USE OF A MULTILAYER PERCEPTRON NEURAL NETWORKS TO PREDICT ARM FORCES FROM EMG DATA

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Abstract. *This paper describes a methodology used to predict forces performed by the hand in a manipulandum attached to a arm-crank linkage, recording only EMG data from arm muscles. An experimental setup was designed to apply a viscosity force field in the hand of the subject by means of a DC motor, while the arm performs a circular closed-chain horizontal plane movement. A voluntary normal adult male was instructed to execute forward and backward arm rotations, while the hand was kept firmly attached to a manipulandum free to spin around its own axis and instrumented with a six-degree-of-freedom load cell. EMG activity from six upper limb muscles was recorded for the whole movement, low-pass filtered, and used as inputs to a three-layered perceptron neural network (MLP). EMG and manipulandum force time series were used to train the MLP. The results have shown that the MLP was able to predict the forces in x and y directions exerted by the hand in the manipulandum, if the applied viscosity by the motor and the movement velocity exerted by the subject was sufficient to generate significant EMG activity.*

Keywords: *arm biomechanics, arm control, EMG, Multilayer Perceptron*

1. INTRODUCTION

Measured electromyoelectric signals *(EMG)* are a result of several bioelectric phenomena that occurs in muscle membranes, and have been used in the diagnosis of neuromuscular disorders (Kumaravel and Kavitha, 1994). These signals contains important information about the motion intention of humans (Wolpert and Ghahramani, 2000), and have been used for controlling active limb prosthesis (Scott and Parker, 1998). The application of EMG signals to control prosthetic devices presents some difficulties, specially the intra and intersubject reproducibility of limb movements, due to signal fluctuations, noise, electrode preparation and positioning and cable artifacts.

Applications of artificial neural networks in biomechanics to find relations between muscle activity (EMG) and motion intention have been investigated primarily by Sepulveda et al. (1993). These authors used a Multilayered Perceptron with backpropagation algorithm to map EMG signals into joint angle and joint torques. Luh et al. (1999) used a three-layered feedforward Neural Network to determine the relations between the EMG activity and isokinetic elbow joint torque.

Alternatively, this work proposes a neural-network-based methodology to map the EMG envelop from six upper limb muscles Fig. 3(a) into planar forces F_x and F_y Fig. 3(b) exerted by the hand in a planar manipulandum. The three-layered feedforward neural network model was trained, validated, and successfully used to predict new muscular contractions.

2. MODEL

2.1 Artificial Neural Networks

Artificial Neural Networks *(ANN's)* are interconnected groups of processing units *"neurons"*, inspired in the behavior of biological nervous system. The ANN's consists of parallelly distributed neurons, which are wired together in a complex communication network. These models have the ability to learn from experience and assimilate the dynamics of the system that was used to train the ANN. The knowledge of ANN's is distributed throughout the network and is stored in the form of weighted connections.

The ANN's are effective dynamical approximators specially in situations where it is not possible to define a parametric model, or the data is contaminated with noisy. ANNs have been applied successfully to speech recognition, image analysis, system identification and adaptive control. The ANNs are considered universal approximators for nonlinear input-output mapping (Haykin, 1994).

2.2 Neural Network Model

In this work, the structure of the proposed neural network model consists of a three-layered feedforward network with all units *(neurons)* wired together between the layers Fig. 1. The input layers has six units, the hidden layer nine, and the output layer has two units. The inputs to the ANN are the EMG envelop magnitudes signals recorded from the upper arm muscles under study (brachioradialis, biceps brachii, deltoideus p. clavicularis, triceps brachii lat., triceps brachii long., and deltoideus p. scapularis) Fig. 3(a), and the outputs are the estimations of the resulting planar forces F_x and F_y Fig. 3(b).

