Neural-Genetic Model for Muscle Force Estimation Based on EMG Signal

Usama J. Naeem1, Caihua Xiong2
1, 2School of Mechanical Science and Engineering, Huazhong University of Science and Technology, Wuhan 430074, China
1Engineering Collage, Basrah University, Basrah, Iraq
USA3J@yahoo.com

Abstract—The aim of this work is to propose a new model to carry out muscle force from electromyography (EMG) signal. Our neural-genetic model consists of two stages (genetic and neural) to predict human muscle force from the right arm muscles; where, the first (genetic stage) is employed to transform the raw EMG signal into muscle activation. The second (neural stage) uses Back-Propagation Neural Network (BPNN) method to extract muscle force from the muscle activation of the first stage. The neural-genetic model can efficiently extract muscle force features from raw EMG signals without passing the signal through signal processing steps. Our results showed that the regression of our neural-genetic model exceeded 99%. We used the mean square error (MSE) to measure the performance of our model. The MSE result of our neural-genetic model was very small.

Keywords- EMG Signal; Muscle Force; Genetic Algorithm; Neural Network

I. INTRODUCTION

Due to the massive amount of clinical applications that utilize it, humans’ muscle force estimation has attracted researches over the years. These facts have motivated researchers to take further steps in muscle force measurement and estimation process direction. Researchers required a method to recode humans’ body variables. Subsequently, manipulate these variables in various ways to estimate different functionalities, such as, muscle force, torque and fatigue. However, recoding such variables demanded an interfacing between humans and machine. This requirement revealed electromyography (EMG) signals.

The EMG can be define as the human-computer interface that converts the generated electrical signals in human muscles into useful variables that can be utilized and studied to understand human bodies. The EMG signal is recorded by placing special sensors (electrodes) on human body skin. This method of operation records unclear signal that consists of high degree of noise. This issue encouraged signal processing researches to unveil methods to extract usable information from the body of this unclear signal. One of the popular methods that outperform other methods and have been heavily used in the muscle functionalities research field is the three steps signal processing ways.

The three steps signal processing procedure is an electrical based method. This method exploits filters and rectifiers to convert the recorded signal into a readable form. Despite the simplicity of the three steps procedure, the output signal of this process encounter accuracy issues since it may eliminate many important features in the recorded signal. This may shortcoming the accuracy of the estimated muscle force [1,2].

To ameliorating the three steps signal processing procedure, genetic algorithm (GA) is being proposed to replace the electrical based method. However, what is GA's and how to carry out them?

The first developments of the genetic algorithms were in the 1960’s, mimicking and emulating the ideas of genetics models from to solve optimization problems [3]. Holland (1975) [4] was the first researcher who utilized genetic algorithms. Genetic algorithms (GA) considered as one of the best solution methods to problem for which little is known. Moreover, GA is one of the artificial intelligence methods that use for solving both constrained and unconstrained optimization problems, which it depends on the natural selection procedures that mimic biological evolution. In general, GA attempts to simulate a simple picture of natural selection in order to find a better algorithm. Where, the algorithm repeatedly changes the population of individual (chromosome) solutions. At each step, the GA randomly selects chromosomes from the current population and uses them as parents to generate the children of the next generation. Over successive individual (fitness function), the population drives toward an ideal solution [5,6].

In general, typically GA requires two things, representation of the solution domain and objective (fitness) function to estimate the solution domain. As soon as, these two conditions exist the procedures of GA is started. Genetic algorithm procedures can be listed as: initialization, selection, genetic operators, and termination [7].

The goal of this paper is to enhance our earlier work [8] by utilizing GA to replace the three-step signal processing steps in the muscle force estimation procedure. The proposed model, as the previous model consists of two layers. The first layer is a genetic layer which operated as an interface between the neural network in the second layer and the recorded EMG signal from...
the human body this layer eliminates the demands of rectified smooth EMG signal (RSEMG) as an input. The second layer is as the earlier model consists of a back propagation neural network (BPNN).

The rest of this paper is organized as follows: Section II, introduces the method that’s used to create the proposed model. Section III, describes the experiment and the measuring procedure. Section IV; represents the results and observations of our work. Finally, this paper ends with a conclusion and summary.

II. NEURAL-GENETIC MUSCLE FORCE ESTIMATOR METHOD

As we have mentioned, our objective is to enhance and simplify the muscle force estimation process. This enhancement takes place by replacing the signal processing layer that operates beneath the accrual method. Our model consists of two stages. The first stage uses the GA’s to extract the muscle activation a(t) from the input measured EMG. The second step is a neural network model that mimics our earlier works model. The technical demonstration of our neural network layer can be found in [8].

