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Development of a Myoelectric Control Scheme Based on a Time Delayed Neural Network

Alan Smith, *Student Member*, *IEEE*, Pooja Nanda, *Student Member*, *IEEE*,
Edward E. Brown Jr, *IEEE*, *Member*

Abstract—**Presented in this work is a possible myoelectric control scheme for a rehabilitation robotic application. The control input is from a time delayed neural network (TDNN). The input to the TDNN is four electromyographic (EMG) signals associated with the movement of the elbow and shoulder joints. The output of the TDNN is the joint position of the elbow and the joint position of the shoulder in the sagittal plane. The results presented here show the possibility of controlling multiple degrees of freedom at once. Prior work has shown that the optimal delay for accurate position prediction from a TDNN was 875ms with a 125ms interval, but this work shows that a delay of 300ms and a 100ms interval achieves similar results. This points to the feasibility of a TDNN based control scheme.**

I. Introduction

Myoelectric control systems have been available for some time [13]. These systems take advantage of the electromyographic (EMG) signals obtained from muscles in order to control a rehabilitation robot, an orthotic or a prosthetic device. The goal of myoelectric control is to identify the user's intended motion during muscle contraction and implement that specific motion via the control system.

The proposed application for this work is the control and teleoperation of a rehabilitation robot. The purpose of a rehabilitation robot is to assist and guide users in regaining limb function and enhancing their mobility. Applications include the rehabilitation of limbs for stroke patients or the assistance of everyday activity for those who have neuromuscular diseases such as muscular dystrophy. An EMG based exoskeleton was developed in [16] to assist movement in the elbow joint. Many assistive devices also offer the flexibility of supporting motion in multiple degrees of freedom (DOF) for the upper-limb [9], [15]. It is recommended to read [5], [6], [8] for a comprehensive review of the work completed in rehabilitation robotics.

Myoelectric interfacing can be an essential aspect of human robot interaction for a rehabilitation application. The typical approach to EMG signal processing and control is feature extraction followed by classification to determine a class of motion. Examples of myoelectric control schemes can be found in [7] and [4]. Recently, more attempts have been made to analyze and characterize the EMG signal from the shoulder [2], [10], [11]. Oskoei studies myoelectric control in [14].

There are two drawbacks to the typical myoelectric control scheme. The first being that myoelectric control systems are usually dependent on isometric contractions that are repeatable. A myoelectric control system based on transient muscle contractions derived from natural motions is highly desirable. The second limitation is that most myoelectric control systems have the ability to only control one DOF at a single instance in time.

The purpose of this paper is to investigate and develop a control scheme that would overcome the above two limitations. Cheron, et. al., were one of the first to show the ability of EMG signals to predict arm kinematics [3]. They demonstrated the ability to predict two dimensional position output from a neural network while subjects moved their arm in a figure eight motion. Au and Kirsch advanced the development of shoulder and elbow kinematic prediction from EMG activity [1].

The work presented here is based on the work by Au and Kirsch. They showed that six EMG channels could be used to predict kinematics for all three DOF in the shoulder and the elbow using a TDNN. They found that the optimal delay was 875ms with 125ms intervals of delay. This work assesses the TDNN as a potential control architecture for a rehabilitation robotic system. To verify performance for this application, the time delay must be less than or equal to 300ms while maintaining accuracy of the TDNN's ability to predict joint position [13]. A simplified version of their approach is implemented by using four EMG channels and limiting movement to only the elbow and shoulder motion in the sagittal plane.

II. Methodology

A. Data Collection

All of the data presented in this work was collected using the Upper Extremity Motion Capture System in the Biomechatronics Learning Laboratory at the Rochester Institute of Technology (RIT) [12]. The developed system captures EMG and joint angle data from the elbow and

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Alan Smith and Pooja Nanda are grad students with the Department of Electrical Engineering, Rochester Institute of Technology, Rochester, NY, USA.

Edward E. Brown Jr. is an assistant professor with the Department of Electrical Engineering and director of the Biomechatronic Learning Laboratory, Rochester Institute of Technology, Rochester, NY, USA (eebeee@rit.edu).

shoulder. The data was obtained from 5 healthy subjects (4 males and 1 female) ranging in ages from 23 to 24 years of age. In the first experiment, one subject's data was used to determine the optimal parameters for the TDNN. The rest of the data from the other subjects were then used to test the optimal TDNN parameters found using the results of the first subject. EMG channels were placed on the biceps, triceps, deltoid, and pectoralis. The sampling rate for the data collection was 960Hz.

