limb,[7] and functional electrical stimulation (FES)-based prostheses.[8-13] In such devices, the system parameters do not remain constant as those are adapted to the patient's condition. Thus, a closed loop feedback control is usually designed where the suitable physiological signals related to the muscle-joint system are continuously monitored. The system parameters, such as stimulation intensity, are adjusted in response to the signals' variations.[9,13] The feedback signals should predict the changes in dynamics of tremor. Especially in the presence of the computational and inherent delays of mechanical actuators and FES systems, a predictive ability is desired. Some researchers have focused on predicting and detecting the onset of pathological tremor.[14,15] In a recent work,[14] a method was proposed to predict the onset of pathological tremor using a noninvasively measured surface EMG (sEMG) and acceleration. In another work,[15] an optimized method was

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presented for tremor detection and temporal tracking based on the second-order moment calculations on the sEMG signal. However, most recently proposed researches have addressed the joint angles as highly potential features to extract context information related to tremors.[16] Recently, two algorithms were presented that enable the robust extraction of joint angles and related features so as to enable long-term continuous monitoring of tremors.[16] Some other researchers have reported their obtained results related to accurate estimation of amplitude and the frequency of wrist joint tremor signals.[17,18] These employed approaches were utilized to track tremor movements.[17,18] The real-time estimation of pathological tremor has been also addressed.[19] The presented algorithm was a two-stage algorithm for the real-time estimation of instantaneous tremor parameters using gyroscope recordings.[19] Some other researchers have explored the characterization of pathological tremors from the sEMG signals.[20] This approach was based on the iterated Hilbert transform.[20] However, it seems that the development of a simple and accurate predictive model to forecast the joint angle position during a tremor burst is still an open issue to research. Accordingly, in the current study, a neural oscillator-based model has been utilized to estimate the wrist angle position as much as 100 ms into the future during a rhythmic postural tremor burst. Such neural oscillators were previously used as a forward controller for tremor suppression via FES.[9] However, in the present work, neural oscillators are the main components of a proposed predictive adaptive model. The robust stability properties of the limit cycle behavior of neural oscillators and their usage for appropriate molding of rhythmic phenomena, such as tremors, are intriguing. The performance of the present model for prediction of joint angle position during inter-burst intervals was also assessed. The recorded data used for design and evaluation of model were recorded from the wrist agonist and antagonist muscles of stroke patients. For further evaluation, the performance of the model was assessed by predicting the joint angle position of a healthy patient during a generated artificial tremor.

MATERIALS AND METHODS

Experimental Data Collection

One stroke patient and one healthy subject volunteered participate in the current experimental study (2 males; age 22). The participating stroke patient was hemiplegic suffered from a wrist muscle postural tremor. Before starting the experiments, a consent form was completed by each participant. The subjects were instructed to perform the experiments according to the defined protocol. The subjects were seated in a comfortable position next to the device with the shoulder extended 90°, arm oriented in a transverse plane [Figure 1] while elbow was fully extended and wrist fully pronated. The subject was asked to keep his arm in this constant position. The conducted experiments on the stroke patient lasted up to 20 s until at least two tremor bursts were observed. While experiments were being conducted on the healthy subject, he was moving his wrist joint in a rhythmic manner that lasted 20 s. In fact, the healthy subject performed two long-time trials. During the movement, the EMG signals of the wrist extensor (extensor carpi radialis) and flexor (flexor carpi radialis) muscles were recorded by a recording system (Model ME6000, Mega Electronics, Kuopio, Finland). For recording, circular Ag/AgCl surface electrodes had been placed in the direction of the muscle fibers.[21] For holding down the impedance, the skin was cleaned with 70% alcohol before recording. The EMG signals were sampled at a frequency of 1 KHz and filtered through a band-pass filter (10–500 Hz). Since the recording device was battery-powered, a notch filter (50 Hz) was not needed. A goniometer (model SG56, Biometrics Ltd, Gwent, UK) was attached to the wrist joint. The joint angle signal was sampled with a frequency of 1 KHz.

