Original Article

Prediction of Biceps Muscle Electromyogram Signal Using a NARX Neural Network

Abstract

Background: This study was conducted to compare the response between the results of experimental data and the results achieved by the NARX neural network model to predict the electromyogram (EMG) signal on the biceps muscle in nonlinear stimulation conditions as a new stimulation model. **Methods:** This model is applied to design the controllers based on functional electrical stimulation (FES). To this end, the study was conducted in five stages, including skin preparation, placement of recording and stimulation electrodes, along with the position of the person to apply the stimulation signal and recording EMG, stimulation and recording of single-channel EMG signal, signal preprocessing, and training and validation of the NARX neural network. The electrical stimulation applied in this study is based on a chaotic equation derived from the Rossler equation and on the musculocutaneous nerve, and the response to this stimulation, i.e., the EMG signal, is from the biceps muscle as a single channel. The NARX neural network was trained, along with the stimulation signal and the response of each stimulation for 100 recorded signals from 10 individuals, and then validated and retested for trained data and new data after processing and synchronizing both signals. **Results:** The results indicate that the Rossler equation can create nonlinear and unpredictable conditions for the muscle, and we also can predict the EMG signal with the NARX neural network as a predictive model. **Conclusion:** The proposed model appears to be a good method to predict control models based on FES and to diagnose some diseases.

Keywords: *Biceps muscle, electromyography, musculocutaneous nerve, NARX neural network model, Rossler model*

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Introduction

In 1993, the National Institute of Health published a rehabilitation research program via the National Center for Medical Rehabilitation Research in the United States to improve daily activities.[1] Rehabilitation research included improving, restoring, and reducing the disability of people with severe physical disabilities so that they can return to the labor market.[2] It is essential to identify the current condition, disability, and ability of the patient before the disease and to use predictive tools to perform rehabilitation.[3] In addition, it includes a sociopsychological model that emphasizes physical function, mobility level, and physiological and environmental conditions and examines the patient's needs for returning to work and the initial condition.[4]

One of the rehabilitation interventions in individuals is on the arm and biceps muscle; if they have a problem, it can cause many problems for the individual.[5] Biceps disease is a common physical disability requiring rehabilitation exercises and various functional electrical stimulations (FESs) to initiate movement and strengthen the weak biceps muscle.[6] Furthermore, it is possible to measure the position of the biceps muscle by electromyography (EMG) and response to various stimuli, helping to analyze the muscle activity produced by the considered muscle and to diagnose some diseases.[7]

EMG refers to the electrical signal of muscles that is controlled by the nervous system and is produced during various muscle contractions or stimuli. This signal indicates the anatomical and physiological properties of muscles and includes two types: surface EMG (sEMG) and muscle

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EMG.[8] Moreover, it is beneficial to use EMG signals as electrophysiological signals in medical and engineering fields;[9] in other words, it is possible to use them in functional stimulation and intelligent artificial limbs by applying accurate information. Correspondingly, because EMG is produced by the nerve activation of the brain and spinal cord, it contains significant information on movement and diagnoses diseases.[10] The main method to understand many behaviors of the human body under normal and pathological conditions is presented by recording EMG signals. Several studies have described the function of EMG signal analysis and the validation of the biceps muscle with different age ranges, protocols, and placement of electrodes on the target muscle.[11] Some researchers have discussed the placement of electrodes on the biceps muscle during EMG measurements. The best place for EMG electrodes is in the area between the nerve and the tendon area to obtain high-quality and stable sEMG signals.[12]

Accordingly, it is highly difficult to analyze and classify EMG signals due to the complex pattern of EMG, particularly when motion occurs, and sometimes, the biological signals become chaotic. Hence, one of the methods of EMG signal analysis is to create nonlinear conditions causing the signal to be chaotic. For this reason, recent studies on biological systems indicate that the structure and behavior of many of these systems, particularly the vital organs of the human body, are nonlinear, complex, and sometimes chaotic.[13-17] Furthermore, most biomarkers enter the chaos applying external stimuli.[18,19] Consequently, it is required to use a black box modeling to model the output EMG signal based on a specific nonlinear stimulation, including chaotic equations. There are many models in the biological field, and each one has its own limitations. The usefulness of biological models is related to the field of various intelligent organs and FES that performs nonlinearly by the initial signals of the body or by the desired stimulation.[20] For example, biological models based on the EMG signal of the arm are utilized about the cybernetic hand. In addition, FES is used for patients with tremors, such as MS, Parkinson, intrinsic tremors, and even concussions, to reduce hand tremor based on contractions of the opposite muscle. It is also undeniable to predict EMG and its parameters to control the FES system. Therefore, one of the significant parameters affecting the control of hand muscles is nerve stimulation. Nerve stimulation depends on various parameters.[21] In other words, it is possible that changing the frequency and amplitude of the stimulation signal to the muscle changes the EMG signal, or changing the frequency and amplitude of the stimulation signal to the muscle can change the angle of the joint.[22] Most of the proposed biological models based on external stimulation to the hand muscles that were previously designed using nonlinear systems and mathematics, including chaotic equations (which are the most similar ones to the biological system), have not been used in this study, and therefore, a new stimulation model derived from the Rossler chaotic equation is specifically utilized to create nonlinear conditions in the muscle. Among the biological models used, artificial neural networks (ANNs) offer a new approach to the parameter estimation of linear and nonlinear models. The ability to learn ANN and generalize the behavior of each set allows to adapt to variable and dynamic environments and to have forecasting tools more flexible than traditional statistical models.[23] Hence, they are considered powerful modeling tools. Studies have indicated that it is possible that joint motion and related biological signals reflect the inherent dynamics of human movement; therefore, motor and biological signals can be applied to model the skeletal neuromuscular system to develop recurrent models for prediction.[24] Various methods have been proposed to predict EMG signals, and some of the related parameters, namely signal parameters such as biceps force, have been estimated for different loads to predict the angle of the joints.[25-28] In some other methods, different parameters belonging to the signal, such as waveform length, root minimum square, slope sign change, zero crossing, and simple square integral, have been applied.[29-35] Machine learning algorithm methods, including the support vector machine and random forest,[36] has been applied to predict muscle activity, none of which has predicted the EMG signal. In general, ANN is one of the most desirable methods for predicting activities related to the EMG signal of the upper limb.[37]

