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ON THE PREDICTION OF TREMOR DYNAMICS MOTION USING NEURAL NETWORK

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ABSTRACT

Pathological tremors significantly affect the quality of life for patients worldwide. Rehabilitation exoskeletons serve as one of the solutions to alleviate these pathological tremors, and voluntary motion prediction-based motion planning has been employed to enhance the performance of these devices. This paper presents a method for predicting future voluntary movement in tremor-alleviating rehabilitation exoskeletons that use voluntary motion prediction-based motion planning. In this study, a Convolutional Neural Network and Transformer architecture based neural network work with EMG sensors to predict future voluntary movements. The results show that approach performs well in predicting future voluntary movements, but there is still a limitation to filter out the tremors completely. In summary, we provide a concept for predicting future voluntary movement, which has the potential to improve the effectiveness of rehabilitation exoskeletons in tremor alleviation.

1. INTRODUCTION

Pathological tremors are involuntary rhythmic oscillations of human body parts that affect millions of people worldwide [1] [2]. The most common pathological tremors are Parkinsonian Tremors (PT) and Essential Tremors (ET), which can be generalized as postural/kinetic tremors from 3 Hz to 12 Hz and primarily affect the hands, arms, and head. Although pathological tremors are not life-threatening, they can adversely affect the quality of patients' lives [3] [4] [5].

One of the solutions to suppress these pathological tremors is the wearable rehabilitation exoskeletons [6] [5] [7]. Voluntary movements are estimated to appear in a bandwidth lower than 2 Hz, these can be distinguished from pathological tremors [5]. Rehabilitation exoskeletons provide counterforces only against involuntary movements via passive or active mechanical loading to suppress pathological tremors. Recently, our team developed a tremor-alleviating wrist exoskeleton (TAWE) [7], which is shown in Fig.1 TAWE is a high-degree-of-freedom wearable exoskeleton that can follow the user's voluntary motion and suppress pathological tremors via active mechanical loading.

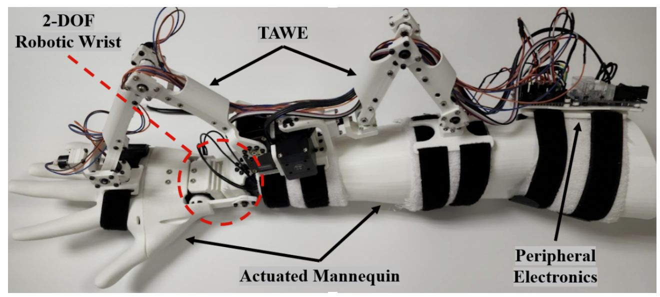

FIGURE 1: THE TAWE ATTACHED TO A RIGHT FOREARM MANNEQUIN [8] [9].

We emphasize that a significant challenge in the field of wearable rehabilitation exoskeletons is achieving a high level of transparency. This further implies that the exoskeleton should avoid producing any additional force that will interfere with voluntary movement while suppressing the involuntary tremor [1] [10]. Thus, voluntary motion prediction-based motion planning is essential to increase transparency [10][11]. Provided that human voluntary motion can be predicted with high precision, the motion of rehabilitation exoskeletons will be more natural and transparent by using the predicted trajectory.

In order to predict future voluntary motion, a sensor may be needed, which can provide information about motion one step ahead. The electromyography (EMG) signal is a biological signal produced by neuromuscular contraction activities and typically precedes actual movement by about 50-100 milliseconds [12] [13]. Therefore, previous studies have used EMG signals and neural networks to predict motion in the same range of 50-100 milliseconds [14] [15] [16]. Further, some studies successfully predicted future motion by 200 milliseconds, combining the movement and EMG signals with neural networks [17]. However,