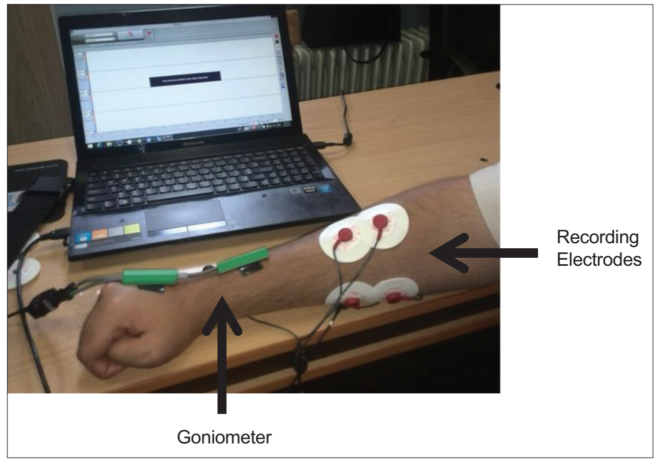

Figure 1: The experimental setup related to data collection

Proposed Predictive Model

Figure 2 presents the block diagram of the proposed adaptive model. It contains three major parts: Oscillators, adaptive neuron, and proportional (P) controller as the compensator. Two neural oscillators are in-charge of pattern generation. The difference between adaptive controller output and the output of *P* compensator adjusts the amplitude of the output signal of the oscillators. The premise of the presented model is based on the rhythmic behavior of a tremor. A tremor is a rhythmic semi-sinusoidal behavior. Such movement at the joints arises from rhythmic involuntary activation of the agonist and antagonist muscles. It has been shown that the EMG signal is very closely correlated with the joint angle.[22] This indicates a direct relation between the muscle activation profile and variations of joint angle during joint movement. It has been shown that some neural oscillators in some areas of the brain and spinal cord are in charge of rhythmic neural activity and rhythmic movements,[23,24] but a tremor is caused by a type of pathological neural oscillator.[9] Accordingly, in the current proposed model, two distinct neural oscillators are selected to simulate the effect of the pathological neural oscillator that generates the motor patterns of involuntary rhythmic movement, also called tremors. The first and the second oscillators correspond to the flexor and the extensor muscles of the wrist joint, respectively. The flexor and extensor muscles have opposite roles and the contraction of one counteracts the torque elicited by contraction of the other. Thus, in the present model, the main rhythmic is provided by finding the difference between the rhythmic output signals of the two oscillators corresponding to each muscle. The adaptive neuron and *P* controller, as will be discussed later, are used to modulate the output of the pattern generator to track the rhythmic changes of wrist joint angle position.

The main parts of the proposed predictive model will be demonstrated in the next three subsections.

Neural Oscillators of the Model

As previously mentioned, in the proposed predictive model, two distinct neural oscillators are chosen to simulate the effect of the pathological neural oscillator that generates the tremor. In the present research, Matsuoka neural oscillator was chosen and implemented. The Matsuoka neural oscillator has been fully investigated in some literature.[25-28] A single Matsuoka neural oscillator is composed of two coupled neurons with self-inhibition.[27] The mathematical description is given below.

$$T_1 \cdot x_i = -\sum_{j=1}^{2} a_{ij} \cdot y_j + s_i - b \cdot f_i \quad (i = 1, 2) \tag{1}$$

$$T_2 f_i + f_i = y_i \tag{2}$$

where

$$y_i = g\,(x_i)[g\,(x_i) = \max\,\{0, x_i\}] \tag{3}$$

The output of the neural oscillator is as follows:

$$O_i = y_2 - y_1 \tag{4}$$

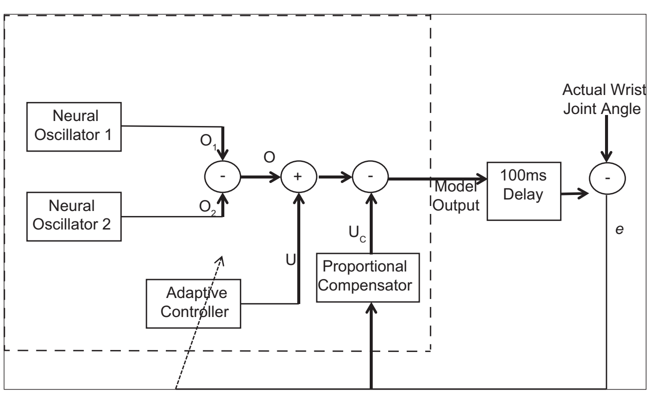

Figure 2: The block diagram related to the structure of the proposed adaptive predictive model

where *aij* (≥0 for $i \neq j$ and $= 0$ for $i = j$) is the weight of inhibitory synaptic connection from the j^{th} neuron to the i^{th} neuron, x_i is the variable of the membrane voltage in neuron, f_i is the membrane current, and $g\,(x_i)$ is a nonlinear function with a unit gain for x_i when it is nonnegative or otherwise is zero. In this model of the neuron, y_i is the output of the neuron and O is the output of the neural oscillator. The parameter s_i is constant drive input and b represents the adaptation constant being related to the self-inhibition of each neuron. The parameter T_1 is the rise time constant and T_2 is the adaptation time constant. Figure 3 shows the structure of the Matsuoka model.

The Matsuoka model can generate a stable rhythm under two conditions; (1) $\frac{a_{12}}{1+b} < \frac{s_1}{s_2}$ $\frac{a_{21}}{1+b} < \frac{s_2}{s_1}$ and (2) $\sqrt{(a_{21}a_{12})} < 1 + \frac{T_1}{T_2}$ while b must be large.[27] In addition, the output frequency of an oscillator is roughly proportional to $1/T_{1.}$[28]

Adaptive Controller and Proportional Compensator

The proposed model is a predictive model. Since the major part of the model is a rhythmic pattern generator, some other parts are needed to modulate the output signal of the pattern generator for predictive tracking of wrist joint angle changes. Because the muscle-joint system is a nonlinear and time varying system,[29] an adaptive modulator should be selected. In the present work, a nonlinear adaptive controller, which had been used earlier,[30,31] was chosen as the nonlinear modulator. The mathematical description is given below.