NARX is an effective way to solve consecutive nonlinear problems, and modeling in relation to the NARX model can better illustrate the nonlinear spatiotemporal correlation structure of the muscle and natural control signals. On the other hand, NARX models are different from other neural networks such that the model outputs as input for future predictions act in the form of feedback.[38]

NARX is extensively used to estimate joint angle, decode shoulder, elbow and wrist movements, and control prosthetic model.[39] Moreover, torque[40] and electrocardiogram signal have been predicted by the NARX neural network to optimal use FES system.[41] Given that the skeletal neuromuscular system is a time-varying nonlinear system, one-step forward prediction of the NARX model is introduced to construct a Gaussian process autoregression model that uses the prediction confidence interval to describe uncertainty.[42] The effect of model uncertainty on the results reduces the prediction and improves the rationality, accuracy, and efficiency of the common angle prediction model.[43] The current study records the EMG signal of the response by designing a new chaotic stimulation function and applying it to the musculocutaneous nerve. The stimulation signal and the EMG signal created by each stimulation are then applied to the NARX neural network to train and validate and retest the trained data and new data.

Ultimately, this study was conducted to predict the EMG signal on the biceps muscle based on nonlinear stimulation applied by the NARX neural network as a new predictive method. Correspondingly, the true EMG signal of a muscle can be compared using the predicted signal with the NARX neural network, based on which some diseases can be diagnosed using this predictive model in addition to intelligent artificial limbs and functional nerve stimulation.

Methods

Study design and material

This study was conducted on 10 healthy and right-handed individuals who were purposefully selected in 2021. This study was approved by the Ethics Committee of Islamic Azad University, Tehran Science and Research Branch. Then, the researcher referred to the place of the study and explained the necessary points on the objectives of the study after identifying the individuals. In cases where the person had the consent to participate in the study, the informed consent form was obtained from him/her, and 10 orders of the resting EMG signal during rest and during 414 s were recorded based on the same type of stimulation signal.

Inclusion and exclusion criteria

Inclusion criteria included individuals who were healthy and right-handed, did not have any musculoskeletal problems, and were willing to participate in the study. Exclusion criteria included left-handed individuals and individuals with musculoskeletal problems and dissatisfaction with participation in the study. Because there is a major difference between normal and paralyzed limbs (for example, spasm in a paralyzed limb), the results presented are not related to spasmodic limbs. Notably, the information of all individuals is confidential, and the researcher will not use the data in any other study.

Tools

In this study, the response obtained from the results of experimental data (response to biceps muscle stimulation) was compared with the results of the NARX neural network model based on the applied stimulation. The study consisted of five stages: (1) skin preparation, and placement of recording and stimulation electrodes, (2) how to place the person to apply stimulation and record EMG signal, (3) stimulation and recording of single-channel EMG signal, (4) signal processing, and (5) training, validation, and NARX neural network testing.

1. Stage 1: Surface electrodes used for recording were identical and were from the Skintact brand
2. Stage 2: The height-adjustable table and chair were adjusted appropriately to each person's height so that when each person sat down and placed his hands on the table, the angle of the shoulder and body was 90°
3. Stage 3: Adinstruments brand Powerlab 26T model, which was calibrated last month, was used as a single channel to record the EMG signal. The stimulation signal designed with the LabVIEW software interface was converted into an analog signal to be applied to the nerve by the National instrument model BNC-2090
4. Stage 4: The noise caused by the power line from a hardware filter related to the powerlab26T device, which is considered a band stop filter and the frequency band of the power line, i.e., 50 Hz, was removed by passing a notch filter. All data obtained from this study were analyzed and validated in LabVIEW (NI company, Austin, TX 78759-3504, USA-TEXAS) 2018 and Matlab (Natick, Massachusetts, USA) 2020 software programs. In addition, the characteristics of the stimulation signal were checked using the Tools box SP of matlab2020 software.

Rossler nonlinear dynamics

Muscle stimulation was performed using a type of chaotic equation, called the Rossler system, and applying stimulation to the musculocutaneous nerve, and the response was received in the form of EMG signals. The Rossler equation was considered in LabVIEW software version 2018 in accordance with Eq. (1) Rossler system.[20]

$$\dot{x} = -\left(y + x\right),\ \dot{y} = x + ay,\ \dot{z} = b + z(x - c) \qquad (1)$$

The Rossler equation consists of three dependent variables x, y, and z with three control parameters a, b, and c $\in$ R; changing each of these control parameters will change the trajectory and variable in terms of time. In some conditions, the shape of variable signal after passing through the period doubling will take chaotic properties.

