CMBES/SCGB 2019 CMBEC42
Ottawa, ON
May 21-24, 2019

EMG-based Force Estimation using Artificial Neural Networks

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Abstract— **In this paper, the surface electromyogram (sEMG) signals acquired from linear surface electrode arrays, placed on the long head and short head of biceps brachii, and brachioradialis during isometric contractions are used to estimate force induced at the wrist using an artificial neural network (ANN). We extracted some features, in time and frequency domain, from sEMG signals and used them as inputs to the ANN model. Different hidden layer sizes were considered to investigate its effect on the model accuracy and find the appropriate number of neurons for our problem. Also, we studied the model accuracy, where we used features individually as the model's input. The best accuracy, during train, validation and test, was obtained for the maximum number of sEMG features.**

Keywords— **Surface electromyogram, High-density surface EMG, and artificial neural network.**

I. Introduction

An accurate muscle force estimation is desired in many applications such as design and control of powered prostheses, medical rehabilitation, and sports medicine. Surface EMG (sEMG), the spatial and temporal summation of dispersed action potentials travelling along the muscle fibers, has been widely used as a non-invasive method to map a relationship between muscle electrical activity (represented by the sEMG amplitude) and the generated muscle force [1–4].

Parametric and non-parametric approaches have been used to estimate muscle force from sEMG signals [5–10]. The parametric approaches use Hill's muscle model [10], which takes muscle activation level as an input to the model, and the generated muscle force is calculated as the output. In non-parametric modeling methods, polynomial functions, artificial neural networks (ANNs), linear regression, and fast orthogonal search (FOS) are used to capture the sEMG-force relation, without requiring any knowledge about muscle and joint dynamics [5–9]. ANNs have been used to estimate muscle force or joint torque from EMG signals [11, 12]. The relation between the EMG signal obtained from the biceps and triceps and the isokinetic elbow joint torque was determined by using a 3-layer ANN network [11]. The EMG signals, elbow joint angle, and velocity were used as inputs to the ANN and the results suggested that the model was able to reliably estimate the joint torque [11]. Mobasser et al. investigated the use of two architectures of ANN for force estimation, under isometric, isotonic and light load conditions [12]. The trained ANNs were able to predict the highly nonlinear relation between the sEMG, the elbow angle and velocity, and the force generated at the wrist [12].

In this study, features extracted from surface electrode arrays with eight monopolar channels are used to map sEMG, obtained from the elbow flexor muscles during flexion, to the induced force at the wrist using the multilayer perceptron ANN. We extracted some features in time and frequency domain from the sEMG signals which are explained in the pre-processing section, as inputs to the ANN model.

II. Method

For this study, 13 healthy subjects (5 females and 8 males; age 27 ± 4 years) were recruited. Subjects provided informed consent before participating in the experiment. The experiments were conducted using the QARM, a single degree-of-freedom (1-DOF) exoskeleton test bed. The QARM holds the shoulder and wrist in a fixed position to constrain the elbow flexion of the right arm to the horizontal plane while limiting the contribution of the shoulder and forearm muscles to force generation at the wrist. The elbow's axis of rotation is aligned with a pivoting aluminum bar, which can be locked in place for isometric contractions.

The sEMG signals were recorded using 3 linear HD-electrode arrays with 8 monopolar channels (5 mm spacing) from the elbow flexor muscles; the long head and short head of biceps brachii, and brachioradialis muscles. The fourth electrode of each array was located on the SENIAM sensor location recommendation for the biceps muscles [13]. For the brachioradialis, the fourth electrode was placed at one-third the length of the forearm measured from the elbow. The sEMG data were collected using the Bioelecttronica EMG-USB2 high density (HD) system, which sampled the EMG data at 2048 Hz. The experiment was conducted for three different force levels, 20, 35 and 50% of maximum voluntary contraction (MVC), at 90 degrees elbow joint angle during isometric elbow flexion. MVC was measured at 90 degrees. The duration of each contraction was 5 seconds. For each subject, the data were collected in one session and three trials. Appropriate rest periods were provided in order to avoid muscle fatigue. Force at the wrist (elbow torque) was measured using an ATI 6-DOF Gamma force/torque sensor with a high stiffness of 9.1×10^6 N/m; force data were sampled at 1000 Hz.