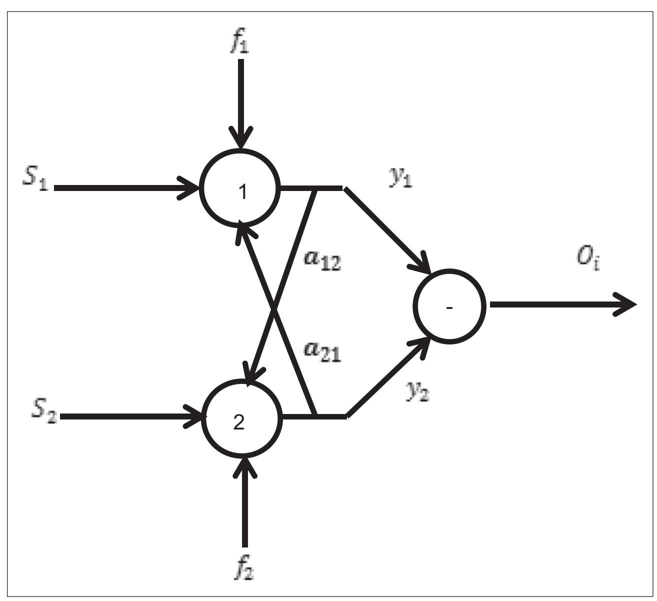

Figure 3: The Matsuoka oscillator model

$$I = e + \dot{e} + \int_0^t e \cdot dt \qquad (5)$$

$$U = f(I) = \alpha \tanh(\beta [I - \gamma]) \qquad (6)$$

where e is the wrist joint prediction error. In other words, e is the error value between the actual wrist joint position and the predicted value by the model 100 ms earlier. In fact, the model is a forward predictor which should estimate the wrist angle position as much as 100 ms into the future. The U is the output of the controller being added to the output of the pattern generator. This signal, as a control signal, adjusts the amplitude of the pattern generator output in such a way that it tracks the actual wrist joint angle and leads to low-prediction error. The parameters $\theta = [\alpha\ \beta\ \gamma]$ are adapted online during the prediction without offline training. To guarantee the globally asymptotically stability of the system, the following adaptation rules have been used:[32]

$$\dot{\theta} = -\delta \cdot e \cdot \frac{\partial U}{\partial \theta} \cdot \mathrm{sgn}\left(\frac{\partial Out}{\partial U}\right) \qquad (7)$$

where $\delta > 0$ is the learning rate parameter, out is the model output [Figure 2], and sgn(.) is a sign function.

The adaptive models inevitably encounter unmolded dynamics. Therefore, as a proportional controller, a fixed parameter proportional compensator (proportional gain = 1) was adopted to compensate for the effect of unmolded dynamics on the performance of the prediction model. The output of the proportional controller is as follows:

$$U_c = K \cdot e \qquad (8)$$

where e is the wrist joint prediction error and $K = 1$ is the proportional gain.

Adjustment of the Design Parameters

Two design parameters should be chosen: Output frequency of the oscillators and phase shift between the outputs of the two oscillators. Since the output of a rhythmic pattern generator should be synchronized with the wrist joint tremor signal, the frequency of the two neural oscillators, as the major parts of the pattern generator, was equal to the computed average of the frequency corresponding to the maximum value of power spectrum related to the rhythmic wrist joint angle signals which had been recorded during tremor bursts. Figure 3 shows the power spectral density related to the two different bursts.

The range of the obtained frequency related to 10 different tremor bursts and the generated artificial tremors related to a healthy subject was from 3.9 Hz to 4 Hz. Therefore, the parameters of the oscillator were chosen in away[26-28] that the frequency of the neural oscillators was 4 Hz [Table 1 and Figure 4].

Table 1: Parameters of adopted neural oscillators

τ_1	τ_2	S_1	S_2	a_{12}	a_{21}	b	f_1	f_2
0.13	0.5	15	15	1.5	1.5	50	0	0

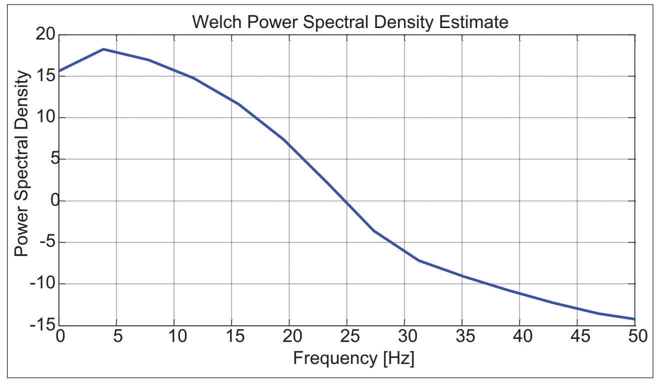

Figure 4: The power spectral density of a recorded joint angle signal during a sample tremor burst

Obviously, the phase shift between the outputs of the two oscillators is a key parameter. As previously explained, each oscillator corresponds to one wrist muscle (extensor and flexor). Thus, a strategy was adopted to determine the phase lag using analyses of the recorded EMG signals of the wrist extensor and flexor muscles. The actual EMG signals were rectified, normalized, and filtered using the 8th order Butterworth low-pass filter with a cutoff frequency of 17 Hz. Figure 5 shows a rectified and normalized sample EMG signal recorded during a tremor burst, its filtered signal, and the corresponding wrist joint angle signal occurring during the same tremor burst. As Figure 5 demonstrates, with such filtering, the actual EMG signal is transformed to a cyclic signal which can reveal the rhythmic behavior of the EMG signal during bursts. Clearly, each cycle of the filtered EMG signals lies within a cycle of rhythmic wrist joint angle signals. It should be emphasized that EMG signals do not contain a voluntary component because of the recording protocol. Therefore, extracting the tremor component, as discussed in some literature,[20] is not an issue raised by the present study. In fact, the rhythmic component of the muscle activation pattern was extracted through a low-pass filter. In this manner, the cycles of tremulous muscle activation become observable and detectable.