In order to make the TDNN more robust, several types of movements were collected. Single joint movements of both the elbow and the shoulder were collected. Single joint movement consisted of movement from rest over the full range of motion for the specified joint and back to rest. Rest was considered to be the arm located at the subject's side at full elbow extension. Full elbow extension was considered to be 180° and full elbow flexion ranged from 50° to 60° depending on the subject. In the shoulder, the rest position was considered to be 0° and the shoulder was elevated to a position ranging between 90° and 120° depending on the subject. Reaching motions were also collected that resulted in the movement of both DOF at once. The reaching motions consisted of reaching towards different points in space from rest and then returning to rest. Each type of motion was recorded for slow and fast repetitions. Slow movements lasted for approximately 3-4 seconds per repetition whereas fast movements lasted for 2-3 seconds. In order to train the TDNNs for variability, the exact times were not constrained. Twelve different trials of data were collected with each trial lasting 30 seconds in length. Six trials were reserved for training, and six trials were used for testing the TDNN. The six trials consisted of elbow, shoulder, and reaching motions for both fast and slow movements.

B. *Signal Processing Methods*

A block diagram of the signal processing methods used in this work is displayed in Fig. 1. The raw EMG signals obtained from the muscles were rectified and filtered prior to being input to the TDNN. The lowpass filter was a fourth order butterworth filter located at 4Hz. The filtering was implemented because the movements had no frequency content above this frequency.

The architecture of the TDNN is displayed in Fig. 2. One should note that multiple inputs come from each EMG channel. Associated with a TDNN is an interval of delay represented by Δt and a total delay which is $n\Delta t$ for n delay intervals. For instance, if the total delay was 300ms, and the time interval was 50ms, then n is equal to 6. Because the goal of this work is to investigate the possibility of using the TDNN output as a myoelectric control input, different time delays were analyzed. The time delays tested were 300ms, 600ms, and 900ms. The different delay intervals tested were 50ms, 100ms, and 150ms. A single layer was used and the number of neurons tested was 10, 20, 30, and 40 neurons.

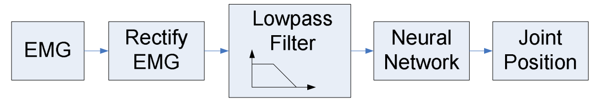

Fig. 1. The signal processing steps followed in the work presented.

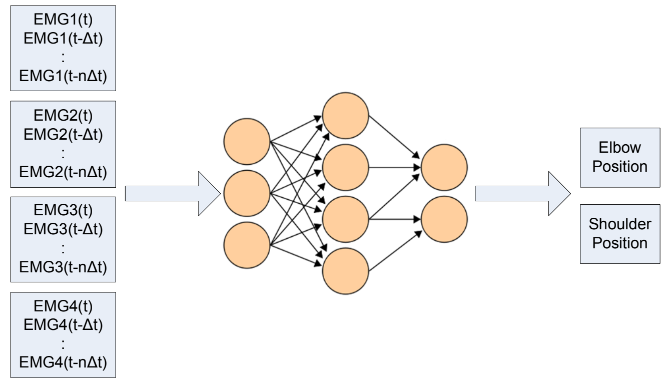

Fig. 2. The time delayed neural network structure. The input came from the EMG channels and the output corresponded to the elbow and shoulder position.

The use of the TDNN is a two step process consisting of training and testing. As recommend by Au and Kirsch, the position data was normalized between 0 and 1. All of the neural network simulations were executed using MATLAB's neural network toolbox, Version 7.6. The neural network created was a feed-forward, back propagation network. The "*tansig transfer function*" was used for the hidden layer and a "*linear transfer function*" was used for the output layer. The training was limited to a maximum of 250 iterations.

III. Results

By varying all of the parameters which included total delay, delay interval, and hidden layer neurons, 36 different neural networks were created for the first subject. Each neural network was trained using the six designated training trials of movement. Once trained, the neural networks were then tested with the six trials of test data. A comparison of the results while varying the number of neurons in the TDNN revealed that varying the number of neurons did not result in a change of accuracy. In order to simplify the presentation of the results it has been chosen to only show the results corresponding to the TDNN with 10 neurons in the hidden layer. This number was chosen because these TDNNs trained faster and will ultimately consume fewer resources in their final application.

The results were analyzed both from a qualitative and quantitative perspective. Table 1 displays the combined average error for the shoulder and elbow combined for subject 1 while varying the total delay and the delay interval. Table 2 presents a more detailed breakdown of the errors for each specific motion and each joint over the different TDNNs for subject 1. For simplicity in presenting the results, only the detailed results for the TDNNs having 100ms as the delay interval are shown in Table 2. This was chosen due to the fact that varying the delay interval did not

Overall TDNN Errors (Degrees)		
Time Delay	Time Interval	Average Error
300	50	16.0±23.2
300	100	15.7±22.9
300	150	15.7±22.8
600	50	17.1±24.2
600	100	16.3±23.8
600	150	16.5±23.5
900	50	17.3±23.5
900	100	16.9±23.7
900	150	22.8±30.5

Table 1. The overall error for each TDNN neural network with 10 neurons in the hidden layer while varying time delay and time interval for subject 1.