A. Pre-processing

Differential sEMG signals were obtained by subtracting neighboring monopolar signals with 5mm spacing. This resulted in seven differential channels. Each differential channel was band-pass filtered from 10 to 500 Hz using a 4th-order Butterworth filter. Then the sEMG signals were rectified and smoothed by using a 300 point moving average filter to obtain the linear envelope (LE) of signal and estimate signal amplitude.

Then, we extracted some of the commonly used features for sEMG signal in time and frequency domain. The extracted features in the time domain were: the maximum, standard deviation and mean of the rectified and smoothed sEMG signals. The signal after filtering (not the rectified-smoothed signal) was used to extract two frequency domain features, the mean frequency and the coefficient of the first component (first PC) of principle component analysis (PCA) of the sEMG signals. To compute the coefficients of the first PC, we applied the FFT to each of the differential sEMG signals acquired from the elbow flexor muscles. Then, the magnitudes of the FFT's were calculated and PCA was applied. The coefficients of the first PC, which represents the maximum variance of the data in the frequency domain, were used as features. Finally, these features were used as inputs to the ANN, where the network output is the induced force at wrist.

B. Force Estimation

ANN network architecture, which mimics the structure of the neural system in the human nervous system, consists of an interconnection of multiple layers of neurons and can have more than one hidden layer, where all the outputs in each layer are connected to the inputs of neurons in the next layer [12]. The general diagram of the network is shown in Figure 1.

As shown in Figure 1, the inputs to the ANN are the obtained features of sEMG signals recorded from three linear electrode arrays placed over the elbow flexor muscles, with seven channels (5 (number of features)$*7 = 35$ features per muscle). The input data include all 105 features extracted from the elbow flexor muscles of all 13 subjects at 90 degree joint angle, and neutral forearm posture. The network output is the estimated force induced at wrist. In the ANN, a hyperbolic tangent sigmoid function and linear function were used as activation functions for hidden layers and output layer nodes, respectively.

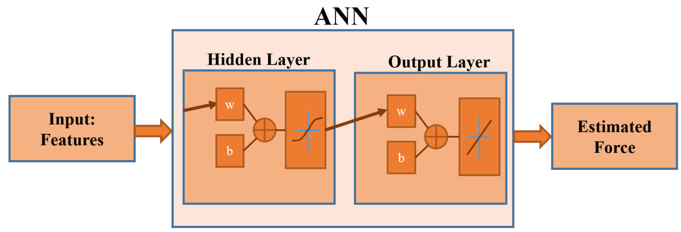

Fig. 1: The general diagram of the ANN network.

C. Neural Network Training

One important parameter for ANN is the hidden layer size, which can be considered as a method to increase the network accuracy. Larger numbers of neurons in the hidden layer give the network more flexibility to optimize its parameters to improve the accuracy. Increasing this number, usually improves the network's training performance, but it does not necessarily help the network generalization. Another possibility to improve the model accuracy can be increasing the dataset size for training. In this study, we investigated the effect of using different number of neurons in hidden layer on force estimation accuracy. We used Levenberg-Marquardt as a training function which is generally the fastest training function. Also, we divided the input data randomly, so that 70% of the samples are assigned to the training set, 15% to the validation set, and 15% to the test set. We increased the number of neurons from 2 to 28 to investigate the effect of hidden layer size on the force estimation accuracy. Root mean square error (%RMSE) between the estimated ($F_{estimated}$) and measured ($F_{measured}$) forces was used as an evaluation criterion, calculated by Equation 1, where N is the sample size.

$$\%\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(F_{measured,i} - F_{estimated,i})^2}{N}} \times 100. \quad (1)$$

III. Results and Discussion

In this study, three linear electrode arrays were used to record sEMG signals, from the elbow flexor muscles, long head and short head of biceps brachii, and brachioradialis during isometric contractions, at 90 degree elbow joint angle. The recorded data were processed to estimate the force induced at wrist.The wrist force was estimated from the sEMG signal acquired from the elbow flexor muscles using ANN. For force modelling, we used the extracted features of sEMG