The first stage of our model is a GA algorithm. This GA replaces the traditional three signal processing steps layer. However, This GA must be trained before it can be used. To train it we used EMG signal processing procedure. In the following sections we will introduce the signal processing steps, the EMG driven model, and the GA algorithm. Finally, we will show how these stages work together

A. EMG Signal Processing

The EMG presents the electrical activity of the muscle at a time-voltages waveform. Due to the amount of noise that EMG contains, most researchers assume that EMG is fuzzy with many unwanted data. Therefore, signal processing techniques must be applied on the EMG to get a suitable statistical data. These signal processing techniques or procedures consist of three steps in order to produce a profitable signal in use [9, 10, 11,12]. The next three subsections introduce these steps.

1) Filtering:

Filtering is the processes of passing a signal through a filter circuit. The transfer function of a filter defines its behaviors. To eliminate noise from EMG signals and to smooth it, two different types of filters are currently in use; low and high pass filters. A high - pass filter is used in the first stage of EMG processing. A low - pass filter is used in the last stage to smooth the signal. The cutoff frequencies of these filters have to be in the ranges of (5 to 30) Hz and (3 to 10) Hz for the high-pass and low-pass filter respectively. Moreover, the filter should contain zero-phase delay properties to prevent shifting of the signal in time. Finally, one thing to be mentioned is the use of filtering techniques requires a great caution to prevent destroying of the information in the raw EMG signal [13].

2) Rectifying:

The EMG signal includes positive and negative phases, which inconstancy about central line of zero voltage. Thus, the researchers presume that the signal doesn’t supply any useful information due to the fluctuation about zero value. Therefore, all negative amplitudes are overturned into positive amplitudes. This operation called rectifying, which is done on the raw EMG signal by taking the absolute value of all EMG data. But, rectifying is a non-linear operation so it can change the spectrum of a signal (changing in amount) [2].

3) Smoothing:

Smoothing is the process of shaping the final signal. Two algorithms have been used widely in this area; moving average and root mean square (RMS). These algorithms are demonstrated as follows:

- Moving Average: This technique is easy to implement comparable with RMS technique. The general procedure of this algorithm considers the removal of baseline fluctuation which existed in the EMG signal instituted on a user explain time window. A specific amount of data is averaged by gliding window technique. This technique reports the area size under the chosen signal epoch. Where, the value of epoch controls the percentage of the smoothing [14].

- Root Mean Square (RMS): it’s the most recommended method for smoothing. This technique is based on the square root calculation. The RMS is taking the mean of the squares data. Where, the length of smoothing is very important in the quality of analyzing EMG signal [15].

In summary, extreme precaution is needed in the interpretation of raw EMG data. The steps of EMG signal processing can be arranged consequently as: high-pass filtering, rectifying, and (low-pass filtering and smoothing). On the other hand, the output signal of signal processing is called the rectified smoothed EMG (RSEMG) signal or e(t).

B. EMG-Driven Dynamic Model
The purpose of the EMG driven model is to convert the RSEMG signal $e(t)$ into muscle activation $a(t)$. However, this process is not a straight forward step. A hidden converting step takes place between $e(t)$ and $a(t)$. This step namely is the calculation of the neural activation $p(t)$. Neural activation represents the twitch response of the muscle. Neural activation is obtained from $e(t)$ by applying differential equation of critical damped linear second order \[16\]. The coefficients of the second order equation need configuration and must be optimized. Finally, to convert $p(t)$ into our muscle activation $a(t)$, muscle activation $a(t)$ equations based on the non-linear shape factor (A) \[17, 18, 19\] is utilized.

C. Genetic Stage

The genetic stage is used to extract muscle activation $a(t)$ from the original raw EMG signal. Program formulation was done for this purpose using GA tool functions on MATLAB platform. A set of the population was generated from GA to produce a best possible solution for the given number of generations. Genetic algorithm consists of three procedures: selection, genetic operation and replacement \[20, 21,22,23\].

On the other hand, to create any GA, there are three important parameters needing to be evaluated; population size and fitness function, crossover, and mutation \[3\], where we illustrate them as follows:

1) Initial population and Fitness function: The initial population consists of a set of individuals that generated randomly. In addition, initial population is involved in the evolution of the new generation, therefore it needs to ensure no concourse in the local optimum \[23,24\].

The fitness function is the evaluation of each series in the population \[25\]. Fitness value is employed in the selection process to produce bias towards fitter individuals \[26\].

In our method the fitness function explains a measure of the GA stage agency to convert the raw EMG signal into muscle activation. Moreover, it’s supported by using regression analysis in order to minimize the errors between trains and implement data. Let our objective function be:

\[
MA = f(EMG,t)
\]

where, $MA =$ estimated muscle activation, $f =$ model function that converts raw EMG signal into muscle activation, $EMG =$ raw EMG signal data, $t =$ time of the EMG signal.