NARX neural network

NARX neural network was used according to the nonlinear and biological nature of the problem. This network can be generalized much faster and better than other networks with recurrent dynamic feature and convergence, and it is a powerful modeling and validation tool. The output of the NARX network during training can be expressed by Eq. (2):

$$y\left(t\right) = f(y\left(t - 1\right), \ldots.y\left(t - 100\right), u\left(t - 1\right),\ \ldots.u(t - D)) \qquad (2)$$

where f is a function approximation describing the behavior of system via ANN; u(t) is the external input of the neural network, which is the signal of stimulation equation; y(t) shows the output of the neural network signal, which is the EMG signal expected for prediction; and D is the number of delay samples considered to start the prediction. In this study, the delay number 100 was selected by trial and error. In fact, u(t) is the stimulation signal, and y(t) is the EMG signal. During the training, the network behavior was predicted based on per 100 samples of the previous time series of the stimulation signal and the corresponding EMG, and it exits the NARX neural network as an ever-stable behavior. In this study, a two-layer NARX network was applied as illustrated in Figure 1. According to Figure 1, y(t) returns to the input based on the values of the previous steps in addition to the output as feedback, and input u(t) is considered independently where IW is the input weights, LW is the layer weights, b is the biases, and f is the function approximation.

Results and Discussion

Stage 1: Skin preparation, placement of recording, and stimulation electrodes

The qualitative criterion for skin preparation is that the electrode site is slightly red due to abrasion; however, this does not mean that the skin surface is injured or damaged. For this purpose, the hair on the surface of the skin, arm, and wrist protrusion was cleaned with alcohol-soaked cotton so that the skin was not damaged or injured. After drying the skin, the skin surface was rubbed with soft sandpaper.

Regarding the site of the electrodes, the individual was asked to fist his hand and bring it closer to the shoulder, which is called arm holding. By holding the arm, the biceps muscle appeared. Then, the peak of the muscle according to Figure 2 was the site of the center of the first electrode. Then, it was placed at a distance of 2 cm from the center of the first electrode and in its direction and toward the elbow of the second electrode. Indeed, the distance between the two electrodes was 2 cm so the first electrode was placed on the tip of the arm. In addition, the reference electrode was placed on the wrist bone.

Regarding the placement of the stimulation electrode, the suggestions provided by physical therapists and physiotherapists as well as previous researches were used. The results indicated that the location of the stimulation electrode should be on the site of 1.3 of the humerus bone and musculocutaneous nerve.[22]

Figure 2 shows that a line was directly drawn at the site of the bending elbow, and a line was horizontally drawn from the site of the coracoid bone appendage that was perpendicular to the line of the site of the bending elbow. It was selected as the site of the stimulation of the musculocutaneous nerve and the placement of the stimulation electrode by selecting 1.3 of this line and in the direction close to the midline of the body.[44] After installing two electrodes with a multimeter, the ohm value was recorded between the two electrodes. When the ohm value was more than 30, it was corrected by changing the recording electrode pair, re-sanding, and increasing the electrolyte gel (electrolyte gel was used to improve the electrical conductivity between the electrode and the skin). Table 1 illustrates the demographic characteristics of the samples.

Stage 2: How to sit to apply stimulation and record the electromyogram signal

The individual was asked to sit behind a desk to record the data. The person sat in a way that the soles of his both feet were completely on the ground, and the back was perpendicular to the back of the chair. The angle of the shoulder with the body was 90°, the angle of the elbow was 45°, and his hand was placed on a flat surface without protrusions. Various studies have evaluated the way of sitting person in this position many times, and the individual in this position sits completely naturally and feels comfortable [Figure 3].[23] Zero angle was defined so that the forearm and arm were aligned with each other, the elbow angle increased with flexion, and complete elbow extension was created. In addition, he was asked to refrain from paying attention to the voluntary movement of the hand as much as possible so that the movement of the limb was only due to electrical stimulation and the limb was at rest (loose).

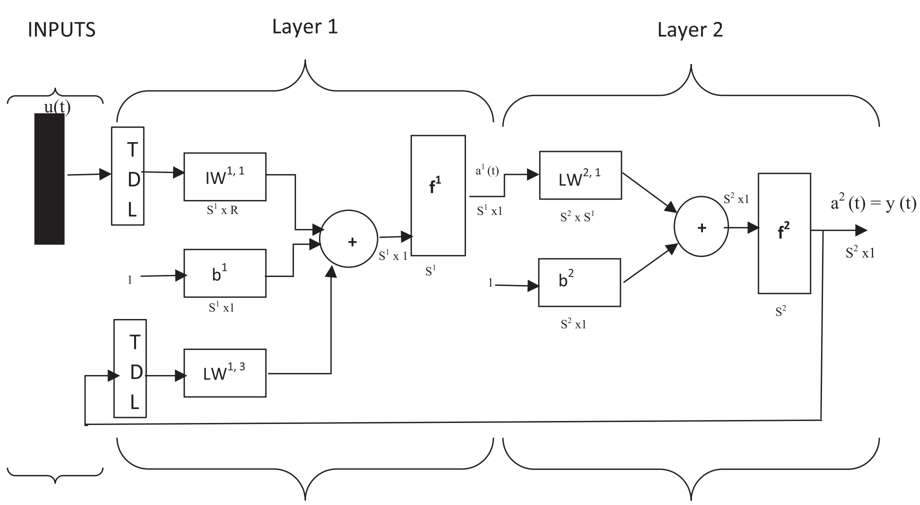

Figure 1: Two-layer NARX network structure with s outputs[21]