Figure 6 provides the filtered EMG signals related to the wrist extensor and flexor muscles. There is a phase lag between the filtered EMG signals of the agonist muscle and the antagonist's muscle. However, each cycle of both filtered EMG signals lies within a cycle of rhythmic wrist joint angle signal. The values of the time intervals between the peaks of extracted cyclic signals during each cycle interval occurring within tremor burst were measured. The obtained average value was 70 ± 2 ms. Therefore, a 70 ms phase lag time was observed between the outputs of the two oscillators.

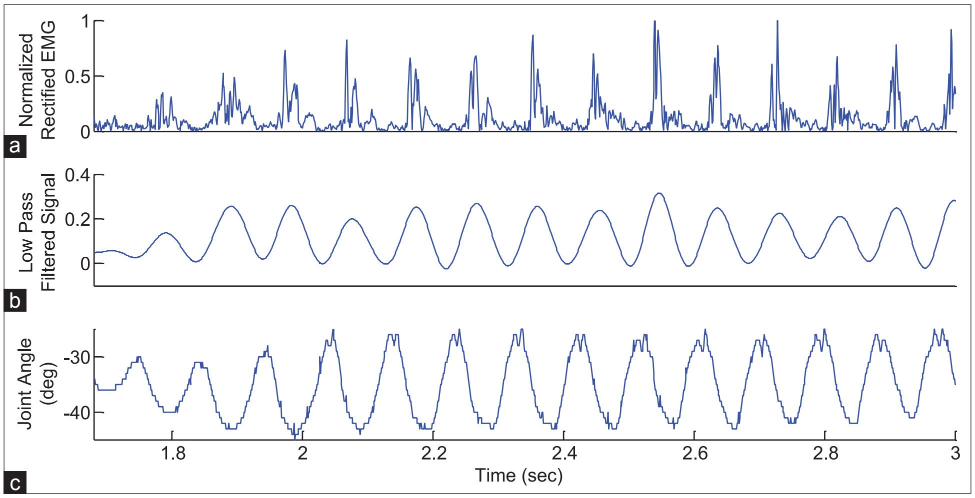

Figure 5: (a) Normalized rectified electromyogram signal related to the wrist extensor muscle during a time interval within the tremor burst, (b) corresponding low passing filtered signal, (c) corresponding angular variations of the wrist joint

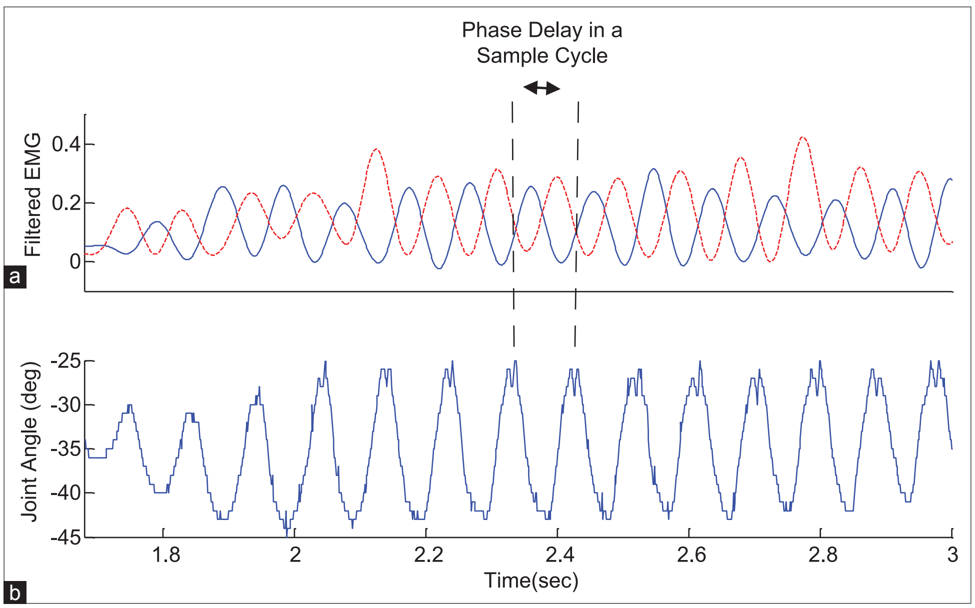

Figure 6: (a) The low passing filtered signal related to the wrist extensor muscle (solid line) and wrist flexor muscle (dash line) during a time interval within a tremor burst, (b) corresponding angular variations of the wrist joint

It is worth mentioning that the proposed model should be identified in a case-dependent manner. In other words, the output frequency of the neural oscillators and the phase lag time between their outputs should be determined for each patient based on analyses of related recorded EMG signals. Here, the aforementioned parameters were determined for a stroke patient.

RESULTS

Prediction of Rhythmic Wrist Movement

Figures 7-9 present some typical results. In fact, these figures show examples of joint angles obtained with the proposed predictive model, along with changes of the adaptive controller output, proportional compensator output during two distinct tremor bursts in the stroke patient, and artificial tremor generated in the abled-bodied patient. The first interesting observation is the fast convergence of the model output. The output of the model converged on the actual wrist joint angle trajectory so fast that no considerable convergence latency can be observed.