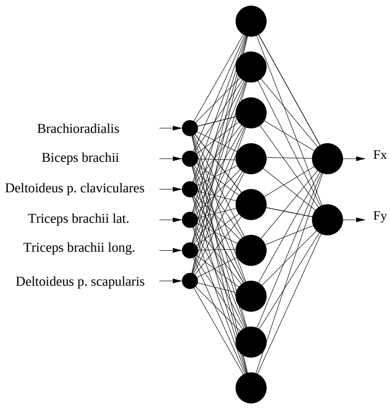


Figure 1. The three-layered neural network model.

The neural model input signal is transformed to an output signal by nonlinear activation functions, this procedure allow the neural model to learn nonlinear and linear relationships between input and output vectors (Haykin, 1994). In the proposed three-layered neural model the units located in the hidden layer have sigmoid activation functions Eq. 1 followed by an output layer, which is composed by two processing units with hyperbolic tangent sigmoid activation functions Eq. 2.

$$\Psi\left(v_j^{(l)}(n)\right) = \frac{1}{1+exp\left(-v_j^{(l)}(n)\right)} \tag{1}$$

$$\Psi\left(v_j^{(l)}(n)\right) = \frac{2}{1+exp\left(-2v_j^{(l)}(n)\right)} - 1 \tag{2}$$

The neural model has a specific procedure to map the information contained in a given input/output data set. This procedure is called *learning process* and is based on the backpropagation algorithm. This is a gradient descent algorithm, in which the network weights are updated along the negative of the gradient. The backpropagation algorithm is composed of two stage: a feedforward stage, where the input data is processing until the output layer through nonlinear activation functions; and a learning stage, where the connection weights and bias terms are updated. These stages are repeated until the output and desired output signals satisfy a stop criteria. The basics of the error back-propagation algorithm are explained in the next subsection.

2.3 Neural Networks Algorithm

During the training stage, the synaptic weights and bias are updated along the negative of the gradient with the finality to find the optimal synaptic weights and bias of the neural model. This procedure is based on the minimization of the feedforward neural model cost function Eq. 3.

$$\xi_i(n) = \frac{1}{2}\sum_{k=1}^{N_o} e_k^2(n) \tag{3}$$

where N_o is the number of output units,
$e_k(n)$ is the error from output node *k* at iteration *n* and
$\xi_i(n)$ is the cost function at iteration *n* for the pattern *i*. The error from each individually output unit can be calculated as follows,

$$e_k(n) = d_k(n) - y_k(n) \tag{4}$$

where:
$d_k(n)$ is the desired response of the output unit *k* at iteration *n* and $y_k(n)$ is the output of the output unit *k* at iteration *n*

The Feedforward Network Training by Backpropagation process can be summarized as follows,

1. *Initialization:* Randomize the weights and threshold levels to small random values that are uniformly distributed to ensure that the network is not saturated by large values of weights.

2. *Forward Computation:*

    Select a training vector [**x**(n), **d**(n)] *(a pair of input and output patterns)*, from the training set and apply them to the network input.

    Compute the activity level for each individually unit $v_j^{(l)}(n)$ for the neuron *j* in layer *l* as follows,

$$v_j^{(l)}(n) = \sum_{i=1}^{p} w_{ji}^{(l)} y_i^{(l-1)}(n) \tag{5}$$

where $y_i^{(l-1)}$ represents the signal from neuron *i* in the previous layer *(l-1)* at iteration *n* and
$w_{ji}^{l}(n)$ is the synaptic weight of neuron *j* in layer *l* that is connected to neuron i in layer *(l-1)* at iteration *n*.
For $i = 0$, we have: $y_0^{(l-1)} = -1$ and $w_{j0}^{(l)} = \theta_j^{(l)}(n)$, where $\theta_j^{(l)}(n)$ is the threshold applied to neuron *j* in layer *l*
Using for example a sigmoidal activation function Eq. 6, the output of the neuron *j* in layer $(l \geq 1)$ at *n* iteration is given by:

$$y_j^{(l)}(n) = \Psi\left(v_j^{(l)}(n)\right) = \frac{1}{1 + exp(-v_j^{(l)}(n))} \tag{6}$$

observe that for the input layer *(l=0)*, $y_j^{(0)}(n) = x_j(n)$
The mean squared error is obtained by:

$$E(n) = \frac{1}{2p} \sum_{i=1}^{p} \xi_i^2(n) \tag{7}$$

Since function $E(n)$ is known analytically, and it is differentiable, it is possible to use gradient-based methods like steepest descent (Smith 1993), or more efficient conjugate gradients method, such as for example Levenberg-Marquardt method.