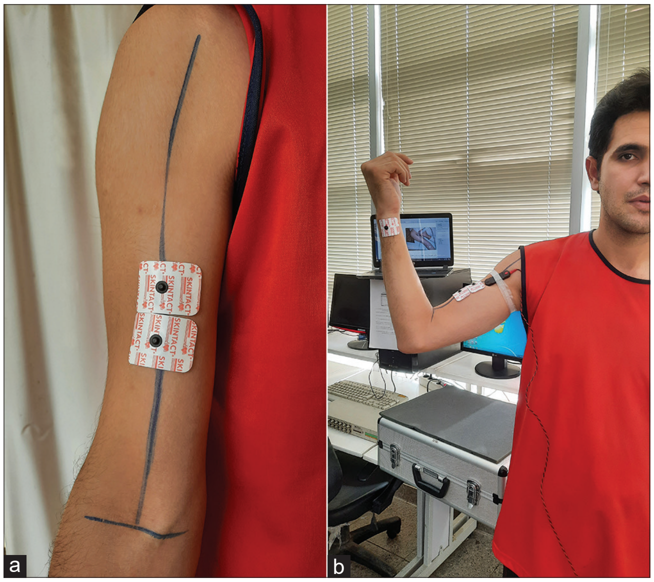

Figure 2: Right figure(b): Location of the stimulation electrode and stimulation of the musculocutaneous nerve as well as placement of the reference electrode on the wrist. Left figure(a): Location of the recording electrodes along the drawing line to identify 1.3 of the humerus bone. The image has been published with the individual's consent

Table 1: The demographic characteristics of the study individuals

Demographic characteristics	*n* (%)	Mean±SD
Sex		
Male	6 (60)	-
Female	4 (40)	-
Age (years)	-	2.41±32.25

SD - Standard deviation

Stage 3: Stimulation and recording of single channel electromyogram signal

The stimulation signal applied to the biceps muscle was defined based on the Rossler chaotic equation so that the stimulation pulse ranging from 0 (without stimulation) to 8 V was continuously transmitted to the biceps muscle in 414 s based on the Rossler chaotic equation, and the maximum current values were 20 mA based on the standard of medical equipment and the range of the device used.[45] Owing to selection of the maximum stimulation voltage considering the maximum standard value of mA applied to the muscle and the skin resistance of the samples, this value was investigated experimentally up to 15V, and it was specified that the EMG signal will be chaotic at 0 to maximum 8V. In the Rossler Eq. (1), there are three chaotic control parameters a, b, and c that changing each of them changes the shape of the trajectory diagram and the diagram of its three variables, x, y, and z, during the time.

The two control parameters, b and c, were kept constant at values 5.7 and 2, respectively, and the control parameter "a" was regarded as the control variable. The control parameter of the stimulation increased from 0.1 to 0.3 during 414 s, each step by increasing 0.001, and the duration of each step was 2070 ms. Changing the control parameter "a" from 0.27 by the period doubling method caused this system to enter the chaos. The Rossler system goes through periods 2 and 4 and then enters the chaos. Since the Rossler device consists of three equations, its third variable, z(t), was used as the stimulation function by solving the equation in terms of time, including a set of period doubling compressed according to Figure 4. Because the maximum value of z was 9.98 V, and the minimum value was 0.17 V, in this study, the amplitude of z(t) equation was normalized between 0 and 8 V during 414 s.

Figure 3: How the person sits when the stimulation signal is applied, and the EMG signal is recorded (the image has been published with the individual's consent). EMG: Electromyogram

In addition, the recorded EMG signal entered the chaos space based on the applied chaotic stimulation, and there was no longer a signal with (repetitive pair period) period doubling so that it had a signal (its chaotic part in infinite) lacking the alternation state of power two. This means that the signal is random and corresponds to the characteristics of biological signals, which is impossible to be predicted normally. All stimulation signals applied to the biceps muscle were simultaneously observed with an oscilloscope to reduce the error. The characteristics of the stimulation wave generated in Table 2 and the characteristics of the stimulation signal shown in Figure 4 demonstrate the complete characteristics of the signal encompassing the total duration of the stimulation signal and the stimulation voltage range at each time, duty cycle, and width pulse.