It should be noted that the main parameters of the model, output frequency of the neural oscillators, and the phase lag time between them, were determined using analyses of the recorded data related to the first trial. These parameters were fixed for evaluating the model performance in the prediction of wrist joint movement using recorded data during the different trials. In other words, no parameter

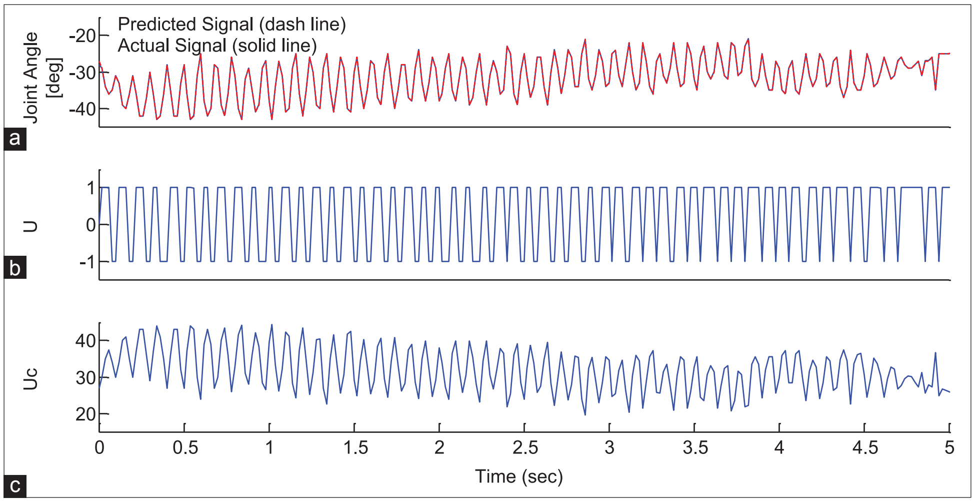

Figure 7: (a) Actual recorded joint angle during a sample tremor burst (solid line) and predicted joint angle during a tremor burst (dash line), (b) output of adaptive controller, (c) output of proportional compensator

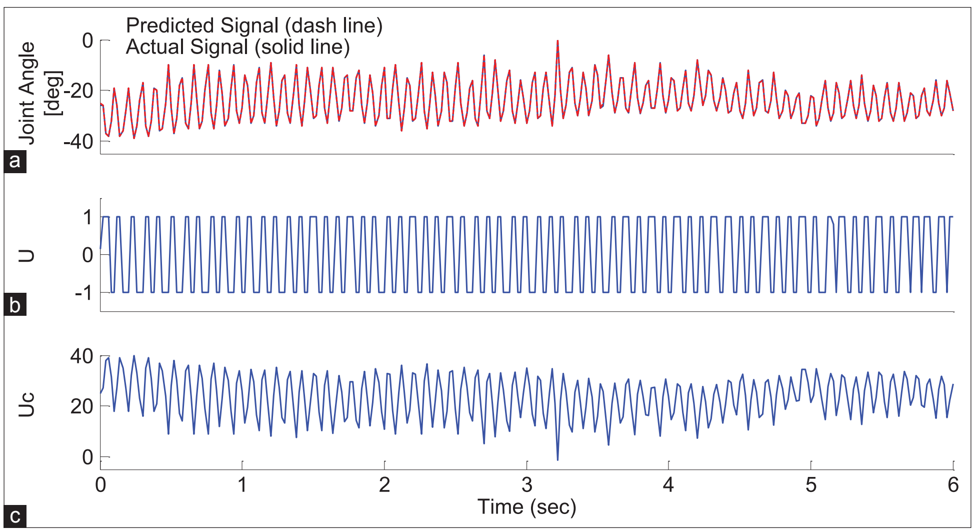

Figure 8: (a) Actual recorded joint angle during a sample tremor burst (solid line) and predicted joint angle during a tremor burst (dash line), (b) output of adaptive controller, (c) output of proportional compensator

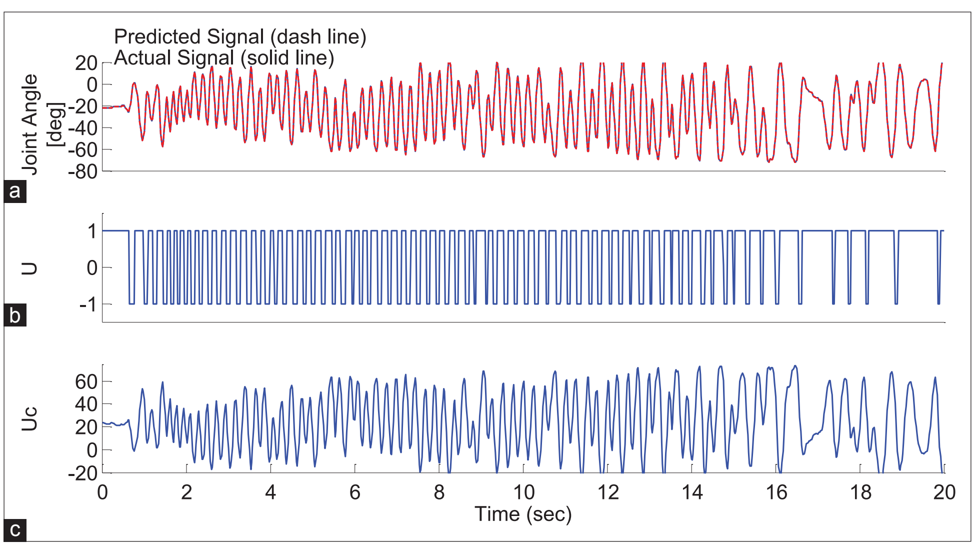

Figure 9: (a) Actual recorded joint angle during an artificially generated tremor (solid line) and predicted joint angle during an artificially generated tremor (dash line), (b) output of adaptive controller, (c) output of proportional compensator

tuning was needed and the model performance in the prediction of the joint position, as recorded during the different trials, was similar.