3. *Backward Computation:*

    In this procedure, the neurons only need to transmit their actual state to all the adjacent input synapses, while the synapses do not need to transfer any information. The local gradients for neuron *j* in output layer *L* is given by the following equation Eq. 8:

$$\delta_j^{(L)}(n) = e_j^{(L)}(n) y_j(n) \left(1 - y_j(n)\right) \tag{8}$$

For neurons *j* located in the hidden layer *l*, the local gradient is given by:

$$\delta_j^{(l)}(n) = y_j^{(l)} \left(1 - y_j^{(l)}(n)\right) \sum_{k} \delta_k^{(l+1)}(n) w_{kj}^{(l+1)}(n) \tag{9}$$

By means of the generalized delta rule the synaptic weights can be adjust by the following equation:

$$w_{ji}^{(l)}(n+1) = w_{ji}^{(l)}(n) + \alpha\left(w_{ji}^{(l)}(n) - w_{ji}^{(l)}(n-1)\right) + \eta \delta_j^{(l)}(n) y_i^{(l-1)}(n) \tag{10}$$

where η is the learning rate and α is the momentum constant. The ranges of value for η and α are typically between [0,1]. The error backpropagation algorithm explores the error surface to minimize the mean square error. This minimization of the error is performed by changes of the synaptic weights $w_{ji}^{(l)}$ and bias $w_{j0}^{(l)}$. These changes is known as *neuronal plasticity*. More details about the backpropagation algorithm, choices of learning rate parameter, and momentum constant are given by (Haykin, 1994).

3. EXPERIMENT AND METHODS

The experiment was realized at Max-Planck Institute for Human Cognitive and Brain Sciences in the laboratory of the *Sensomotorische Koordination Group*, Munich.

Firstly, a voluntary healthy adult male was seated in a rigid chair. In order to minimize shoulder movement during the study the subject's torso was stabilized using automobile seat belts Fig. 2(a).

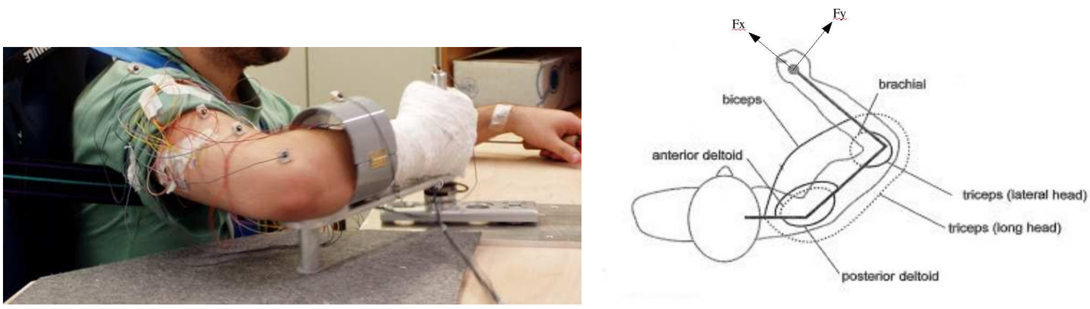
A cast approximately with 12 cm wide was made on the subject's distal forearm just proximal to the ulnar styloid Fig. 2(a) to constrain the degrees of freedom between the hand and the elbow. Surface electrodes were placed into the following muscles under study (brachioradialis, biceps brachii, deltoideus p. clavicularis, triceps brachii lat., triceps brachii long., and deltoideus p. scapularis). The electrodes and ground were connected to a analogic amplifier/filter *GRASS* and the signal was processing as follow: band-pass filter 30-300-Hz cutoff and a gain of 3000.