Electromyogram signal recording

A total of 10 orders of EMG signal were received from each individual based on ten orders of the same stimulation, and the distance between the two recordings was considered at least 10 min for each individual to prevent muscle fatigue and saturation of nerve stimulation. Furthermore, the human movement control system always controls the activities of the body in such a way that the highest efficiency is achieved with the least amount of fatigue in the muscles

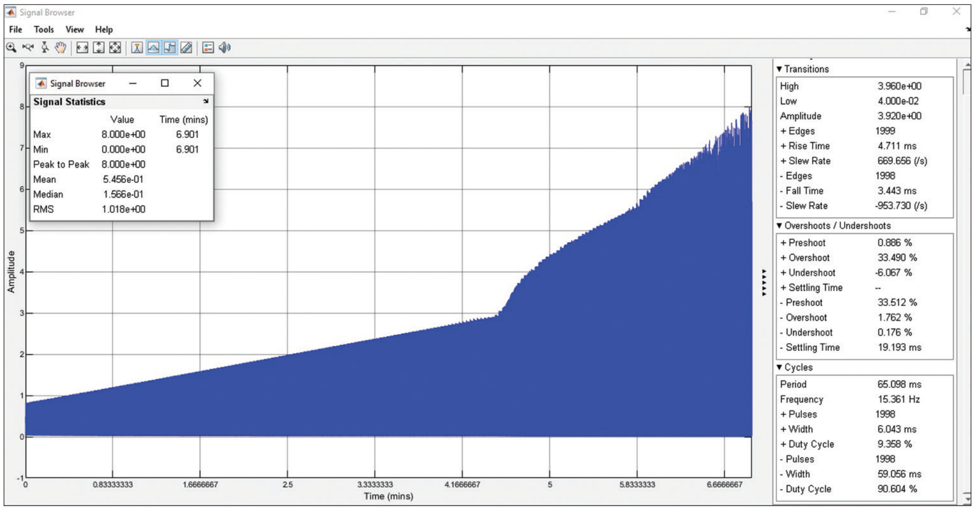

Figure 4: The characteristics of the stimulation signal ($z(t)$) applied to the muscle as a whole in 414s ranging from 0 to 8V

Table 2: The characteristics of the stimulation signal

Stimulation wave	Unit
Frequency range	0-200 Hz
Maximum frequency	15.361 Hz
Mean	0.5456 V
Median	0.1566 V
The largest peak value	8 V
The minimum peak value	0 V
Pulse	1999

involved, and this type of activity is regarded as muscle synergy. Indeed, synergy creates a coordinated and optimal movement by creating a coordinated relationship between a group of role-playing muscles in bending or opening the forearm. In this study, only the single-channel EMG signal of the biceps muscle was examined instead of considering several muscles for bending and opening the forearm, and the issues related to force, torque, and so forth were not considered.

In this study, the synchronization of the stimulation signal with the EMG signal was performed; for this purpose, the Powerlab 26T device had the capability to generate the stimulation wave and to receive the EMG signal simultaneously. The two signals were synchronized by defining a pulse as a stimulant wave and using that pulse as a trigger wave in the national instrument. Moreover, the signal sampling rate was adjusted 4000 samples per second to preserve important samples of the signal and to comply with the Nyquist sampling condition.

Stage 4: Signal preprocessing

In this stage, the signal was preprocessed, and the unwanted artifacts and noise caused by the power line used during recording and stimulation were removed after recording the EMG signal from the previous stage. To remove the noise caused by power line, the pass signal was announced from a hardware notch filter.[46] The received digital signal was then passed through a high pass Butterworth filter with a cutoff frequency of 5 Hz and order 3. It was then passed through a low-pass Butterworth filter with a cutoff frequency of 500 Hz and order 3. In addition, the recorded EMG signal was validated from 1 to 10 regarding the selection of the filter order, and in the third order, it had signal-noise ratio of 28.63, which was higher than the other orders. In addition, the reason for choosing the selected cutoff frequencies is that it was formed out of the frequency range of 5–500 Hz, which was more than the noise in the EMG signal.[47] Figure 5 depicts the EMG signal diagram of one of the samples after passing through two filters for a 414 s. As Figure 5 shows, the maximum amplitude of the EMG signal is 0.68 mV, and the minimum amplitude is −0.35. Figure 5 illustrates a part of the EMG signal in 5–13 s for better display.

Stage 5: NARX neural network

At this stage, the NARX neural network with two layers was applied for training and modeling after recording 100 EMG signals and their processing in the previous stages. By trial and error, there were 20 neurons in the hidden layer; the purelin transfer function was used in the first layer and in the output layer of the tan sigmoid. The initial values of weights and bias were considered zero. Then, 100 initial delays were considered to define the NARX neural network equation. In other words, 100 prototypes of the stimulation equation time series and 100 samples of the EMG signal time series in proportion to the stimulation performed predicted the EMG signal time series for later times.

The initial input of the neural network was the first 100 samples of the EMG signal and the first 100 samples of the stimulation signal. The output of the next predicted sample of the EMG signal as a recurrent with the sample of the stimulation signal was in proportion to the predicted sample number of the network input. To improve the results of back-propagation training, three improvement methods were validated: Conjugate Gradient, Quasi-Newton, and Levenberg-Marquardt, respectively, and the results indicated that the learning time and error of the Levenberg-Marquardt method were reduced more rapidly than those of the other methods. In this study, this algorithm was used to train and improve the results.

The maximum number of epochs to train was 1000, the performance goal zero, the maximum validation failures 6, the minimum gradient value 10^{-7}, the initial mu values 0.001, the decrease factor mu value 0.1, increase factor value 10, and the maximum value for mu 10^{10} in the training of this algorithm. Moreover, the loos function was considered the mean square error (MSE). The training data included 100 EMG signals in which the stimulation signal was the same for every 100 signals. In addition, 70% of the data were used for training, 15% for evaluation, and 15% for testing. The number of training repetitions was 40 training repetitions, and the network was trained during 1:14:54. Furthermore, the best MSE occurred in repetition 27 during the neural network training, which is shown in the performance neural network diagram selected based on MSE in Figure 6. Furthermore, architecture and performance of the NARX neural network training are displayed in Figure 7 and Table 3. Figure 8 and Table 4 illustrate the regression of all 4 data sets; it was well matched to the target vectors and had an acceptable *R*-value.