Therefore, the fitness function that evaluates the performance of the solution will be:

\[
FS = \sum_{i=1}^{N} (MA_{act} - MA)^2
\]

\[
= \sum_{i=1}^{N} (MA_{act} - f(EMG,t))^2
\]

where: $FS =$ fitness value, $MA_{act} =$ actual muscle activation.

2) Crossover: Crossover algorithm is initiated when the selection process was completed. Where, it’s defined as a generation operation to produce a new two chromosome from good old parents’ chromosomes. Genetic process manipulates the chromosome characters directly by assumption of the certain individual gene codes \[26\].

3) Mutation: Crossover operation generates a spadesful of different strings. This problem is overcome by mutation operation, which is considered an occasional random replacement of the value of a string position. Moreover, it’s represented a background operator in the GA \[22\].

D. The Muscle Force Estimator

The neural stage represents the second stage of our proposed model, which based on back propagation algorithm. Neural stage utilizes to extract muscle force from the input muscle activation $a(t)$. The architecture of the neural stage consists of three layers. First layer is the input layer, where muscle activation is the input of the model. Second layer, is a hidden layer with eight nodes and tan-sigmoid transferring function. The third layer is the output layer, which represents the human muscle force.

On the other hand, the input data to the neural stage are divided into three phases; training phase, to adapt the input weights according to the algorithm we used; testing phase, which evaluates the capability of the network to generalize; validation phase is related to the ability of the network in reality, where no information about the output is given \[27\]. The whole process of our method can be shown in the Fig. 1.
III. THE EXPERIMENT

This section will be split into two parts: first, the measurement procedures, which elucidate the profile of our volunteer, exercise procedure and steps to record the EMG signal; second, model configurations.

A. Measurement Procedures

Subject: The profile of our volunteer how involve in this work is non-athletic healthy male, weight 80 kg, and height 170 cm. We used four muscles in our experiment: biceps brachii, brachioradialis, triceps brachii, and Flexor carpi ulnaris muscles of the right arms to construct our models. These muscles and their descriptions can be shown in Table I. In addition, the experiment starts after we informed our volunteer of the type of exercise according to the Helsinki Declaration.

<table>
<thead>
<tr>
<th>Muscle Name</th>
<th>Description</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biceps brachii</td>
<td>The biceps is located on the upper arm between the shoulder and the elbow.</td>
<td>M1</td>
</tr>
<tr>
<td></td>
<td>Its main function is flexes the elbow and supinates the forearm</td>
<td></td>
</tr>
<tr>
<td>Brachioradialis</td>
<td>It is one of the forearm muscles that act to flex the forearm at the elbow</td>
<td>M2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Triceps brachii</td>
<td>It is the large muscle on the back of the upper limb in the arm.</td>
<td>M3</td>
</tr>
<tr>
<td></td>
<td>It is responsible for extension of the elbow joint</td>
<td></td>
</tr>
<tr>
<td>Flexor carpi ulnaris</td>
<td>Is a muscle of the human forearm that acts to flexion of wrist and adduction of the wrist</td>
<td>M4</td>
</tr>
</tbody>
</table>

Testing Procedure: The subject required to perform an isometric exercise. In this exercise, the subject’s upper arm will be sited on a horizontal surface without moving. The subject is required to rotate his lower arm up and down with an angle 90 degree with the elbow point. Moreover, the hand palm will sway back and forward with the motion of the hand. This operation will last for two mins. EMG recording starts with the first second of these two mins.

Surface EMG Recording: Before recording the EMG signal, the places of electrodes on the skin were cleaned and shaved to improve the contact. Twelve surface electrodes (M-00-S), were set on the muscles according to standard steps [28], as shown in Fig. 2. Four channels, four pre-amplifier cables (ME6P) and EMG Bio-monitor (ME60008ch.) device were involved in recording the surface EMG signal of the four muscle activity. In addition, the signals were rectified and filtered using a band-pass Butterworth filter (1-400 Hz) and 1500 Hz sampling rate.

![Fig. 2 position of the electrodes on the right arm muscles](image)

M1: Biceps brachii, M2: Brachioradialis, M3: Triceps brachii, M4: Flexor carpi ulnaris
B. Model Configurations

Genetic Model: The steps of our genetic procedures can be summarized as: GA starts with a random selection of the population and uses operators to evaluate the next generation; the fitness function (objective function) is used to provide the optimal classifier of the individuals performed in the problem (converting to muscle activation); crossover and mutation operators are used in the selection of the next generation of the individuals (how has the best fitness); the process will end when all the sizes of the individuals have been accomplished. In addition these step procedures can be illustrated as in Fig. 3.

