

Original Article

Prediction of Above-elbow Motions in Amputees, based on Electromyographic(EMG) Signals, Using Nonlinear Autoregressive Exogenous (NARX) Model

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Abstract

Introduction

In order to improve the quality of life of amputees, biomechatronic researchers and biomedical engineers have been trying to use a combination of various techniques to provide suitable rehabilitation systems. Diverse biomedical signals, acquired from a specialized organ or cell system, e.g., the nervous system, are the driving force for the whole system. Electromyography(EMG), as an experimental technique, is concerned with the development, recording, and analysis of myoelectric signals. EMG-based research is making progress in the development of simple, robust, user-friendly, and efficient interface devices for the amputees.

Materials and Methods

Prediction of muscular activity and motion patterns is a common, practical problem in prosthetic organs. Recurrent neural network (RNN) models are not only applicable for the prediction of time series, but are also commonly used for the control of dynamical systems. The prediction can be assimilated to identification of a dynamic process. An architectural approach of RNN with embedded memory is Nonlinear Autoregressive Exogenous (NARX) model, which seems to be suitable for dynamic system applications.

Results

Performance of NARX model is verified for several chaotic time series, which are applied as input for the neural network. The results showed that NARX has the potential to capture the model of nonlinear dynamic systems. The R-value and MSE are 8.3×10^{-3} and 0.99, respectively.

Conclusion

EMG signals of deltoid and pectoralis major muscles are the inputs of the NARX network. It is possible to obtain EMG signals of muscles in other arm motions to predict the lost functions of the absent arm in above-elbow amputees, using NARX model.

Keywords: Electromyography, Above-Elbow Amputation, Recurrent Neural Network, Signal Prediction.

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1. Introduction

Many individuals with amputations and other physical disabilities live in our society. Recent progress in biomechanics has helped increase the mobility of above-elbow amputees in their daily activities. Arm muscles, acting as actuators for elbow motion, carry the load of forearm and hand during elbow movements. The forearm consists of muscles which facilitate grasp/release motions of the forearm, wrist, and hand[1].

A transhumeral or above-elbow prosthetic arm is used to make amends for the lost functions of the above-elbow amputees. Currently, myoelectric prostheses are the most advanced, commercially available, externally powered transhumeral prostheses. Skin surface electromyographic (EMG) signals of amputee's residual muscles are used as input signals for controlling myoelectric prosthesis. The EMG signals are among the most important biological signals, reflecting the exact human motion intentions. The EMG signals, measured by surface electrodes, are then amplified and properly filtered for feature extraction. The feature values of EMG signals are used to control electromechanical active joints of prosthesis and activate prosthetic arm parts. EMG signals of three muscles including triceps brachii, pectoralis major, and deltoid were obtained from three healthy subjects. The goal was the prediction of triceps brachii EMG signals, based on pectoralis major and deltoid EMG signals[1].

Many processes in various domains such as biology, physics, and economics are described by time series. In formal terms, a time series is a sequence of vectors, depending on time t :

$$y(t), t = 0, 1, 2, \dots \quad (1)$$

Accordingly, EMG signal, in nature, is a type of time variable signal. Prediction by feature values of vector y is highly required for choosing a control strategy or optimizing activity and production[2]. In formal terms, prediction problem can be formulated as finding a function in order to obtain an estimated $\hat{y}(t + D)$ of the vector y at time $t + D$ ($D = 1, 2, \dots$), considering the values of y up

to time t and a number of additional time-independent variables (exogenous features) u_i :

$$\hat{y}(t+D) = \Gamma(y(t), \dots, y(t-dy), u(t), \dots, u(t-du)) \quad (2)$$

In this function, $u(t)$ and $y(t)$ represent the input and output of the model at time t , respectively; du and dy are the lags of system input and output, respectively, and Γ is a nonlinear function. For instance, $D=1$, meaning one-step ahead, can take any value larger than 1 (multi-step ahead) [2].