A summary of the results over 12 recorded experimental data on the two subjects is founded in Tables 2 and 3. The average root mean square (RMS) predicting error for about a 95° range of joint movement during rhythmic movement is 0.27° ±0.09° for the able-bodied subject and 0.071° ±0.03° for about a 35° range of joint movement during tremor bursts for the stroke patient. The calculated average value of the RMS predicting errors related to all computed RMS predicting errors was 0.079° ±0.04°. The average correlation coefficient between the model output and the actual wrist joint angle for the able-bodied and stroke patient was about 1. Such results indicate that the model was able to achieve an acceptable prediction performance.

Table 2: The calculated root mean squared predicting errors related to the prediction of the wrist joint angle during the tremor burst in the stroke patient

Tremor burst	1	2	3	4	5	6	7	8	9	10
Root mean squared (°)	0.068	0.085	0.096	0.10	0.14	0.14	0.11	0.083	0.06	0.087

Table 3: The calculated root mean squared predicting errors related to the prediction of the wrist joint angle during the 20 s of artificially generated rhythmic motions in the healt hy subject

Rhythmic motion	1	2
Root mean squared (°)	0.034	0.20

It is worth noting that the time duration of the observed tremor bursts in the stroke patient varied. It was between 2 s and 5 s.

Prediction of Wrist Movement During the Inter-burst Interval

Intriguing observation is a low prediction error even during the inter-burst interval. Figure 10 shows a typical wrist joint trajectory during the 2.62 s time segment of an inter-burst interval. The average RMS predicting error of the wrist joint movement during the recorded intra-burst intervals is 0.093° ±0.017°. Such a low-average value elucidates that the presented model has tracked the dynamics of joint angle changes, in a predictive manner, even between two consecutive burst. The neuromuscular system is a dynamic system.[30] Thus, the behavior of this system during the burst and inter-burst intervals cannot be considered as two independent behaviors. Therefore, such results can indicate the effective role of the adaptive controller. Because the model performance (RMS predicting error) had not dropped during the inter-burst interval, the output frequency of the neural oscillators and phase lag time between them were set using the analyses of the wrist joint changes and EMG signals recorded during the tremor bursts.

According to the results [Figure 10], during the inter-burst interval, the adaptive controller output was mostly saturated while the proportional compensator output changed. It can be concluded that during the inter-burst interval, when the amplitude of fluctuations lowered considerably, the contribution of the adaptive controller in subtly tuning the model output decreased. In this manner, the role of the proportional compensator on subtly adjusting the output of the neural oscillator-based pattern generator is further clarified.

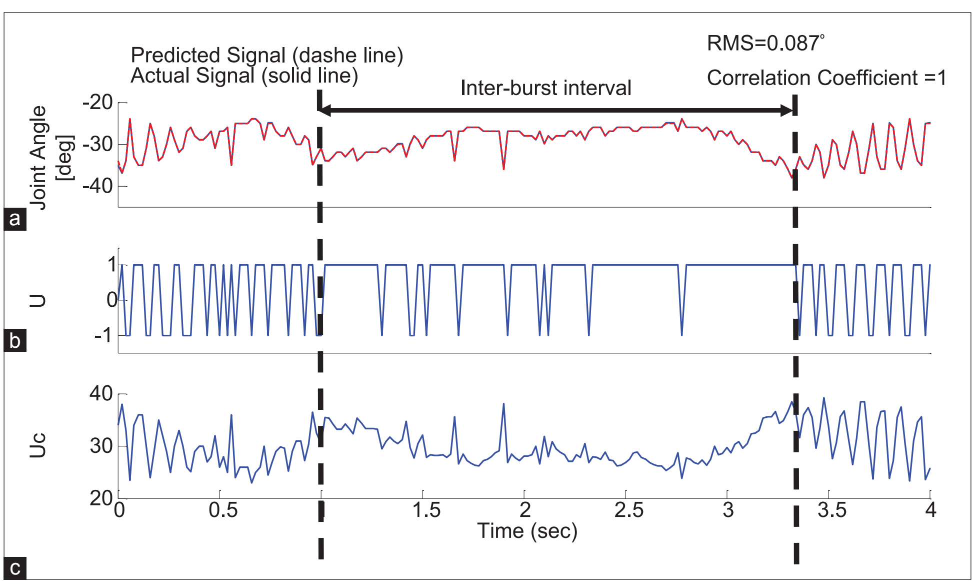

Figure 10: (a) Actual recorded joint angle (solid line) and predicted joint angle (dash line), (b) output of adaptive controller, (c) output of proportional compensator

Sensitivity Analysis with Respect to Initial Values

When using an adaptive model, one of the crucial issues that should be analyzed is the assessment of model sensitivity with respect to the initial values. Since a major part of the presented model is an adaptive controller, such analysis is vital. It was observed that if is set as 1 and two other parameters are adapted, the prediction error will significantly decrease. Therefore, α was fixed while β and γ were adapted using the adaptation rules. In this study, the initial values of controller parameters β and γ were set as random variables with uniform distribution between 0 and 1 while the other parameter, α, was fixed as 1. It was observed that the initial values beyond this range leads to instability of the control system. Figures 10 and 11 show two typical trajectories for two different sample initial conditions related to controller parameter changes, along with changes of the adaptive parameters, during the same tremor burst. According to several simulation studies that were carried out, the range of the RMS of the prediction error for 10 different initial conditions was within 0.0075° to 0.11° while the value of the correlation coefficient was 1. As previously mentioned, the reported results [Figures 7-9] were obtained while the initial values of the parameters were 0. Of course, such results show the dependency of model performance on the initial condition of the adaptive controller. Nevertheless, concerning the range of wrist joint movement during the observed rhythmic motions, about 35° for the stroke patient and about 95° for the healthy subject, the calculated RMS prediction errors are acceptable [Figures 11 and 12].