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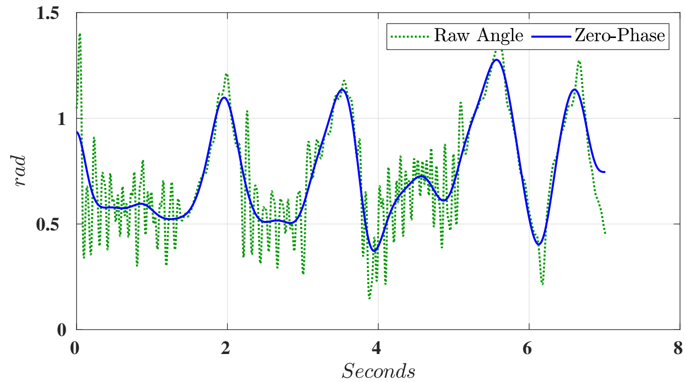

FIGURE 2: COMPARISON BETWEEN THE RAW ANGLE CONTAINING TREMOR AND THE SAME ANGLE FROM A ZERO-PHASE FILTER WITH A CUTOFF FREQUENCY OF 1 HZ.

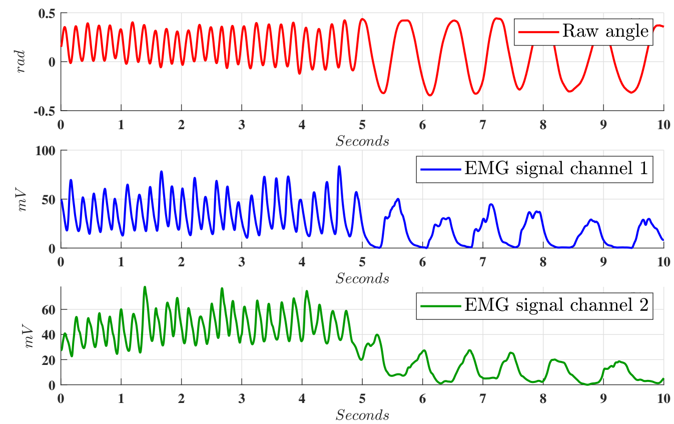

FIGURE 3: COMPARISON OF DUAL-CHANNEL EMG SIGNAL WITH RAW ANGLE

these studies did not involve the signals containing pathological tremors. While some techniques achieved good results in estimating voluntary movement [1] [18] [19]. They do not explicitly address the challenges of filtering and predicting movements simultaneously. Therefore, these studies may not be suitable for tremor suppression exoskeletons. Hence, there is a need for a new method to predict future voluntary movement so that it can be applied to tremor-alleviating rehabilitation exoskeletons for motion planning.

To address this need, this paper explores the method to predict future voluntary movement for tremor alleviation rehabilitation exoskeletons. To demonstrate this, we collect EMG signals and movement trajectories containing tremors from a human to predict future voluntary movement. The rest of the paper is organized as follows: Section 2 introduces the correlation between EMG signal characteristics and wrist movement, while Section 3 describes the processing of EMG signals. Section 4 presents the structure of the neural network and the prediction process. Finally, Section 5 presents the results, and Section 6 provides a summary of the study.

2. EMG SIGNALS WITH MOVEMENTS

This section explores the relationship between EMG signals and movements with and without tremors. First, this method relies on one assumption: in basic daily activities, the frequency distribution of voluntary motions is lower than pathological tremors [5]. This assumption allows voluntary movements to be extracted using a low-pass filter from the tremor movement signals. Fig.2 demonstrates that a zero-phase digital infinite-impulse response (IIR) filter can extract voluntary movement. In the rest of the paper, we assume that the voluntary movement is the trajectory extracted by the zero-phase filter. However, a non-causal filter relies on future input data to produce the current output, which is theoretically impossible in real-time applications.

Since the raw angle is derived from the wrist's flexion and extension, two channels of EMG signals are used to obtain muscle signals from the flexor carpi radialis and extensor carpi ulnaris muscles. Fig.3 presents signals for two distinct movement patterns: intentional tremor and slow-rhythmic motion. The angle changes due to the continuous contraction and relaxation of the muscles on either side of the wrist. During the intentional tremor phase, the EMG signal intensity is noticeably higher than the EMG signal during slow movement.