Finally, one of the 100 samples of signals present in the network training, testing, and validation process was randomly selected after completing the neural network training and applied to the trained NARX neural network. In other words, the first 100 samples of the EMG signal and the first 100 samples of the stimulation signal were applied to the model, and the model predicted the EMG signal based on the external stimulation from sample 101 onward. Figure 9 shows the predicted EMG signal matched the actual signal well.

The predictor model of the stimulant-based EMG signal was presented based on the NARX neural network and tested on one of the datasets. For better validation, the model was applied to five new EMG signals not included in the training, validation, and testing process as the

Table 3: Performance table of the NARX neural network training

Algorithms	Data division	Random
	Training	Levenberg-Marquardt
	Performance	Mean Squared Error
	Calculation	MEX
Progress after training	Epoch	27 iteration
	Time	1:14:54
	Performance	2.27e-5
	Gradient	0.00246
	Validation check	6

NARX - nonlinear auto regressive with exogenous input

Table 4: Output of the training, validation, and testing dataset

Output	*R*
Training data	0.94
Validation data	0.91
Testing data	0.74
Total	0.9031

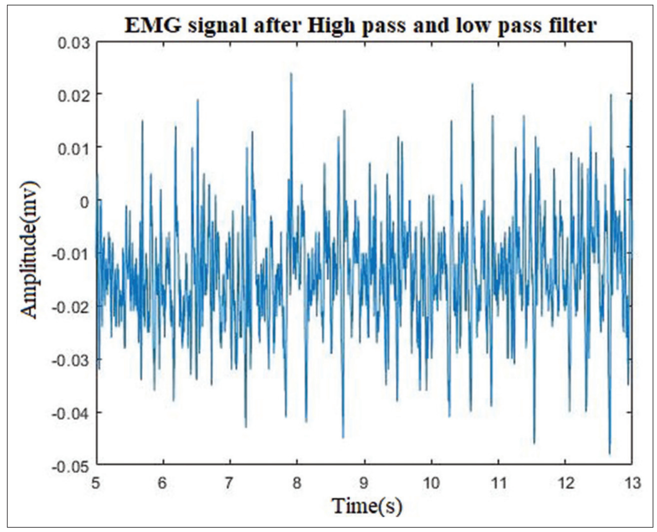

Figure 5: EMG signal of one of the individuals after passing through the high-pass and low-pass filter for 5 to 13 s. EMG: Electromyogram

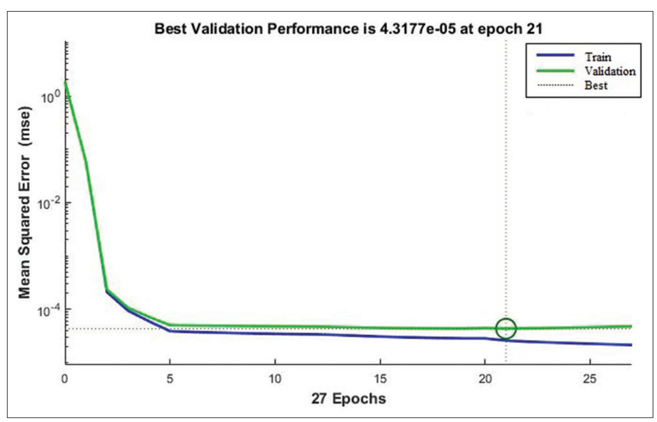

Figure 6: Network performance diagram based on the number of epochs and MSE for all three categories of training, testing, and validation. MSE: Mean square error

