Using Artificial Neural Network to Model EMG Signals from the Prime Movers of the Shoulder for Rehabilitation Robotic Systems.

D. Matheson Rittenhouse, Hussein A. Abdullah, R. John Runciman and Otman Basir.
School of Engineering, University of Guelph
Guelph, Ontario, CANADA N1G 2W1
Tel: (519) 428 4120 ext.3346, Fax: (519) 836 0227
Email:habdulla@uoguelph.ca

ABSTRACT

Artificial neural networks have demonstrated some ability to model the electromyogram (EMG) signals from prime movers of the joint under investigation. This paper demonstrates the ability of a fully connected feed forward neural network (FF NN) to predict EMG signals from eight muscles of the shoulder. Robots used for physical rehabilitation can incorporate the information from EMG as an input to an intelligent decision making algorithm used to adjust the level of difficulty according to patient performance.

INTRODUCTION

There have been a number of machines developed to date for use in a rehabilitative setting. For a review of recent robotic prototypes developed for rehabilitation see Edward [1]. However, the field of rehabilitative robotics is still in its infancy in terms of understanding the full potential of machines in physical rehabilitation clinics. The implementation of a robot in physical rehabilitation clinics is quite different from industrial applications. Industrial robots work in a specified protected workspace with predefined tasks and are separated from human operators. Rehabilitation Robotics must provide a safe environment where humans and machines will interact together. Safety, flexibility, reliability and human-machine interface are even more important in rehabilitation robotics and are fundamentally changed with the more intimate human machine interactions.

One major limitation of the different robotics devices developed for rehabilitation is their inability to sense the response of the patient to treatment. Unlike its human counterpart, the robot used to provide physical therapy lacks the cognitive capacity to prescribe, observe and alter treatment according to patient performance. A number of researchers have suggested or used electromyography as a means of providing information on patient behavior [2-7]. This paper will determine how well a fully connected feedforward neural network (FF NN) can map shoulder and elbow joint moments and angles to EMG data collected from eight muscles of the shoulder for use in a rehabilitation robotics system.

EMG and Rehabilitation

EMG has been used in rehabilitation for over 40 years [2] and is the most common feedback device used in rehabilitation [3]. “EMG Biofeedback” is a general term used to describe treatment in which electromyography (EMG) provides information concerning the performance of a muscle or muscle group to the patient. EMG data is presented either visually or as an audio signal to the patient so that he/she can try to elicit a desired response [4]. While various Meta-Analysis concerning Biofeedback (BF) show its benefits [5, 6], there is still doubt concerning it being cost-effective [5] and has been generally criticized for not providing more quantifiable results [7].

Artificial Neural Networks and EMG

Recent interest in artificial neural networks (ANN) in the area of Biomechanics have opened one avenue to quantify, in a much more rigorous fashion, the desired response of a patient undergoing a specific activity. Robotic systems could be made more autonomous by including EMG as feedback for adjusting the level of difficulty of the physical therapy according to patient performance. The patient could be trained to reproduce a healthy pattern as opposed to simply increasing or decreasing muscle activity during a given activity.

Backpropagation Neural Networks

A number of researchers have used the Backpropagation (BP) algorithm in the area of Biomechanics. BP has been used to map EMG to muscle force [8], EMG to shoulder and elbow kinematics [9], EMG to joint angles and joint moments [10], EMG and joint kinematics to isokinetic joint torque about the elbow [11], static loads to muscle activation of a number of lumbar muscles at steady state [12]. However, few studies have tried to map joint moments and kinematics to EMG, and a review of the literature has not shown any studies using neural networks to predict EMG response of the shoulder.

EXPERIMENTAL PROCEDURE

Data Collection and Processing.

In total, five subjects performed two sets of the following exercises: Push-ups, chin-ups and press-ups. The Muscles used in this study, with their abbreviations and electrode type are: Deltoid Anterior (Da, Surface), Deltoid Middle (Dm, Surface), Deltoid Posterior (Dp, Surface), Infraspinatus (Is, Fine Wire), Latissimus Dorsi (LD, Surface), Subscapularis (Subs, Fine Wire), Supraspinatus (Sups, Fine Wire), Triceps Brachii (TB, Surface).