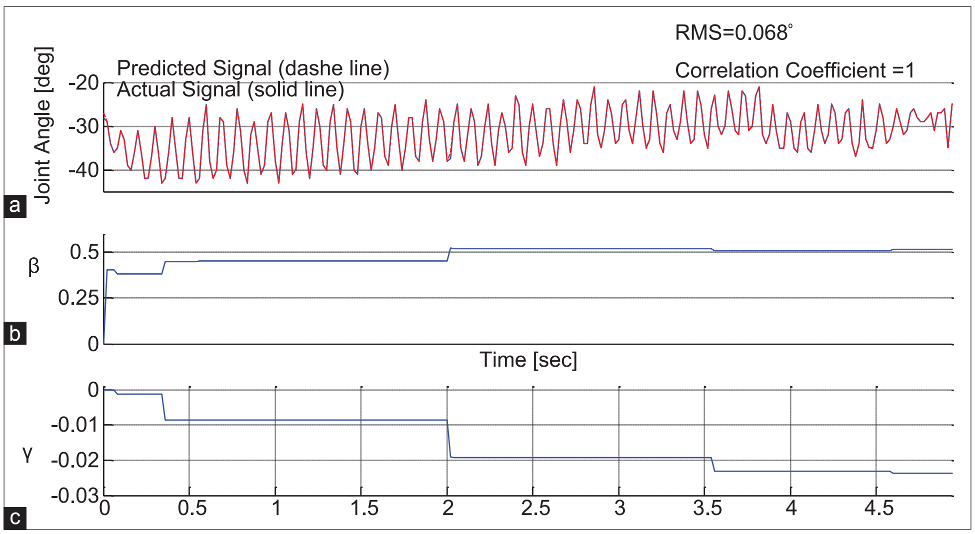

Figure 11: (a) Actual recorded joint angle during a tremor burst (solid line) and predicted joint angle during a tremor burst (dash line), (b) changes of β parameter over time, (c) changes of γ parameter over time while $\beta(0) = 0$ and $\gamma(0) = 0$ are the initial conditions

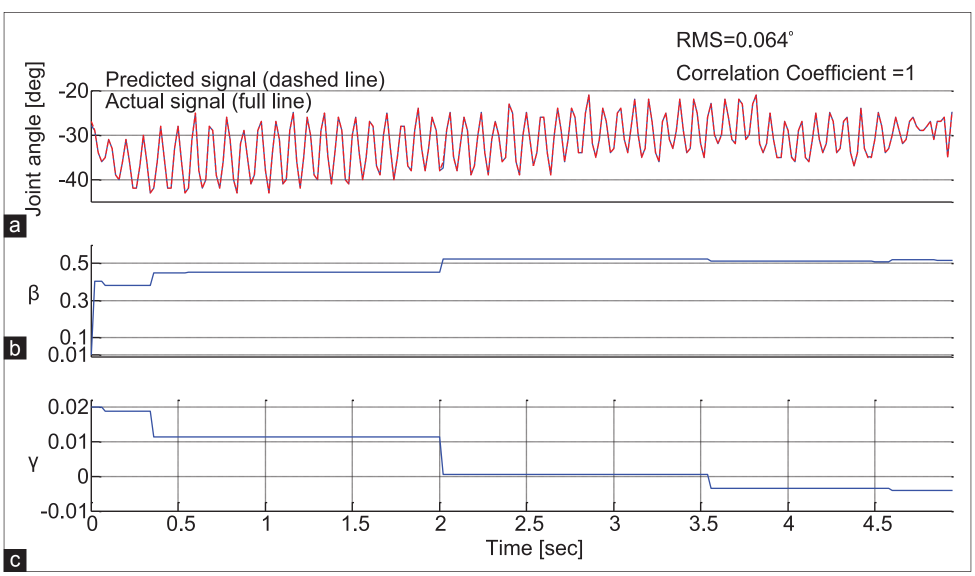

Figure 12: (a) Actual recorded joint angle during a tremor burst (solid line) and predicted joint angle during a tremor burst (dash line), (b) changes of β parameter over time, (c) changes of γ parameter over time while $\beta(0)=0.01$ and $\gamma(0)=0.02$ are the initial conditions

It is worth noting that the convergence time of the model output has remained nearly constant and independent of initial conditions.

Sensitivity Analysis with Respect to Phase Lag Time

As previously explained, the value of the phase lag time between neural oscillator outputs was obtained through the analyses of the phase shift value between two filtered EMG signals related to the first patient trial. This value was constant and no more tuning was needed. The model performance was similar to prediction of the joint position as recorded during the different trials. Figure 13 shows the three obtained results. Each result was achieved as a different value of the phase lag time within its range (70 ± 2 ms) while the predicted signal was the same, which was a sample recorded signal from the stroke patient. In each of three observed simulations, the phase lag time was determined through the analyses of three different recorded data. Nevertheless, the calculated RMS and correlation coefficients were 0.068° and 1, respectively. The computed RMS and correlation coefficients were equal. According to several studies that have been carried out, the similar results were seen. According to such results, it can be claimed that a single recording trial is enough for determining the phase lag time between the neural oscillators.