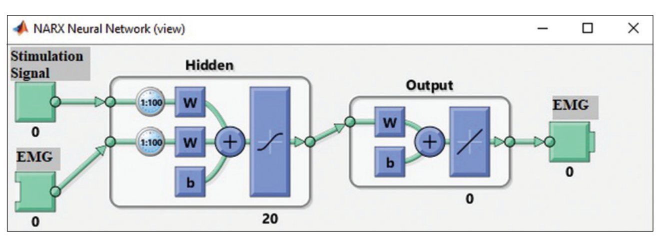

Figure 7: Architecture of the NARX neural network of proposed model

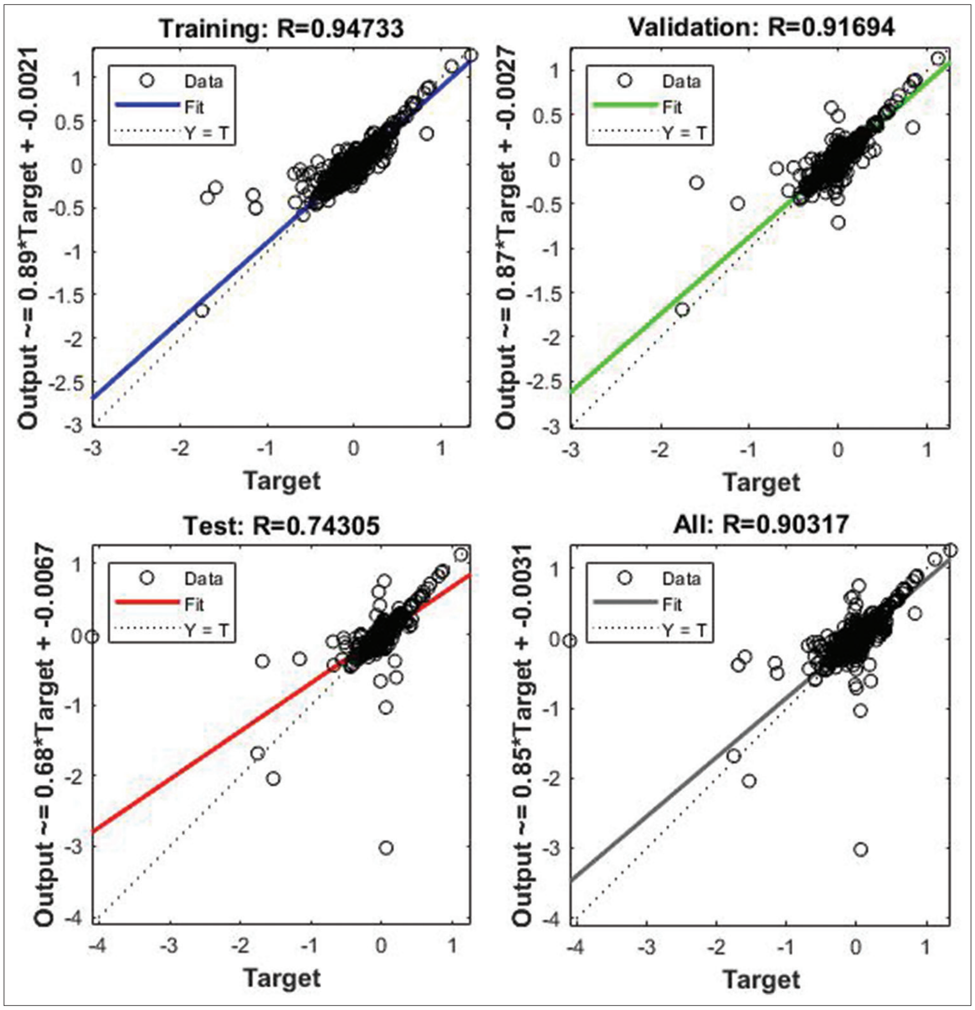

Figure 8: NARX neural network plot regression graph

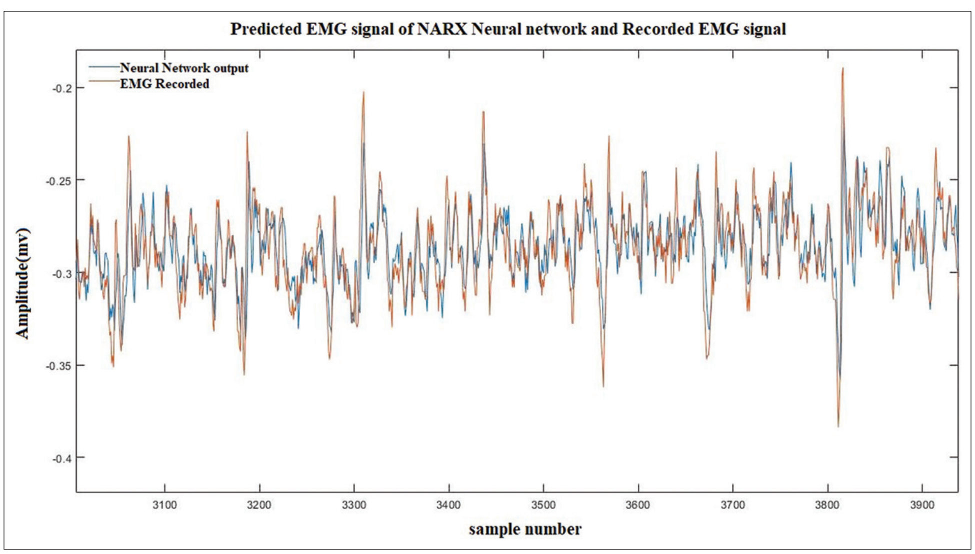

Figure 9: Part of the predicted EMG signal existing in the network training process, along with the recorded signal. EMG: Electromyogram

network input. The network input, which was the first 100 samples of the stimulation signal time series, in other words, the variable Z(t) of the Rossler equation, along with the first 100 samples of the EMG signal time series, was proportional to the stimulation, and the output predicted the EMG signal time series instantaneously proportional to the stimulation. Figure 10 displays the EMG signal predicted by the neural network for a new signal, along with the actual recorded signal. The actual signal and the EMG signal highly correspond to each other. Moreover, the prediction error signal shows an insignificant error. In addition, the average prediction MSE for five new signals by the proposed model is 0.0205.