Therefore, prediction becomes a function approximation problem, where the goal of the method is to estimate the continuous function Γ as closely as possible. Consequently, in case of function approximation or regression problems, many methods can be applied from this domain. Usually, the evaluation of prediction performance is carried out by computing an error measure 'E' over a number of time series elements such as a validation or test set[2]:

$$E = \sum_{k=0}^N (\hat{y}(t-k), y(t-k)) \quad (3)$$

Here, E is a function computing the error or gap between the predicted and real sequence elements. Normally, a distance measure (e.g., Euclidean distance) is used, but depending on the problem, any function can be applied [e.g. a function computing the costs resulting from an incorrect prediction of $y(t+D)$]. The problem of chaotic time series prediction is studied in various disciplines including engineering and medical applications. Chaotic time series are the output of a deterministic system with a positive Lyapunov exponent. Therefore, the behavior of time series becomes unpredictable and the prediction of chaotic time series becomes a difficult task unless the initial conditions are specified with precision[2].

Neural Networks (NN) are powerful when used for problems whose solutions require knowledge which is difficult to specify, but for which there is an abundance of examples.

Prediction of chaotic processes implies finding interdependencies between time series components. These dependencies are minimal

in random time series and maximal in complete deterministic processes. However, random and deterministic time series are only margins of the large set of chaotic time series signals with weak dependencies between components in short or long term. A special case is represented by fractal time series, characterized by auto similarity or non-periodic cycles [2,9].

2. Materials and Methods

In order to find the relationship between the motions and activities of human upper-limb muscles in elbow extension mode (according to the defined protocol), the experiment was performed on three healthy male subjects, aged 24, 30, 32 years old (subjects Y, H, and T, respectively). Informed consents were obtained from each of the participants. In this experiment, the upper-limb motions and selected activities were performed five times by each subject. EMG and kinematic data of the upper limb were recorded for each subject, while making a specified movement (Figure 1).

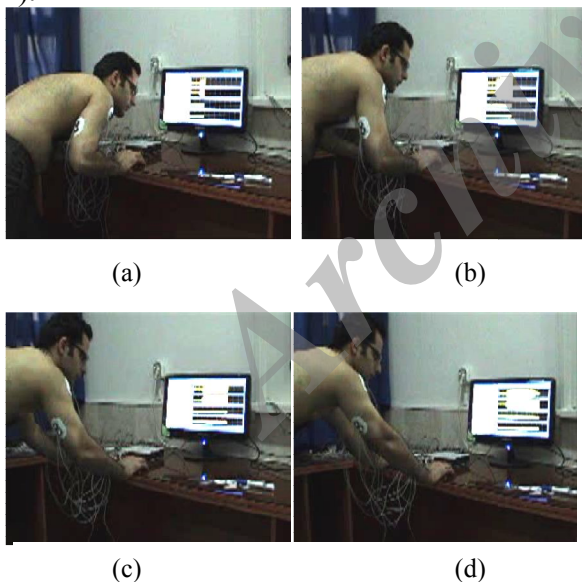


Figure 1. Arm extension movement protocol. (a), (b), (c), (d) shows motion sequences.

The subjects performed push-ups, which fully flexed their elbows and raised their bodies. Recording electrodes, with a bipolar electrode configuration, were placed on 3 target muscles, which control the movements of the

upper limb (pectoral is major, anterior deltoid, and triceps brachii)(Figure 2).