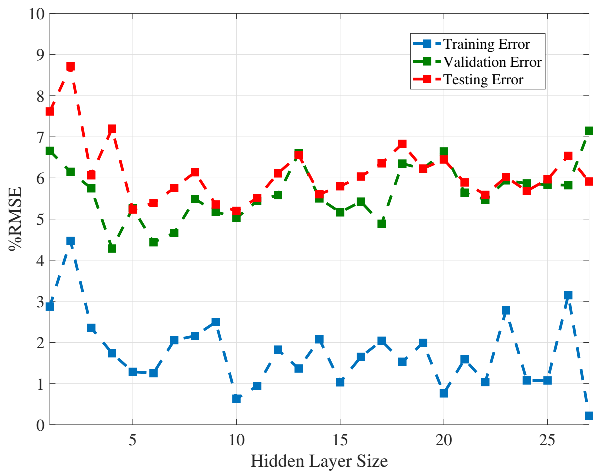

Fig. 2: The effect of hidden layer size on force estimation accuracy, during training, validation, and testing the network.

signal in time and frequency domain as inputs to the ANN, and the network output is the induced force at wrist.

The %RMSE values for different number of hidden layer neurons, during training, validation and testing the network are presented in Figure 2. Each network was trained and tested 10 times using different training, validation and test sets, and the %RMSE valued were averaged.

Selecting an appropriate hidden layer size is a challenging issue, since many factors should be considered such as obtaining lower errors for the train,validation and test phases, avoiding overfitting, and developing a model which is not overly complex. Based on Figure 2, it seems that ANNs with fewer than 10 neurons are appropriate, because the validation and testing errors are not improving, as hidden layer size increases to more than 10. The results of estimated force versus the measured force for three different phases; training, validation and testing, using an ANN with the hidden layer size of 5 are presented in Figure 3. The %RMSE values for the train,validation and test phases are 4.54, 7.95, and 6.21 respectively.

In this study, we developed a model to estimate force based on the sEMG signal, across all subjects, so that the model's input was a feature set extracted from all subjects' data. However, in other pattern recognition studies, where sEMG was used for classifying the motion [14] or for force estimation [6, 7, 12, 15], their models were subject dependent and were developed for each subject individually.

Also, we investigated the effect of using features individually on the accuracy of the ANN. For each feature, we trained the ANN, 10 times and we considered the different number of neurons in the hidden layer, from 2 to 10. Our results are