The subjects were first scrubbed with alcohol before type Blue Sensor N-00-s (Medicotest, Oelstykke, Denmark) surface electrodes were applied over the middle of the muscle belly. A type Blue Sensor VL-00-S ground electrode was placed over the bony region of the wrist. Fine wire electrodes were made from polyurethane insulated 0.025 mm cooper wire, which were inserted using a large bore hypodermic needle [13].

The EMG data was sampled at 1000 Hz, rectified, and time averaged using a 0.2 second linear envelope. For each muscle resting activity values and maximum voluntary contraction values were collected and used to normalize the EMG signal between 0 and 1. Electrogoniometer data used to measure joint angles was sampled at 50 Hz and also time averaged with a 0.2 second linear envelope [13]. Joint moments were calculated from hand force data provided by either a force plate (push-ups) or a six-degree of freedom component force and moment transducer (chin-ups and press-ups) [14].

Subjects & Activities

Data was collected from five male subjects, ages 24 - 32 (mean 27). None of the subjects had any previous shoulder problems, shoulder surgery or had undergone any athletic training geared towards strengthening the shoulder. The subjects body mass ranged from 64 to 80 kg (mean 68). Chin-up data was collected using two handles mounted 2 m off the ground with hands in a supinated position. Push-ups were done on a pair of hand platforms mounted 0.2 m off the ground. Press-ups were done using parallel bars.

Training Data and Validation

The inputs to the networks are the moments about the shoulder in the transverse, sagital and coronal plane, the moments causing elbow flexion and rotation, joint angles of the shoulder, elbow flexion and the angular velocity of the angles measured. The outputs of the network are the processed EMG data from the eight muscles.

The data was collected in two stages. Initially EMG data and elbow joint angle was collected. Hand force, elbow flexion joint angle and shoulder joint angles were collected separately. The two data sets were matched using elbow flexion as the common measurement between the two sets. Training sets consisting of push-up, chin-up, and press-up data was collected for four of the five subjects. The network was then validated against data collected from the fifth subject for each of the three activities. Training was considered complete when the mean squared error averaged across all data points in the training set was $< 10^{-6}$.

RESULTS

The ability of the network to predict data from a subject not used for training is considered as the r^2 value between the predicted and measured EMG values for each muscle. Table 1 shows the r^2 values for trials used to determine whether the NN could be used to predict data from a subject not used for training. The results are presented in Table 1 and Figure 1.