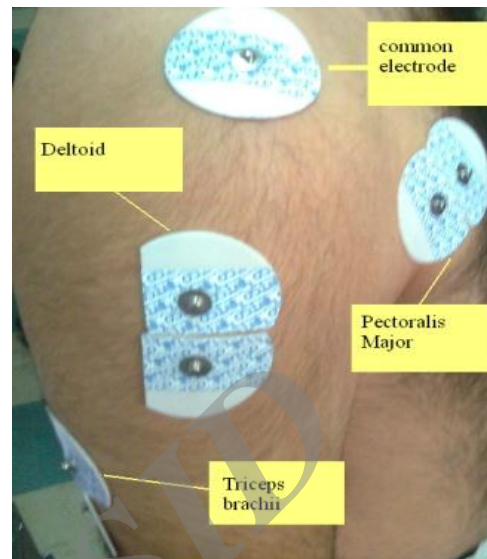


Figure 2. Upper-limb target muscles including pectoral is major, deltoid, and triceps brachii

EMG signals, acquired from the 3 muscles, were amplified using a differential amplifier and 10Hz low-pass filter (sixth-order Butterworth zero-phase filter), and were sampled at 1200 Hz. The lower frequency limit of the filter was chosen to minimize movement artifacts [3].

Overall, the recording lasted 9 seconds for each session. The subjects were asked to relax their muscles for 2 seconds, and then performed push-ups for approximately 5 sec; finally, they remained in the full extension mode for 2 seconds (Figure 1). None of the subjects reported muscle fatigue.

2.1. EMG Processing/Pre-Processing

All off-line processing was performed using MATLAB(R2013a) software. At first, all negative amplitudes were converted to positive ones, and all negative spikes were reflected by the baseline or were moved up to positive. Based on the square root calculation (4), Root Mean Square (RMS) reflects the mean power of the signal (also called RMS EMG) and is the preferred recommendation for smoothing (Figure3).

$$\text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^N V_i^2} \quad (4)$$

In this research, 70 ms time window was selected and EMG signals were normalized to

the maximum value of amplitude detected signal[9].

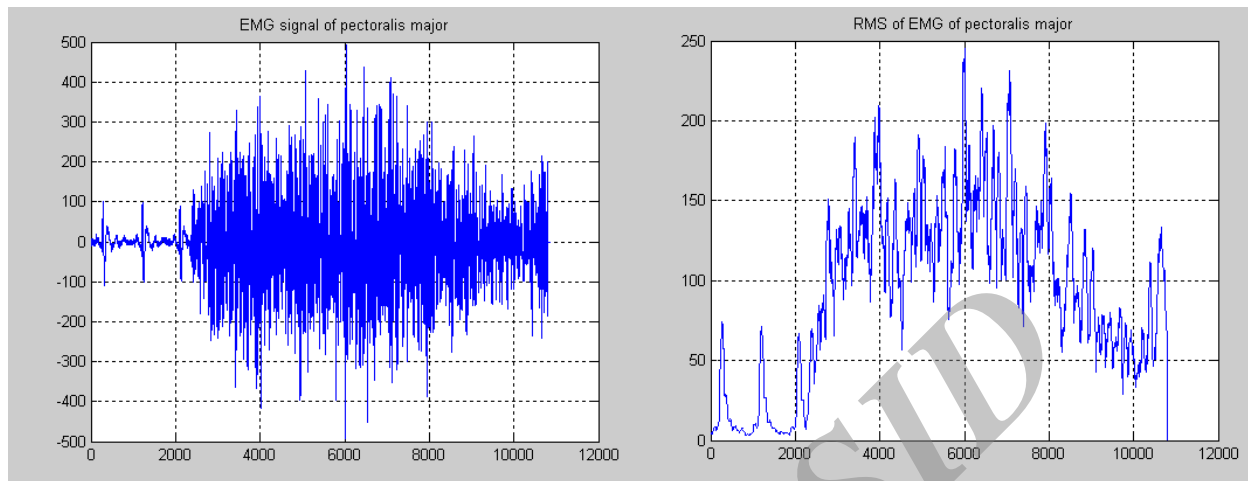


Figure 3. Left: raw EMG signal of pectoralis major muscle; Right: RMS of pectoralis major muscle

2.2 NARX Networks

In this study, we applied a type of recurrent neural network (RNN) of Nonlinear Autoregressive Exogenous (NARX) model to predict the triceps brachii EMG signals based on the EMG signals of the other two muscles (deltoid and pectoralis major). This powerful model has been shown to be well suited for modeling nonlinear systems, particularly time series. One principal application of NARX dynamic neural networks is controlling systems. The context input for NARX is not selected from the hidden layer but from the output layer with certain time delays [4]. The important qualities of NARX networks with gradient-descending learning algorithm include: 1) more effective learning in NARX networks, compared to other neural networks (gradient-descent learning is better in NARX model), and 2) faster converging and generalizing of NARX model, compared to other networks [2].