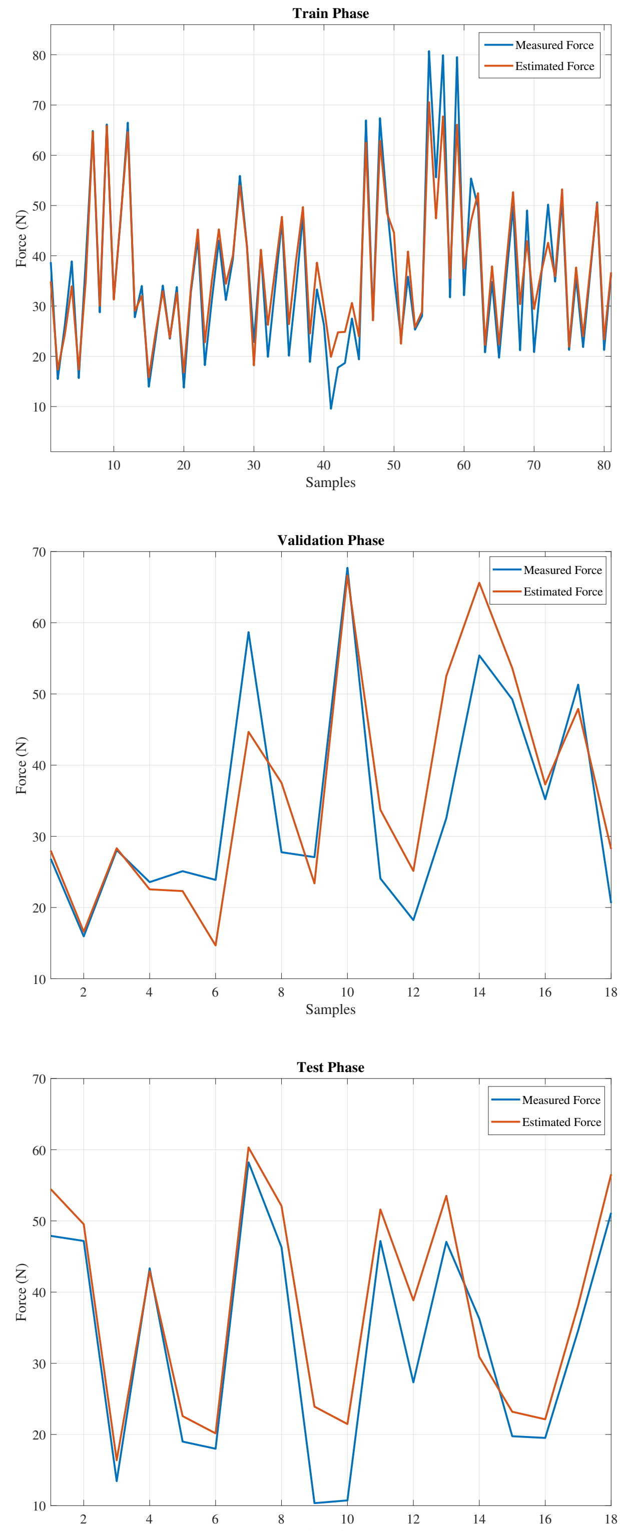

Fig. 3: Estimated force vs the measured force for three different phases; training, validation and testing, for the hidden layer size of 5.

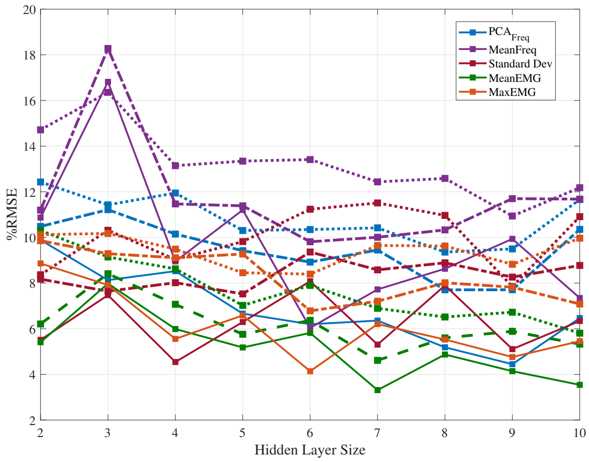

Fig. 4: The effect of using each feature separately on force estimation accuracy, during training, validation, and testing the network. The solid line represents the training phase, while the dash-dotted line (-.-.) represents the validation, and dotted line (....) shows the testing phase.

presented in Figure 4, where the solid line shows the training phase for using each feature separately, for different hidden layer size. The dash-dotted line and dotted line represent the validation and testing phases respectively. According to Figure 4, it is clear that different features results in different force estimation errors, and that the maximum and mean EMG features gave lower %RMSE values for training, validation and testing phases compared to other features. This result indicates that certain features are able to estimate the output more accurately compared to other features, which emphasizes the importance of feature extraction.

Different combinations of these features might affect the force estimation accuracy differently. Therefore, as a future work, feature selection should be done to find the best subset of features that leads to more accurate force estimation. In addition, channel selection can be considered as another issue that might have an impact on the model accuracy. In this study, we used 3 linear electrode arrays with 7 bipolar channels per muscle, which gives some redundant information. We have suggested that using a smaller number of channels is able to improve the force estimation accuracy, if those channels are selected appropriately [15].

IV. Conclusion and Future Work

As a conclusion, we used features extracted from the sEMG signal acquired from the elbow flexor muscles to estimate force induced at the wrist using the ANN model. Our results indicated that the hidden layer size affects the accuracy of the model. Generally, increasing the number of neurons, more accurate estimation would be obtained during train, validation and test phases.However, overfitting and complexity should also be considered in determining hidden layer size. Also, we investigated the impacts of using features individually on the model accuracy, where the maximum and mean of sEMG showed the lowest errors. Therefore, feature selection is an important step to be considered in order to select those features which are the better representatives of the input.

As a future work, we will work on feature selection algorithms to select more appropriate features and their combinations in terms of improving our model accuracy for estimation.

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