DISCUSSION

The main interest and purpose of the current study were to exploit neural oscillators for development of an adaptive model to predict the wrist joint position during postural tremor bursts. While some literature had addressed the issue of tremor tracking and tremor estimation, in the present work, the estimation of the wrist angle position has been addressed with as much as 100 ms into the future during the rhythmic postural tremor burst. The neural oscillator was formerly adopted to develop the feed-forward controller for tremor suppression using FES.[9] In this work, the neural oscillator was applied as the major part of a predictive model for the forward prediction of the wrist joint during a tremor burst. In addition, in the proposed modeling strategy, an adaptive controller was adopted for adjusting model output. Incorporating a controller into a model, as such, can be considered an innovation.

Since the main idea lying behind the proposed model structure is related to the role of rhythmic muscle activation on rhythmic wrist joint movement, the performance of the presented model was evaluated not only with recorded data related to a stroke patient but also with recorded data related to three able bodies. In the first step, the output frequency of neural oscillators and the phase lag time between them were determined by power spectral analysis of the wrist joint trajectory and analyses of EMG signals from the first recording trial. The mean values of the calculated quantitative evaluation measures [Tables 2 and 3] testify to proposed model's promising performance because the mean value of the RMS for a range of movement of about 35° is 0.071° ±0.03°, and the mean value of the correlation coefficient is very near to 1. The fairly fast convergence time of model output is also convincing.

As such, the neuromuscular system is a dynamic one. It has been suggested that a tremor can be generated by pathological activity within a sensory feedback loop.[13] In addition, it has been shown that increasing gain within the muscle spindle reflex loop can determine system instability resulting in tremor-like oscillations.[14] Accordingly, the

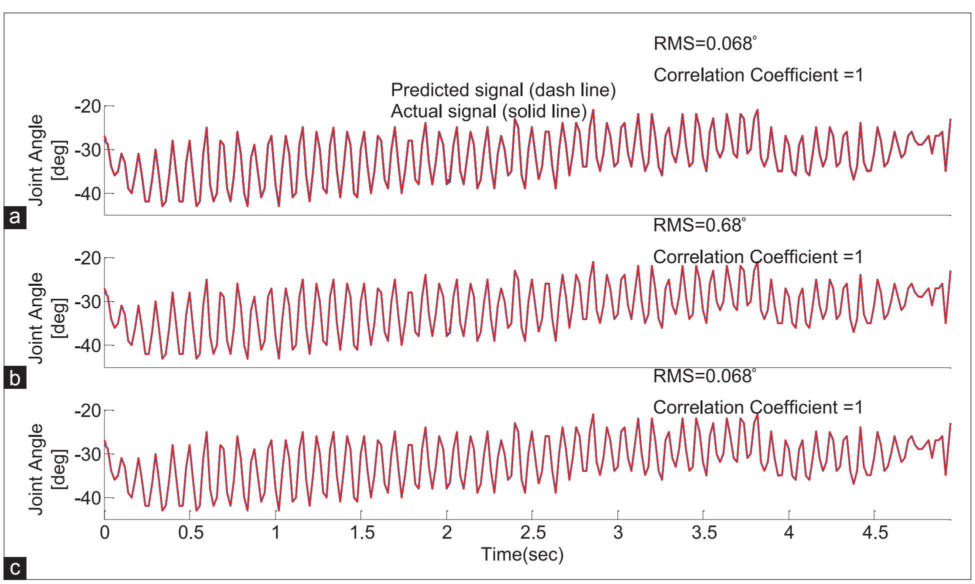

Figure 13: Actual recorded joint angle during a tremor burst (solid line) and predicted joint angle during a single tremor burst (dash line). (a) The phase lag is 70 ms, (b) the phase lag is 68 ms, (c) the phase lag is 72 ms

oscillatory behavior of the neuromuscular system during a burst interval is related to a change in system dynamics. Thus, the assessment of the proposed model by tracking dynamic changes after a tremor burst was enticing. The model performance was acceptable as regards the furcating of the wrist joint movement during a tremor burst. In any case, in the next step, the ability of the presented model to predict of wrist joint movement during an inter-burst interval was evaluated. According to the results, its performance in predicting the wrist joint movement during a burst interval and an inter-burst interval was comparable. Such findings elucidate the intriguing ability of neural oscillator-based model for tracking the dynamics of a neuromuscular system after the onset of a tremor burst. Another point observed is the part played by the adaptive controller and proportional controller in adjusting the amplitude of the pattern generator output during an inter-burst interval. The results show that the contribution of the adaptive controller and proportional compensator in modulating the output of the pattern generator differs during burst intervals from what is observed during inter-burst intervals. This indicates the presence of an elicited interaction between the adopted controller and the compensator which leads to acceptable model performance.

In different trials, the time duration of the observed tremor bursts differed, lying within a range of 3 s (between 2 s and 5 s). Thus, according to such data, model performance is not dependent on the time duration of a tremor burst.

The present study analyzed the sensitivity of the presented model with respect to the initial condition of the adaptive controller's parameters and the value of the phase lag time between the oscillators. It was found that the prediction error is not sensitive to these parameters. This finding can be considered an advantage as it shows that the model's basic parameters can be set manually in a person-driven manner employing recorded data related only to a single recording trial.

In the current work, numerous studies were conducted to evaluate the performance of the presented model from various aspects. From an overall perspective, it can be stated that the performance of the proposed model is acceptable in predicting rhythmic wrist joint movement, especially during an involuntary posture tremor burst. Future work will focus on design of a control strategy for tremor suppression based on this model.

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Conflicts of Interest

There are no conflicts of interest.

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