A state space representation of recurrent NARX neural networks can be expressed as(5):

$$z_k(k+1) = \begin{cases} \varphi(u(k), z_i(k)) & i = 1, \\ z_i(k) & i = 2, 3, \dots, N \end{cases} \quad (5)$$

where the outputs $y(k) = z_i(k)$ and $z_i, i=1, 2, \dots, N$ are state variables of RNN. The RNN exhibits forgetting behavior if:

$$\lim_{m \rightarrow \infty} \frac{\partial z_i(k)}{\partial z_j(k-m)} = 0 \quad \forall k, m \in K, i \in O, j \in I, \quad (6)$$

Here, 'z' is a state variable, 'I' denotes the set of input neurons, 'O' indicates the set of output neurons, and 'K' denotes the time index set [9].

Several methods have been proposed to eradicate the problem of vanishing gradient in training RNNs. Most of these methods rest on embedding memory in neural networks, whereas several others suggest making better learning algorithms such as the extended Kalman filter, Newton type, and annealing algorithms [2].

Embedded memory is of significance particularly in NARX RNN. This embedded memory can help speed up the propagation of gradient information and consequently reduce the vanishing gradient effect. There are diverse methods for introducing memory and temporal information into neural networks. These include creating a spatial representation of temporal pattern, setting time delays in the neurons or their connections, employing

recurrent connections, and using neurons with activations that sum the input over time[2,4].

3.2. Architecture and learning

The NARX model for the estimation of function Γ can be implemented in many ways. However, the straight forward method seems to be using a feed-forward neural network with embedded memory, as shown in figure 4, and

a delayed connection from the output of the second layer to the input layer[2].

Making the network dependent on du previous sequence elements is similar to using du input units fed with du provides adjacent sequence elements. This input is usually referred to as a time window since it provides a limited view on parts of the series. It can be also viewed as a simple method of transforming the temporal dimension into another spatial dimension [2].

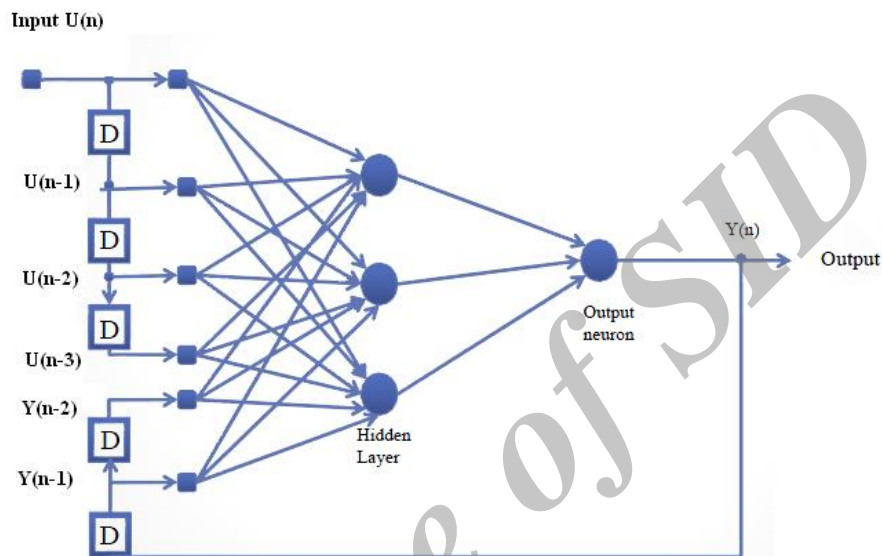


Figure 4. NARX model with tapped delay lines at the input

In practice, it was observed that the prediction of a time series would be enhanced by simultaneous analysis of related time series. A generalized implementation of this model allows the input and output to be multidimensional and thus be applied to the “multivariate” type of time series[2].