Shoulder Error for Subject 1 (Degrees)							
Time Delay	Time Interval	Slow Elbow	Fast Elbow	Slow Shoulder	Fast Shoulder	Slow Reaching	Fast Reaching
300	100	6.0±6.3	7.5±10.2	16.4±19.7	13.2±17.0	11.2±15.1	14.5±21.4
600	100	7.0±7.6	9.0±11.5	15.2±19.0	15.3±19.0	11.0±15.8	14.2±18.7
900	100	6.0±8.3	9.8±12.7	14.9±18.6	13.2±17.4	10.9±15.8	16.8±24.6
Elbow Error for Subject 1 (Degrees)							
Time Delay	Time Interval	Slow Elbow	Fast Elbow	Slow Shoulder	Fast Shoulder	Slow Reaching	Fast Reaching
300	100	25.9±33.5	21.7±28.8	20.4±19.6	18.2±18.6	16.1±20.6	17.7±24.9
600	100	25.3±32.1	22.0±28.3	20.7±20.3	18.6±22.1	17.4±25.7	20.4±27.6
900	100	29.7±36.9	24.3±27.0	17.3±12.2	18.6±13.3	17.6±20.9	23.9±31.1

Table 2. The error of shoulder position and elbow position for subject 1 for each type of movement. The TDNNs shown here had 10 neurons in the hidden layer and a delay interval of 100ms.

Shoulder Error (Degrees)						
Test Subject	Slow Elbow	Fast Elbow	Slow Shoulder	Fast Shoulder	Slow Reaching	Fast Reaching
1	6.0±6.3	7.5±10.2	16.4±19.7	13.2±17.0	11.2±15.1	14.5±21.4
2	19.1±24.1	21.2±25.7	12.0±10.8	21.6±13.3	20.3±27.4	20.1±26.3
3	6.4±8.2	11.0±14.6	27.7±27.0	27.6±33.5	20.1±24.6	19.7±26.2
4	15.2±24.9	19.2±27.8	26.1±36.9	29.8±41.9	29.6±39.6	35.6±43.4
5	4.2±5.1	6.9±10.5	11.6±12.6	12.1±15.8	14.6±17.6	15.9±19.1
Elbow Error (Degrees)						
Test Subject	Slow Elbow	Fast Elbow	Slow Shoulder	Fast Shoulder	Slow Reaching	Fast Reaching
1	25.9±33.5	21.7±28.8	20.4±19.6	18.2±18.6	16.1±20.6	17.7±24.9
2	6.5±9.2	10.3±15.3	13.7±16.4	18.4±23.2	18.8±24.9	22.5±25.5
3	34.3±40.0	29.1±33.6	26.8±21.0	30.1±22.8	23.3±28.1	27.6±32.7
4	28.4±29.9	22.8±30.6	10.4±10.2	16.0±14.5	11.5±15.0	13.3±17.6
5	21.2±24.7	31.8±36.3	17.8±23.5	22.3±23.6	29.6±35.2	21.0±26.8

Table 3. The error of shoulder and elbow position over each movement for each subject. Each TDNN had 10 neurons in the hidden layer with a delay interval of 100ms.

Test Subject	Average Error
1	15.7±22.9
2	17.0±23.2
3	23.6±30.6
4	21.5±31.4
5	17.4±25.3

Table 4. The average error of the shoulder and elbow position combined for all movements for a TDNN having 10 neurons in the hidden layer with a delay interval of 100ms.

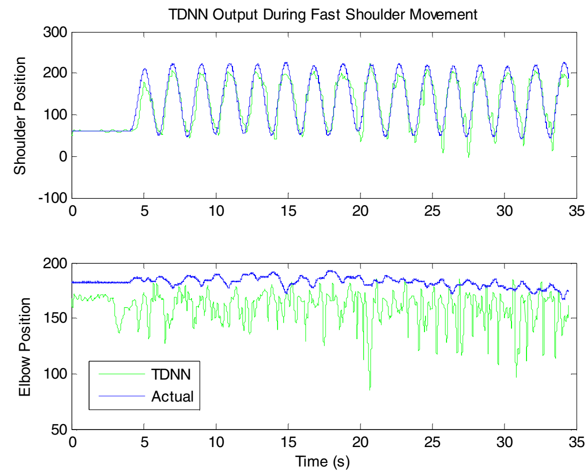

Fig. 3. The output of the TDNN during fast shoulder movement for subject 2.