3. PROCESSING THE EMG SIGNALS

After showing the relationship between the EMG signal and wrist movements in Section 2, Section 3 will detail the methodology for processing the EMG signals. The raw EMG signals may encompass noise attributable to ambient environmental factors, poor electrode contact, or the inherent noise from the equipment itself. Such noise can adversely impact the performance of neural networks; therefore, prior to their utilization, it is imperative to mitigate this noise to the greatest extent possible and to render the signal smoother. To realize this outcome, the treatment of the EMG signals entailed the implementation of mean averaging, Wavelet Denoising, and Exponential Moving Average methodologies which also the order for processing the signals.

A. Mean Averaging

The equation for calculating the mean average(MA), commonly known as the "mean," is given by:

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

where x_i represents each value in the dataset, $\sum$ denotes the summation of all values x_i, and n is the number of observations in the dataset.

B. Wavelet Denoising

Wavelet denoising(WD)[20] is a signal processing technique that removes noise from a signal while preserving its essential features. It is based on the mathematical concept of wavelet transformation, which involves breaking down a signal into components that vary in time and frequency. WD is beneficial for non-stationary signals, where the frequency content changes over time, such as in audio signals or image processing. The subsequent text will delineate a series of steps inherent to the wavelet denoising process.

1. Wavelet Transform: Compute the wavelet transform of a measured signal, the wavelet transform of the signal $f(t)$ can be represented as:

$$W_f(a,b) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{a}} \varphi\left(\frac{t-b}{a}\right) dt \tag{2}$$

where a is the scale parameter, b is the translation parameter, and $W_f(a,b)$ is the wavelet coefficient at scale a and position b. $\varphi(t)$ is the mother wavelet function.

2. Thresholding: After computing the wavelet coefficients, each coefficient $W_f(a,b)$ is compared to a threshold λ. The thresholding function can be described as follows for soft thresholding:

$$\begin{gathered}\hat{W}_f(a,b) = \\ \operatorname{sign}\left(W_f(a,b)\right) * \max\left(0, |W_f(a,b)| - \lambda\right)\end{gathered} \tag{3}$$

where $\hat{W}_f(a,b)$ is the thresholded wavelet coefficient.

3. Inverse Wavelet Transform: After thresholding, the denoised signal $\hat{f}(t)$ is reconstructed by applying the inverse wavelet transform using the modified coefficients:

$$\hat{f}(t) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \hat{W}_f(a,b) \frac{1}{\sqrt{a}} \varphi\left(\frac{t-b}{a}\right) \frac{da\, db}{a^2} \tag{4}$$

C. Exponential Moving Average

The Exponential Moving Average (EMA)[21] is computed using a formula that applies a weighting factor to each data point, diminishing exponentially for older observations. This weighted average emphasizes the contribution of more recent data points, rendering it exceptionally responsive to recent changes in the data set:

$$\mathrm{EMA}_t = (V_t * C) + \mathrm{EMA}_{t-1}(1 - C) \tag{5}$$

where EMA_t is the Exponential Moving Average at time t, V_t is the observed value at time t, C is the exponential smoothing constant that can be adjusted based on the desired level of weighting for the most recent data point, and EMA_{t-1} is the Exponential Moving Average of the previous period.