In the architectural model in figure 4, the notation used is $NN(du, dy; N)$ which denotes the NN with du input delays, dy output delays, and N neurons in layer 1. Similarly, in the architectural model in figure 2, the notation used is $NN(du1, du2, dy; N)$.

In this study, for the NN models with level 1 as the input layer and level 2 as the output layer, the general prediction equations for computing the next value of time series $y(n+1)$ (output), using the model in figure 4, the previous observation $u(n), u(n-1), \dots, u(n-du)$

and outputs $y(n), y(n-1), \dots, y(n-dy)$ as inputs may be written in the following form[2]:

$$y(n+1) = \Phi_o \left\{ w_{bo} + \sum_{h=1}^N w_{ho} \cdot \Phi_h \left(w_{ho} + \sum_{i=0}^{du} w_{ih} u(n-i) + \sum_{j=1}^{dy} w_{jh} y(n-j) \right) \right\} \quad (7)$$

4.2. Learning algorithms

For learning purposes, a dynamic back-propagation algorithm is required to compute the gradients. Additionally, error surfaces for dynamic networks can be more complicated than those for static networks[2,9].

The selected training method in this study uses the benefit of availability at the training time of real output set. In fact, it is feasible to use the true output instead of the predicted output to train the network[9].

The training process has some difficulties. One is related to the number of parameters, which refers to the number of links or weights in the network [9]. This number is usually large and there is a possibility of “overtraining” the data and producing a false fit, which does not produce reliable predictions. For the NARX neural network model, the number is given by $p=(du + dy + 2)N$. One solution to this problem is penalizing the increase in the parameter [2]. This motivates the use of an algorithm based on regularization technique, which involves modifying the performance function for reducing the values of parameters. Practically, the typical performance function used in training, mean squared error (MSE) is as follows(8):

$$MSE = \frac{1}{N} \sum_{i=0}^N (e_i)^2 = \frac{1}{N} \sum_{i=1}^N (t_i - y_i)^2 \quad (8)$$

In this function, t_i is the target. The network training function, which updates the weight and bias values based on Levenberg-Marquardt algorithm (LMA) optimization, was modified to include the regularization method. In mathematics, the LMA, also known as the damped least-squares (DLS) method, provides a numerical solution to the problem of minimizing a function (generally nonlinear) over a space of function parameters. These minimization problems arise especially in least squares curve-fitting and nonlinear programming [2].

The LMA interpolates between the Gauss-Newton algorithm (GNA) and gradient descent method. LMA is more robust than GNA, i.e., it can find a solution in many cases even if it starts very far off the final minimum. For well-behaved functions and reasonable starting parameters, LMA tends to be a bit slower than GNA, and can be also viewed as Gauss-Newton using a trust region approach[2,9].

LMA is a very popular curve-fitting algorithm, used in many software applications for solving generic curve-fitting problems; however, LMA finds only a local minimum, not a global minimum. In general, in function estimation problems for networks containing up to a few hundred weights, LMA has the fastest

convergence. This advantage is of high importance if highly accurate training is required [6].

3. Results

We used parameters of EMG signals of triceps, pectoral is major, and deltoid muscles, mentioned in section 2, to characterize the network prediction performance. Simulations in this study were performed using the neural network tool box in MATLAB® software (R2013a). We used a network with 1 hidden layer, and applied a hyperbolic tangent sigmoid transfer function (tansig) for the first hidden layer and a linear transfer function (purelin) for the output layer. The hidden layer had 10 neurons and the output layer had 1 neuron. We adopted MSE as the performance function of the network model. For all other parameters, the default values were adopted in MATLAB.