![Fig. 3 Genetic algorithm flow chart](image)

Neural Network: To provide a suitable output from neural stage we examined a different number of layers, node, and function. Therefore, the neural model configuration of our neural stage in the number of nodes, epochs, layers and function type that used can be showed in TableII.

<table>
<thead>
<tr>
<th>Configuration</th>
<th>Number or Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of inputs</td>
<td>1</td>
</tr>
<tr>
<td>Epochs</td>
<td>5000</td>
</tr>
<tr>
<td>Hidden layer</td>
<td>1 hidden layer</td>
</tr>
<tr>
<td>Nodes</td>
<td>8</td>
</tr>
<tr>
<td>Function</td>
<td>Triangular</td>
</tr>
</tbody>
</table>

IV. RESULTS AND DISCUSSION

In this section we will demonstrate the output of our neural-genetic model, which represents the muscle force of human right arm. In addition, we show the validation of our proposed model to employ for any human muscle by utilizing different muscles. On the other hand, we compare our results with our previous work, back-propagation neural network (BPNN), to validate our results. Moreover, we will elucidate our model performance.

A. Output Analysis of the Proposed Model

Our result indicates that our neural-genetic model improves the estimation of the human muscle force, as shown in Fig. 4. The muscle force in this figure obtains from the raw EMG signal by using the two stages of our neural-genetic model. Moreover, in Fig. 4 we can observe the similarity between the output of our previous BPNN model and neural-genetic model for the biceps brachii muscle of the human arm. This also proves that our proposed model can replace all of the complex steps of the traditional estimation method to reach the estimated muscle force. Consequently, neglect all the complexity of puzzle out the parameters of the EMG-driven dynamic model and the configuration of force-length and force-velocity relationship in Hill-type model.
B. Validation of the Proposed Model

To prove that our proposed model can be applied for any human muscle, we took three different muscles of the human arm (brachioradialis, triceps brachii, and Flexor carpi ulnaris). As shown in Fig. 5, which represents the muscle force of these three muscles, this figure demonstrates a comparison between the muscle forces estimated from BPNN model and predicted force from neural-genetic model. Moreover, our proposed model indicates the ability to extract muscle force from the original raw EMG signal neglecting the signal processing procedures that used to produce the RSEMG signal. Also, override the mathematical equations in the traditional method estimation. One important thing, our model needs to train for each muscle to predict muscle force.
C. Performance of the Model

This section demonstrates the performance of our proposed model in two parts. First part illustrates the performance and output parameters of genetic stage, which represent the estimation of muscle activation. Second part demonstrates the efficiency of the neural stage, which represents the estimation of muscle force.

Genetic Stage: The result of our genetic stage can be summarized in Table III. Also, in Fig.6 which represents the fitness function (objective function) against the generation’s number at the genetic processed in our proposed model. Where, the fitness value refers to the most possible solution. Thus, it's showing the desired value to get the muscle activation from the raw EMG signal in our objective function. In addition, Fig. 6 shows that the best fitness is taking place at the 51th generation. On the other hand, Fig. 7 shows the distance between the individuals, where it starts to take closed distance from 18th generation until it reaches the optimum solution in the 51th generation. The optimum solution obtained in less than 20s, where the optimization was carried out for the raw EMG signal to produce the muscle activation.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>The number of generations</td>
<td>51</td>
</tr>
<tr>
<td>The number of function evaluations</td>
<td>1300</td>
</tr>
<tr>
<td>The best function value found</td>
<td>0.00181859</td>
</tr>
<tr>
<td>Probability of crossover</td>
<td>0.85</td>
</tr>
</tbody>
</table>

Neural Stage: To demonstrate the performance of our neural stage we used the regression value as efficiency measured. We amelioration the new model performance compared to the previous BPNN model; where, the regression became $R=0.99974$ instead of $R=0.99965$ for the previous BPNN model as shown in Fig. 8. In addition, the mean square error RMS equals to $1.021x10^{-08}$ instead of $1.39x10^{-07}$ for the BPNN model. On the other hand, this performance was done on 60% of data as training for our model and the remaining 40% used in testing and validation for the proposed model as 20% for each one.
This paper investigates the enhancement of muscle force estimation using neural-genetic model. Where, this model predicts human muscle force from the original raw EMG signal. Our model consists of two stages: the first one employing a genetic algorithm to transform the raw EMG into muscle activation; the second stage which is implemented based on back propagation neural network extracts muscle force from muscle activation. Our results elucidate that neural-genetic model improves the force estimation accuracy. The neural-genetic model can efficiently transform the raw EMG signal to muscle force, overlooking all the steps of EMG signal processing and parameters configuration of the mathematical equations.

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