The subject was instructed to execute forward and backward arm rotations *ad libitum*. The data related to EMG activities and resulted handle forces were collected simultaneously during 30 seconds using RTAI-Linux *(Real Time Application Interface Linux)* with 1000 Hz sampled frequency. A moving average filter Eq. 11 of dimension 10 was performed to the whole recorded data. The EMG data were processed as follow: artefacts removed, full-wave rectified, normalized and low-pass filtered at 5 Hz to obtain the linear envelop. Finally the load cell data were normalized between [-1,1] based in the maximal and minimal recorded forces. The preprocessed time series of the EMG envelop and normalized planar forces were used to train and to validate the generalization capacity performance of the proposed neural model.

$$y(n) = \frac{1}{M}\sum_{k=0}^{M-1} x(n-k) \tag{11}$$

where *M* is the order of the filter.

The experiment setup and the planar movement idealization are shown in Fig. 2(a) and Fig. 2(b).



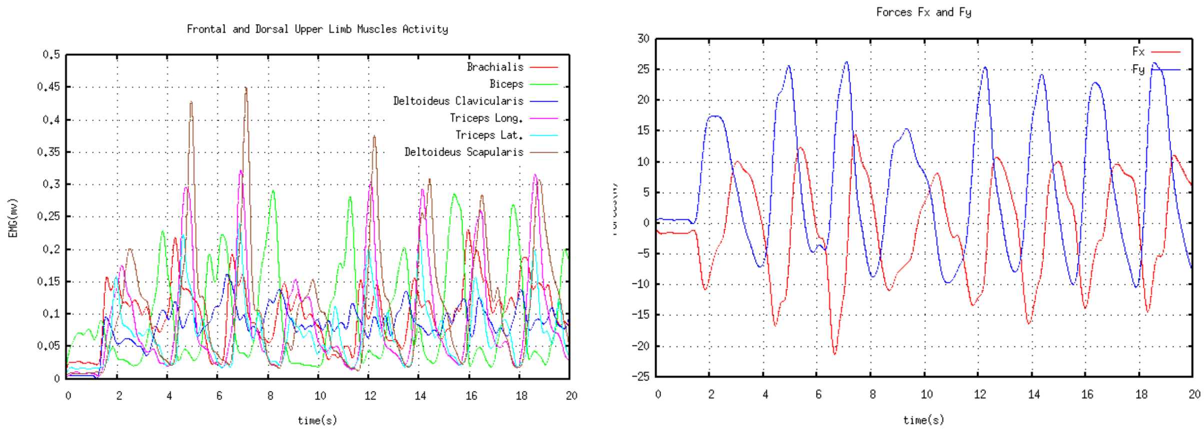
(a) Experiment setup

(b) Planar movement idealization, adapted from (Shadmehr R. and Wise S. P., 2005)

Figure 2. Experiment setup and planar movement idealization.

4. RESULTS

The experimental data set corresponding to the first twenty seconds time series were used for training the proposed neural-based model, the input/output time series are shown in Fig. 3(a) and Fig. 3(b), respectively.



(a) EMG Activity (b) Forces f_x and F_y

Figure 3. Training data set.