Triceps EMG prediction using NARX neural network

The aim of this experiment was to verify the algorithm used to predict EMG signal of triceps muscle in the arm extension mode of the specified protocol. The duration of push-up was 9 seconds and data sampling frequency was 1200 Hz; therefore, there were 10,800 samples for each muscle.

To reliably detect such a nonlinear behavior, a NARX-based approach was used. We selected participant H to train the network. The performance of a trained network can be measured by the errors in training, validation, and test sets; therefore, data were arbitrary divided into three segments: 70% for network training, 15% for validation, and 15% for network testing. Network training continued until the desired level of error was obtained; the MSE was 0.01 after 534 iterations (figure 5). In this study, the correlation coefficient R between the outputs and targets of the neural network was used. In fact, R is a measure of the variation between the generated outputs and targets. The R -value was 0.99, Figure 5 shows the predicted output(+) and the desired output (.)

Afterwards, we set the EMG signals of deltoid and pectoral is major muscles of participant H as the input sets of the trained NARX network and set the EMG signals of subject T as the target. Figure 6 shows the response of network output and target. The R-value and MSE are 8.3×10^{-3} and 0.99 respectively.

If we set the pectoral is major and deltoid signals of subject T as the input of NARX network (which was trained by subject H) and included the triceps signals of participant Y as the target. The R-value and MSE are 3.5×10^{-2} and 0.99 respectively. Figure 7 shows the responses of network output and target.

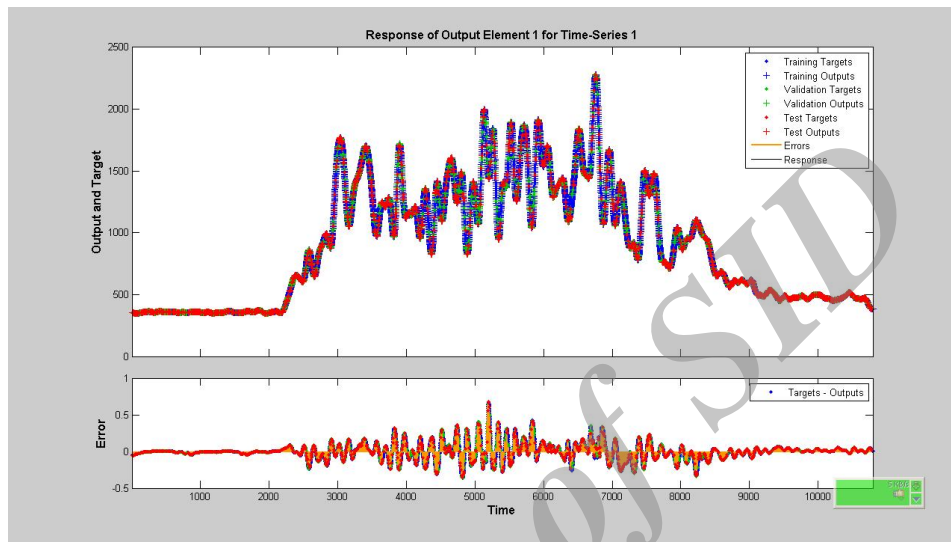


Figure 5. Response of network output(+) and target(.);the network was trained by subject H, and the red points show the errors; bottom figure shows the error variations