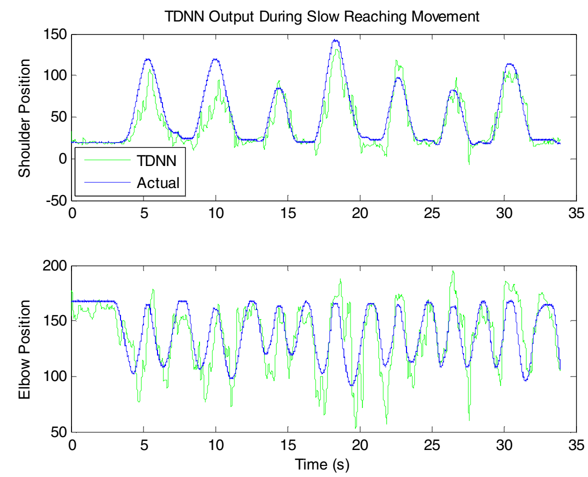

Fig. 4. The output of the TDNN during slow reaching movement for subject 1.

have a significant effect on the results. The 100ms interval did perform slightly better than the 50ms and 150ms intervals as seen from Table 1. Displayed in Table 3 is the average error of each joint for each subject during each type of movement. The results in Table 3 are for the use of a TDNN having a time delay of 300ms and a time interval of 100ms, parameters determined by the results of subject 1. Table 4 displays the average error of the shoulder and elbow combined for all the subjects using a TDNN with a delay of 300ms and a time interval of 100ms. All average errors are presented with a standard deviation.

A key feature of the suggested TDNN control approach is the ability to track more than 1 DOF at a time. Two test trials of the TDNN having a delay of 300ms and intervals of 100ms are displayed in Fig. 3 and 4. Fig. 3 shows the output of the TDNN for a fast shoulder movement by subject 2. Fig. 4 shows the output for a slow reaching movement by subject 1.

IV. Discussion And Conclusion

One of the main goals of this project was to study the applicability of the work completed by Au and Kirsch as a possible control scheme for a rehabilitation robot application. The feasibility of this was investigated by analyzing the effect of decreasing the total delay of the TDNN in conjunction with varying the delay interval. It was found that changing the number of neurons in the hidden layer and changing the delay interval did not have an effect on the accuracy of the TDNNs. Using a 150ms, 50ms, and then 100ms intervals resulted in a slight increase in accuracy as determined by the first experiments from subject 1. The most significant result to take away from this work is that it is possible to decrease the time delay without affecting the accuracy of the TDNN. In fact, the results here show a slight increase in accuracy when the total delay is decreased. Both a total delay of 300ms and 600ms achieved similar results in position accuracy, but increasing the delay to 900ms degraded the accuracy. Because there is no gain in accuracy by increasing the delay from 300ms to 600ms, the 300ms is more desirable for a control application. Once the optimal TDNN parameters were found for the first subject, these parameters were tested with other subjects. The other subjects had similar results, but were slightly less accurate. Another significant result is the ability of the TDNN to track both the shoulder and elbow joint at the same time during reaching motions as shown by Fig. 3 and 4. Test trials having large errors are probably a result variations between the training and testing data. Overall, the results show that the shoulder joint had better accuracy than the elbow joint.

Since it is possible to decrease the time delay while maintaining accuracy in the TDNN, it may be desirable to develop a real time control scheme based on this method. It should be noted that an additional delay would occur due to the time needed for TDNN computation. The average time for the TDNN in the MATLAB environment is 14ms, which is small compared to the time delay of 300ms. A control scheme based on the TDNN approach would also allow for the control of more than one DOF at the same time. Control of multiple DOF simultaneously is not thoroughly discussed in the myoelectric control literature. Although the decrease in delay has been proven, and a myoelectric control scheme made more possible, the output of the TDNN is not completely ideal for control. Different approaches would need to be implemented to try and stabilize the control input as well as decrease the amount of error. Error of the immobile joint during single joint motions could possibly be improved by using training data that consists of only rest data. Another approach could also be to use a single TDNN for each joint.

V. Future Research

Future research will entail performing a larger population study in order to further verify the results presented. Current myoelectric control systems are being developed in the Biomechatronic Learning Lab at RIT for a harmonically driven, rehabilitation robotic arm. The actual real time implementation of the TDNN scheme will be considered for the robotic arm. A comparison of the actual implementation of the classical myoelectric control schemes based on feature classification with a TDNN control scheme will also be pursued.

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