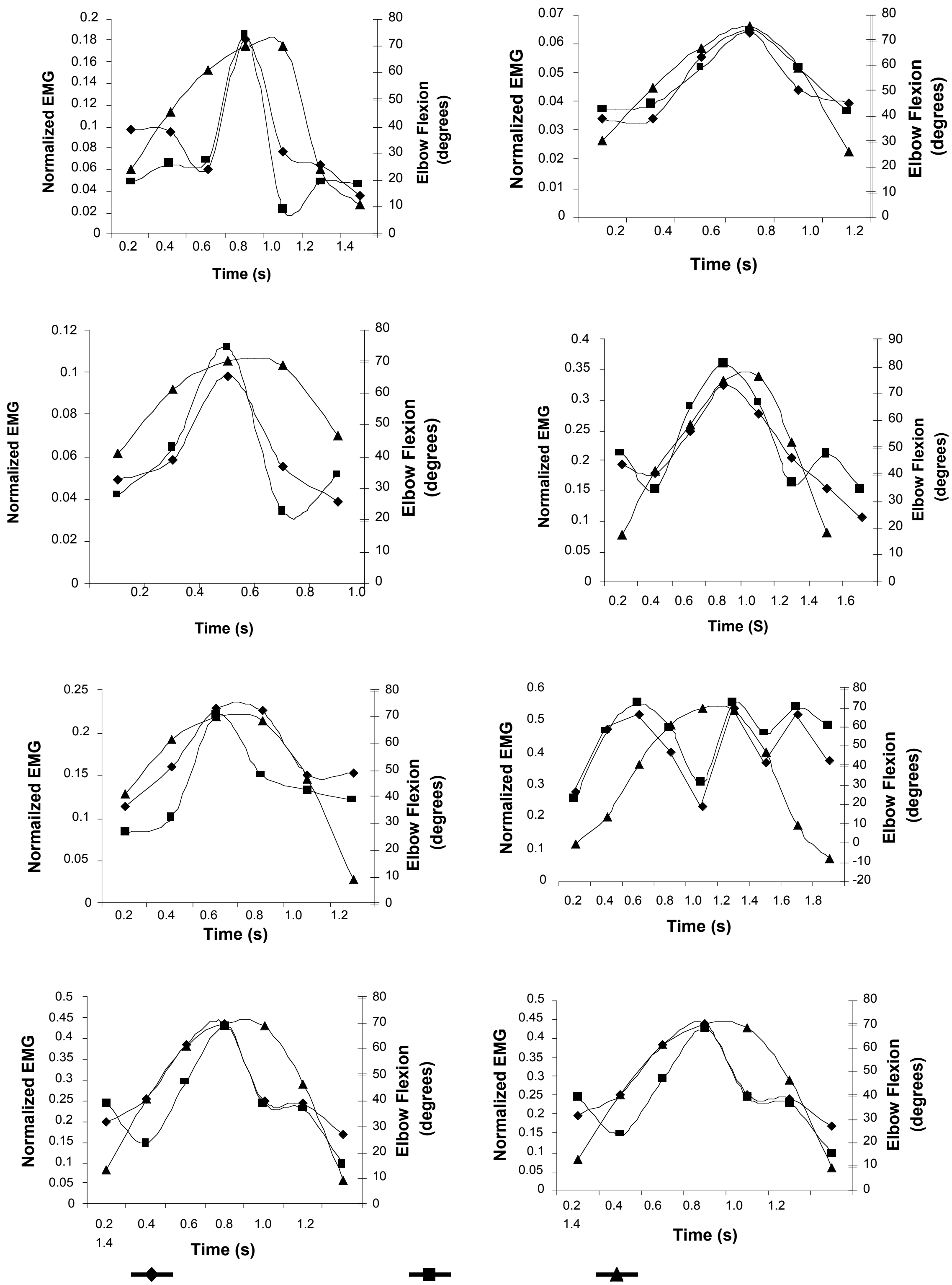

Fig. 1, Performance of the FF NN in predicting EMG signals from eight muscles of the shoulder and upper arm for a subject not used to train the NN performing a press-up. Muscles are, from top left: Da, Dm, Dp, Is, LD, Subs, Sups, TB. Note that one network was used for each muscle under consideration. Discrepancies in elbow flexion are a result of data set consolidation.

Muscle/Activity	Push-Up	Press-Up	Chin-Up	Average
Da	0.71	0.72	0.78	**0.74**
Dm	0.66	0.84	0.83	**0.78**
Dp	0.81	0.77	0.35	**0.64**
Is	0.60	0.78	0.71	**0.70**
LD	0.66	0.71	0.82	**0.73**
Subs	0.79	0.78	0.73	**0.77**
Sups	0.81	0.80	0.33	**0.65**
TB	0.60	0.74	0.82	**0.72**
Average	**0.71**	**0.77**	**0.67**	

Table 1: r^2 values between measured EMG and predicted values from a NN used to map joint moment and position to EMG signals from eight muscles of the shoulder and upper arm for one subject not used for training.

DISCUSSION AND CONCLUSIONS

While the FF NN's predictive ability is good, it is possible that a larger set of inputs may further improve prediction. Muscle control schemes are, in all likelihood, very complicated, depending on the required action, history of movment and curent position. The network showed a good predictive ability for subjects not used for training (r^2 between 0.33-0.84) Mean correlation values for the FF NN ability to predicting the EMG response from a subject not used for training was $r^2 = 0.66$. Good correlation existed for these data sets despite the fact that the inputs to the network were collected separately from the outputs

These results indicate that EMG can be incorporated into a robotic system and used for: i) providing a more complete BF to the patient, ii) providing quantitative information concerning the success of the treatment to doctors and physical therapists and iii) as an input to an intelligent control system which adjusts the level of difficulty of the treatment according to patient performance.

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