As an exact two-second EMG signal with a sampling frequency of 1024 Hz, shown in Fig.4(a), the dataset comprises 2048 data points. A mean averaging procedure is applied to refine this signal for analysis, grouping every four data points, which is shown in Fig.4(a) in comparison with the original EMG signal. This processing yields 256 averaged values, each representing the mean of its respective quartet of points, thereby condensing the original signal while preserving its overall structure and dynamics for subsequent analysis. Although there is an extra step of the calculation, it reduces a lot of computation time for the subsequent steps. Fig.4(b) presents the EMG signal before and after applying Wavelet Denoising, illustrating a significant noise reduction. However, the current EMG signal still contains some redundant small peaks, which can be reduced by changing the threshold but will increase the delay as well. These peaks could degrade the performance of neural networks. Therefore, the Exponential Moving Average is applied to minimize these

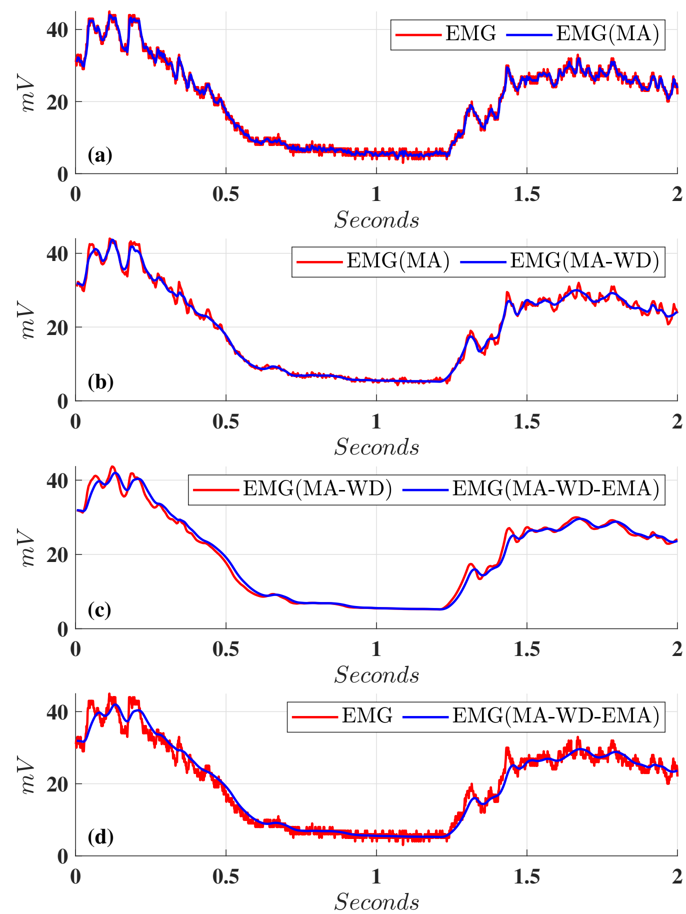

FIGURE 4: THIS FIGURE SHOWCASES THE STAGES OF EMG SIGNAL PROCESSING: (A) INITIAL AVERAGING TO REDUCE DATA TO 256 POINTS, (B) NOISE REDUCTION VIA WAVELET DENOISING, (C) SMOOTHING WITH EXPONENTIAL MOVING AVERAGE, AND (D) THE COMPARISON OF THE FINAL PROCESSED SIGNAL AGAINST THE ORIGINAL.

extra peaks, ensuring that the input the neural network receives is as smooth as possible, as shown in Fig.4(c). Fig.4(d) compares the final processed and original EMG signals, demonstrating that a significant amount of noise has been filtered out, resulting in a smoother signal.

4. PREDICTION USING NEURAL NETWORK

In Section 3, after comprehensive processing of the EMG signals, we integrate wrist angle, angular velocity, and the refined EMG data as inputs to a combined neural network that includes a 1-D convolutional neural network(1-D CNN) and self-attention network(SAN).