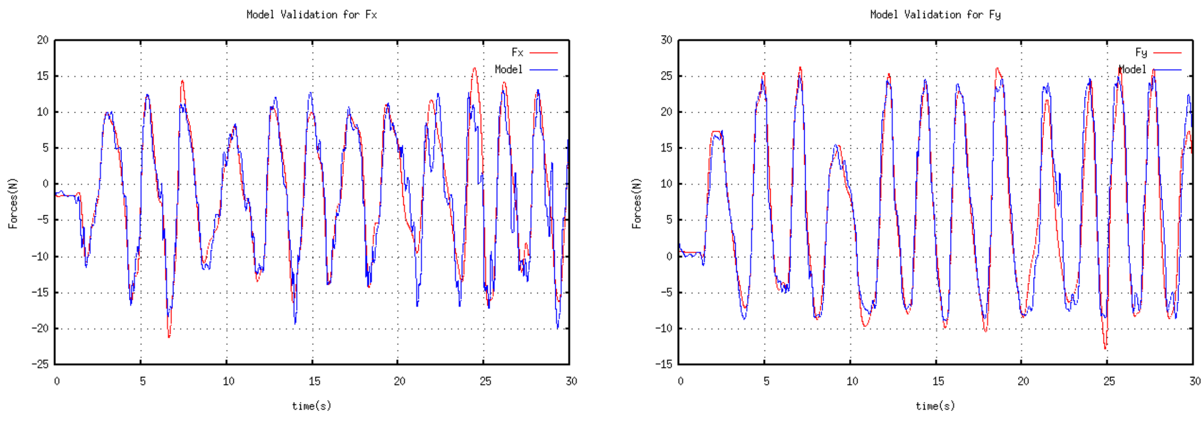
The neural model was trained and validated. The validation accuracy performance of the neural model was evaluated against all data sets *(training and predicting time series)* with two criteria, Average Absolute Error (AAE) Eq. 12 and Cross-Correlation (CC) Eq. 13. The crosscorrelation is a measure of similarity of the y and $\bar{y}$ regardless of scaling. The closer the value is to 1, the higher the level of similarity is between signals Liu et. all(1999).

$$AAE = \frac{\sum_{i=1}^{N}(y_i - \bar{y}_i)}{N} \tag{12}$$

$$CC = \frac{\sum_{i=1}^{N}(y_i . \bar{y}_i)}{\left(\sqrt{\sum_{i=1}^{N} y_i^2} . \sqrt{\sum_{i=1}^{N} \bar{y}_i^2}\right)} \tag{13}$$

where y_i and $\bar{y}_i$ are respectively the measured and the estimated resulted planar forces, and N is the number of samples.

The neural-based model output and the obtained experimentally data are shown in Fig. 4(a) and Fig. 4(b).



(a) Force F_x (b) Force F_y

Figure 4. Model Validation and Prediction

The quantitative performance analysis of the neural-based model for all data set (training and prediction time series) are presented in Tb.1.

Table 1. Quantitative accuracy performance analysis of the proposed neural-based model.

Data sets	Average Absolute Error	Cross-Correlation
Training f_x	1.20	0.98
Training f_y	1.13	0.99
Prediction f_x	3.41	0.89
Prediction f_y	3.03	0.96

5. DISCUSIONS

The measured EMG activity is a result of several bioelectric phenomena that occurs in muscle membranes and is dependent of the electrodes placement. Therefore, the experimentally recorded EMG signals are not an exact representation of the muscle activity. The data were collected during a dynamical task, consequently it may occur contact area variations between the electrodes and the skin. Thus, those variations can affect the confiability of the obtained EMG time series.

The cross-correlation and average absolute error were calculated to access the accuracy of the proposed neural model for all data set (training and prediction time series). Observing Tb. 1, it is possible to infer that the model is able to capture more efficiently the relationship between the EMG envelop and the planar force f_y. This is a common finding observed for all data set and suggest that the recorded EMG envelop time series doesn't contain the same information about the planar forces f_x and f_y. A possible reason for this occurrence is related to the experiment setup, which was designed such that the load cell coordinate system f_x was oriented in the forearm's subject axis Fig. 2(b). Consequently, the load cell coordinate system will maintain its orientation independently of the manipuladium position in the workspace. This procedure was adopted to avoid mathematical transformation between the load cell coordinate system and any other coordinate system. Possibly, only the anterior and posterior deltoideus recorded EMG activity may contain relevant informations about the planar force fx. This hypothesis is based on the experiment setup Fig. 2(b) and can explain the different observed performance accuracy for the analyzed planar forces f_x and f_y.

The obtained results of the present study demonstrates that the proposed neural-based model, with an adequate data preprocessing, was able to capture essential features of the nonlinear mapping between the EMG activity and resulting planar forces.

6. ACKNOWLEDGEMENTS

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