Conclusion

Numerous studies have applied the neural network as a black box model to model the muscle and have reported successful results.[48] However, the neural network is usually applied to model or predict part of EMG signal parameters, such as prediction of torque using the NARX neural network,[49] prediction of the wrist angle based on the intensity of different loads on the muscle using the genetic algorithm,[50] prediction of the wrist angle based on the neural network and Kalman filter,[51] and prediction of the EMG signal from the Gait Kinematics and Kinetics using the NARX neural network.[52]

However, nonlinear electrical stimulation was not considered in any of the previous methods to predict the EMG signal. Because the behaviors of the muscle are nonlinear, it was required that the muscle to be stimulated via a nonlinear model, in which a new chaotic stimulation equation was applied to the muscle. The results indicated that this type of stimulation could cause nonlinear and chaotic behavior in the EMG signal. Afterward, the EMG signal, which had chaotic properties, along with the stimulation signal, was applied to the NARX neural network as a new predictive model for training and validation. The results indicated that the NARX neural network could well predict the EMG signal under a nonlinear stimulation; in addition, owing to its recurrent properties compared to the predictive methods based on the Kalman filter or the feed forward network, ARX, Hammerstein-Wiener had fewer errors. There was also a maximum and significant agreement between the EMG output response and the output response caused by the NARX neural network. Therefore, it can be stated that the NARX neural network can be useful to predict the EMG signal of the biceps muscle; however, it should

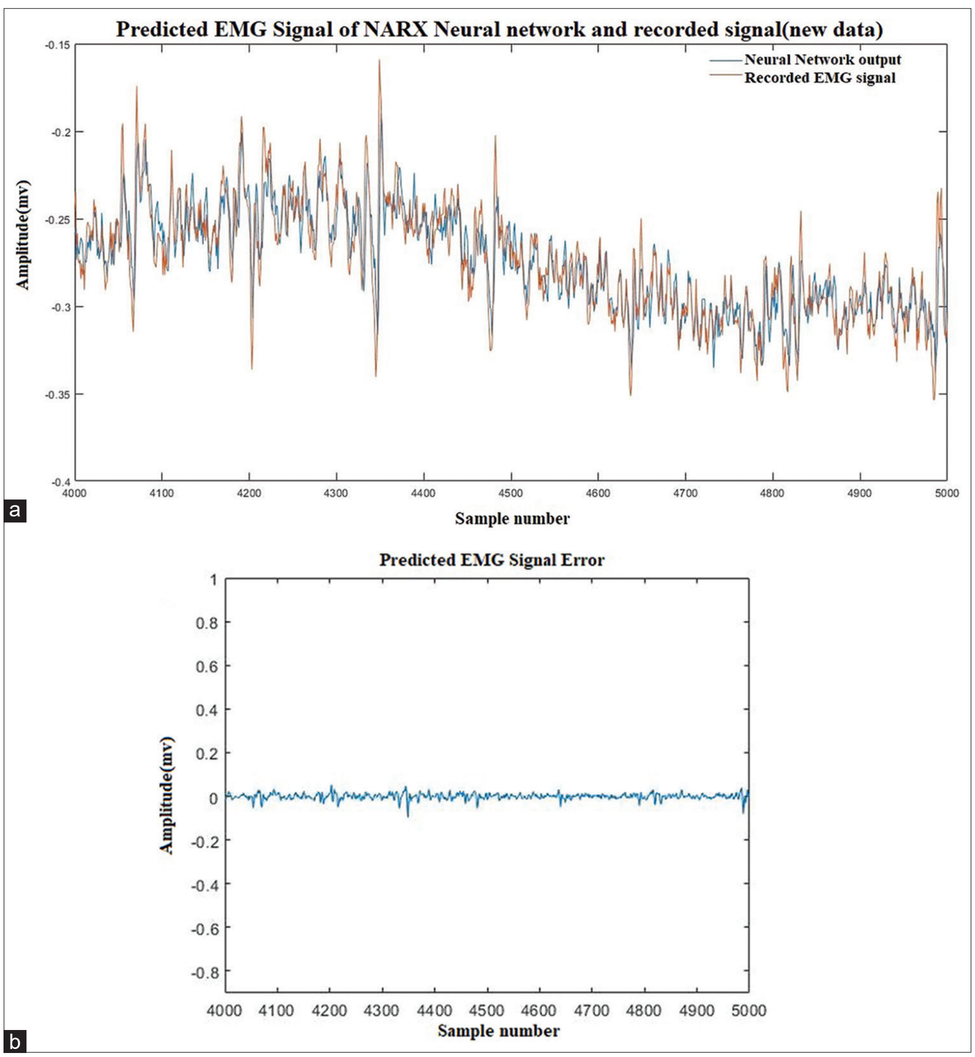

Figure 10: (a) Part of predicted new EMG signal along with the recorded signal. (b) Part of the predicted new EMG signal error. EMG: Electromyogram

be noted that the model made for the biceps muscle in this study cannot be used for other muscles. Finally, it is possible to use the predictive model in this study to diagnose diseases of the biceps muscle by applying the nonlinear stimulation to it and receiving the stimulation response and then comparing the response between the model and the recorded signal from the muscle. Hence, we can validate and diagnose the clinical disorder to optimally control FES systems.

Ethical code

The current study was approved by the Ethics Committee of the Islamic Azad University, Science and Research Branch of Tehran, with the Ethics Code: IR.IAU.SRB.REC.1399.162.

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Declaration of patient consent

The authors certify that they have obtained all appropriate patient consent forms. In the form, the patient(s) has/have given his/her/their consent for his/her/their images and other clinical information to be reported in the journal. The patients understand that their names and initials will not be published and due efforts will be made to conceal their identity, but anonymity cannot be guaranteed.

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Conflicts of interest

There are no conflicts of interest.

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