A. Convolutional Neural Network

Convolutional neural networks[22] are deep learning algorithms designed to process inputs by utilizing filters or kernels that can effectively extract input features. 1-Dimensional Convolutional Neural Networks are a specialized variant of convolutional neural networks that are specifically designed for processing one-dimensional data. Unlike their 2D counterparts, typically used for image data, 1-D CNNs are ideal for analyzing sequential data, which makes them particularly suitable for applications like time-series analysis, audio processing, and natural language processing. Therefore, since the wrist angle and EMG signal are one-dimensional sequential data, the 1-D CNN is an appropriate choice. This choice has improved the neural network's overall performance by approximately 20%. The one-dimensional convolution operation for the sequence data is shown as follows,

$$(d * g)(t) = \int_{-\infty}^{\infty} d(\tau)\, g(t-\tau)\, d\tau \tag{6}$$

where d is the input data, and g is the activation function. The following equation is used to determine the output size of the convolution operation:

$$d_{\text{out}} = \frac{d_{\text{in}} + 2p - k}{s} + 1 \tag{7}$$

where p is the padding size, k is the kernel size and s is the length of each stride. When using multiple convolution layers, the output size of each convolution layer is important for the lower convolution layer.

B. Self-attention Network

Self-attention networks, commonly called Transformer architectures[23], are effective in natural language processing (NLP). Their structure allows for efficient handling of sequential data and captures long-range dependencies, which makes them also suitable for various predictive tasks.

An attention mechanism can be conceptualized as mapping a given query with a set of key-value pairs to an output, the output is computed as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V \tag{8}$$

where d_k is the dimension of the input consisting of queries and keys, Q is the query vector, K is the key vector, and V is the value vector. This equation describes how to compute attention weights using query vectors, key vectors, and value vectors. These weights are then used to perform a weighted sum of the value vectors, thereby capturing long-range dependencies in the input data. Therefore, when the input consists of continuous human motion angles and EMG signals, this is a suitable choice, as the input data is continuous and highly correlated.

Fig.5 presents a simplified structural diagram of the neural network employed in our study. The structure commences with four group-convolutional layers, and each can convolute the inputs respectively. These layers utilize a filter size of 3 and comprise eight filters each. Following each group-1D-convolutional layer(group-1D-CNN) is a group-normalization(group-Norm) layer. After this, the network includes four self-attention layers, and each is followed by a fully connected layer comprised of 64 neurons, thereby contributing to eight distinct layers within the network, which is a basic encoder of the Transformer model. Then, considering the initial input layer and the regression layer, the overall architecture of the neural network encompasses 18 layers.

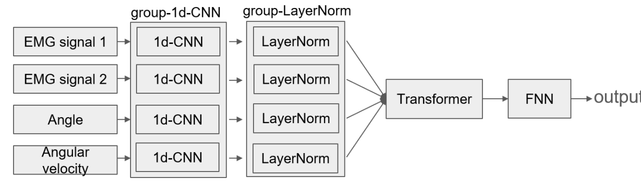

FIGURE 5: THE NEURAL NETWORK SEQUENTIALLY INTEGRATES FOUR GROUPED 1-D CONVOLUTIONAL LAYERS AND FOUR GROUP NORMALIZATION LAYERS, THEN FOLLOWS A SIMPLE TRANSFORMER MODEL.

5. RESULTS BASED ON EXPERIMENTAL DATA

In this section, we evaluate the performance of the 1-D CNN-SAN model. Data were collected from three healthy participants performing two types of wrist movements: smooth movement and tremorous movement. Those participants were instructed to either engage in simple wrist movements or remain stationary for 5 minutes, followed by rapidly oscillating the wrist at a speed exceeding 2 Hz for another 5 minutes. This sequence was repeated to gather the data. These collected data sets were then used for predictions at intervals of 100 milliseconds using the 1-D CNN-SAN model. Furthermore, the Exponential Moving Average was applied to the predicted data to smooth the prediction values. Although this introduces a slight delay, the lead time in prediction is sufficient to compensate for this latency. Fig.6 and Fig.7 show the outcomes for two distinct data sets. In these figures, comparisons are drawn between the predicted wrist angles and the recorded angles and with the voluntary movements. Moreover, they also display the discrepancy between the predicted angles and the voluntary movement where the latter are advanced by a duration of 100 milliseconds.