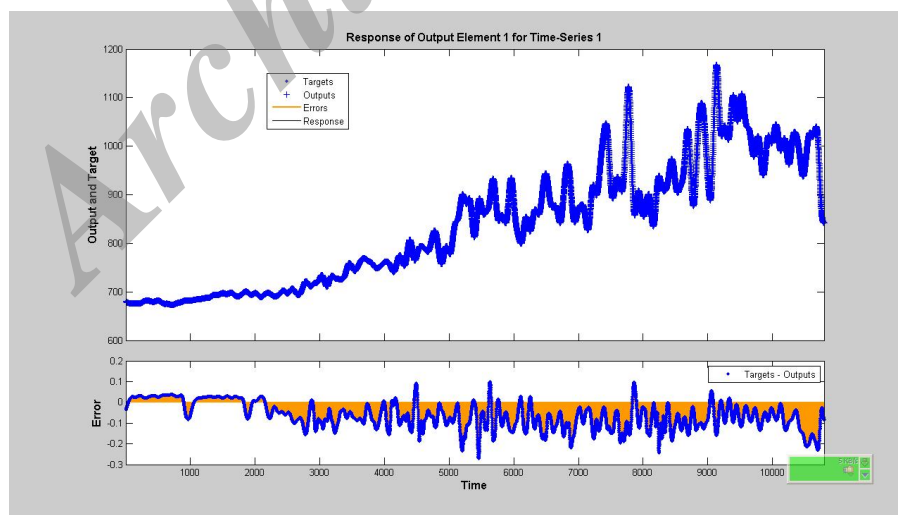


Figure 6. Network response with subject T as the target and subject H as the input (the network was trained by subject H)

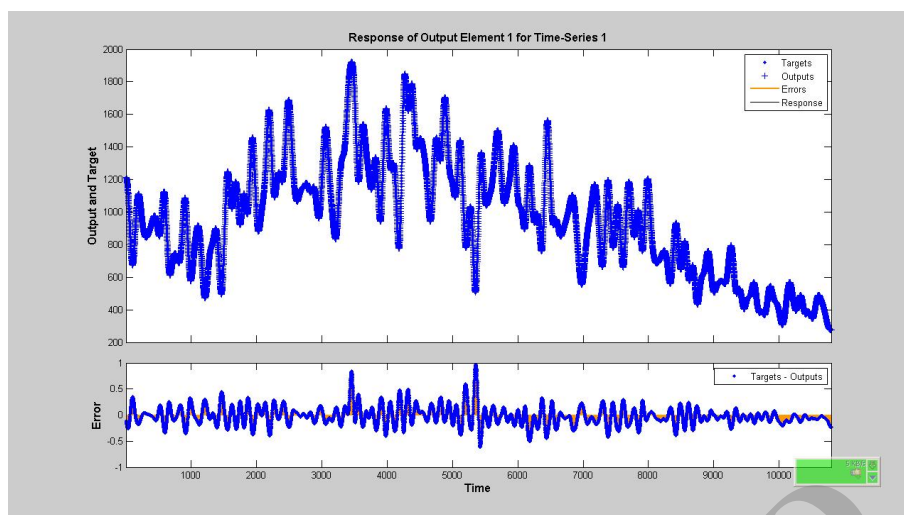


Figure 7. Network response with subject T as the input and subject Y as the target (network was trained by subject H)

4. Discussion

However, in [3], by using probabilistic methods was not greater than 0.74. In [7], the FFNN (feed forward neural network) method was proposed and the maximum value of R was obtained ($R=0.89$) but in this study the R -value and MSE are 8.3×10^{-3} and 0.99 respectively. In [8], the correlation coefficient (R -value) was not greater than 0.80, given the use of post-hoc method.

5. Conclusion

In this study, the prediction of EMG signal was tested using a NARX dynamic RNN. The results showed that NARX RNN has the potential to capture the dynamics of nonlinear dynamic systems. The R -value and MSE are 8.3×10^{-3} and 0.99 respectively, as shown in the evaluations. This is based on the fact that

correlation coefficient R , estimated for the target and network output, was close to 1 in many cases, and the prediction could be considered of real interest and significance if $R > 0.98$. Therefore, it is possible to obtain EMG signals of muscles in other arm motions to predict the lost functions of the absent arm in above-elbow amputees, using NARX model.

Acknowledgment

The authors would like to express their sincere gratitude to Dr Hosseini, physiotherapist at Mashhad Ghaem Hospital, for his suggestions about arm motions and Dr H.R. Kobravi for his medical engineering advice.

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