It is observed that, for the most part, the model effectively predicted voluntary wrist movements 100 milliseconds into the future. However, a slight decline in prediction accuracy for voluntary movements was evident during wrist movements exceeding 2 Hz.

The regression performance of the neural network is often assessed using root-mean-square error (RMSE) and normalized root mean square (NRMSE), which is based on the L2 norm, defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(p_i - a_i)^2} \tag{9}$$

$$\text{NRMSE} = \frac{\text{RMSE}}{y_{\max} - y_{\min}} \tag{10}$$

where n is the number of investigated points, p represents the actual voluntary movement, a represents the predicted voluntary movement, and $y_{\max}$ and $y_{\min}$ are the maximum and minimum values of the input position. We also experimented with predicting over varying time intervals, and the results were shown in Table 1.

The 1-D CNN-SAN model is capable of predicting short-term future voluntary movements, maintaining the NRMSE within 5% for predictions up to 175 milliseconds ahead. Furthermore, when implemented using MATLAB on a GPU (GTX

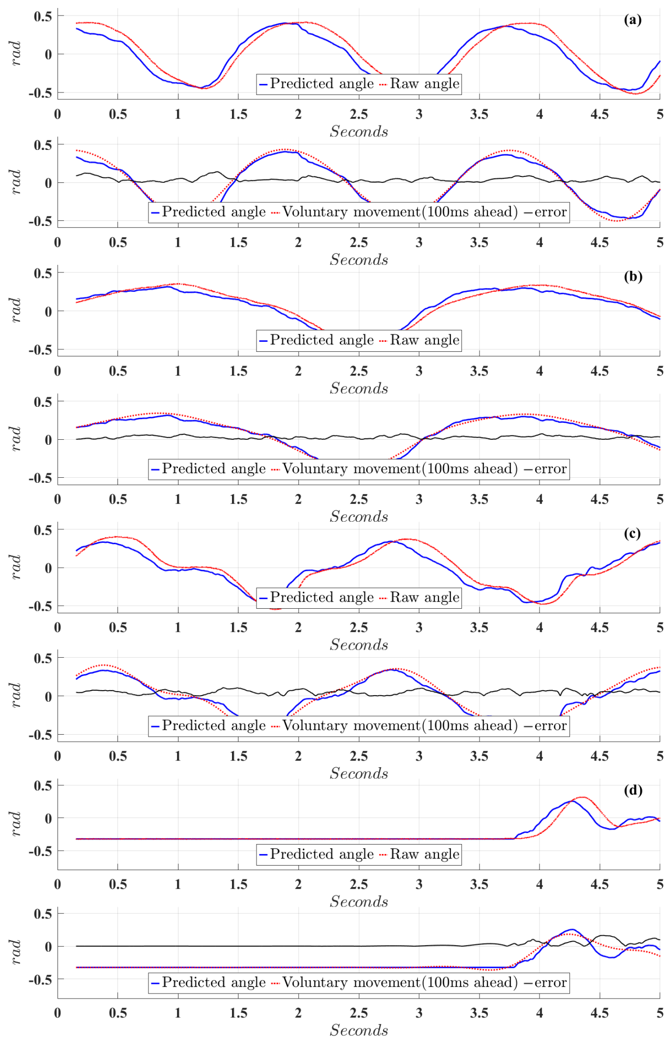

FIGURE 6: THE PERFORMANCE OF 1-D CNN-SAN MODEL ON EXPERIMENTAL MOVEMENT ANGULAR POSITION SIGNAL.

1080TI), running a loop 10,000 times, and simulating a new data set at each step, processing it, inputting it into the neural network, and obtaining the result, the total time is recorded. It shows that the algorithm operates at approximately 200Hz.

6. CONCLUSION AND FUTURE WORK

This study introduces an innovative approach for predicting future voluntary movements from motion signals with pathological tremors. Our algorithm is designed to serve as a tracking reference for exoskeleton control systems that incorporate voluntary motion prediction-based planning. In clinical applications, the exoskeleton can provide more precise and responsive assistance by accurately predicting voluntary movements. This reduces the risk of incorrect reactions to tremors and improves patient safety. Additionally, the exoskeleton can minimize unnecessary resistance by effectively distinguishing between voluntary movements and tremors, thereby reducing user fatigue.

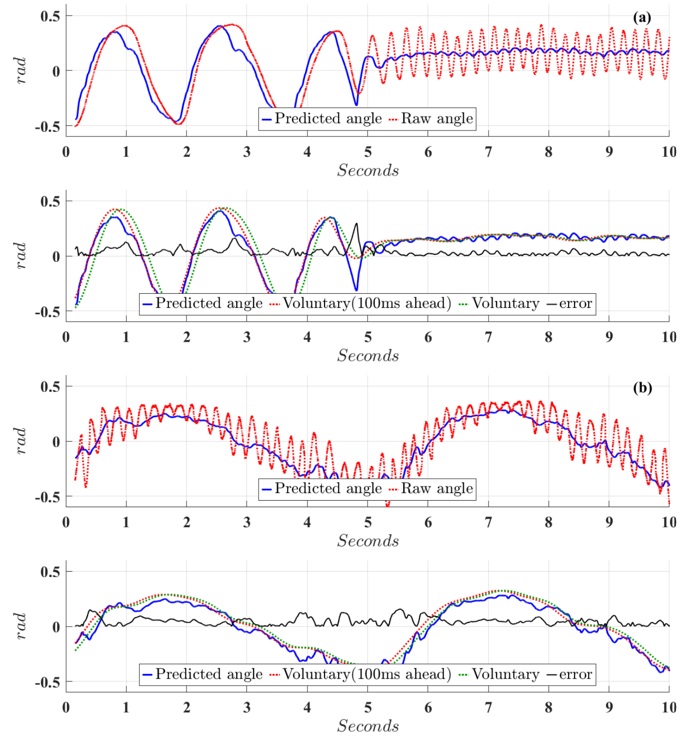

FIGURE 7: THE PERFORMANCE EVALUATION OF THE 1-D CNN-SAN MODEL ON EXPERIMENTAL INTENT TREMOR MOVEMENT ANGULAR POSITION SIGNAL INVOLVES ERROR ANALYSIS, COMPARING THE PREDICTED MOVEMENT TO THE VOLUNTARY MOVEMENT SIGNAL THAT 100MS HAVE SHIFTED FORWARD.

We derived the voluntary movements using zero-phase low-pass filtering building on the assumption that the frequency band of voluntary movements is lower than that of pathological tremors. By integrating Convolutional Neural Networks and Self-Attention Networks, we utilized EMG signals, wrist angles, and wrist angular velocities as inputs to predict future voluntary movements. This combined approach leverages the strengths of both CNNs in feature extraction and SANs in capturing temporal dependencies, thus enhancing the prediction accuracy of voluntary movements. Subsequent comparative analysis of the 1-D CNN-SAN model's predictions over varying time frames with actual voluntary movements revealed that within a prediction window of up to 175 milliseconds, the Normalized Root Mean Square Error could be maintained below 5%. However, it was also observed that the model's effectiveness diminishes in rapid wrist tremors. Overall, the 1-D CNN-SAN shows promise in accurately predicting future voluntary movements, and future work will focus on addressing its limitations. Also, further validation through real-time experiments will be undertaken to enhance its practical applicability.

ACKNOWLEDGMENTS

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TABLE 1: PERFORMANCE IN PREDICTING ACROSS DIVERSE TIME INTERVALS

Prediction(ms)	RMSE(rad)	NRMSE(%)
75	0.032	2.564
100	0.039	3.152
125	0.046	3.721
150	0.056	4.562
175	0.062	4.982
200	0.073	5.921
225	0.085	6.923
250	0.089	7.213

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