

Full Length Research Paper

Electromyographic (EMG) signal to joint torque processing and effect of various factors on EMG to torque model

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Accepted 8 November, 2011

This study present electromyographic (EMG) signal to torque model and investigates the effects of various factors on EMG signal and EMG to torque model. Pre-processing techniques are applied on EMG signal in order to remove the DC offset, 60 Hz noise and to estimate the EMG amplitude. The estimated EMG amplitude is then mapped to joint torque using a new non-linear equation. This equation uses some parameters, whose values are obtained using nonlinear regression. Ten subjects took part in the experiments and performed variable force maximal voluntary contractions (MVC) and sub-maximal voluntary contractions (SMVC). The resulting elbow joint torque and EMG signals were pre-processed and entered to the model to find value of the parameters using nonlinear regression. Once these values were obtained they were put into the model and thus joint torque was estimated. Also EMG is analysed for effect of various factors like muscle fatigue, cross talk and different joint velocity. The results obtained from this model are highly correlated with the true values of the torque and the average correlation and mean square error for different experiments are 0.9997 and 0.047 Nm respectively. This new mathematical equation can be used to design a control system for rehabilitation and wearable robots.

Key words: Electromyographic (EMG), maximal voluntary contractions (MVC), power spectral density, levenberg-marquardt algorithm, non-linear regression.

INTRODUCTION

Muscle is a source of force and joint torques in human body. In the upper limb of human body the bicep and tricep muscles consist of muscle fibres and joint movements are realized by contraction of these fibres, controlled by Central Nervous System (CNS). When the muscle fibres receive the command (electrical activity) from CNS, an electric signal is generated on the muscle

surface and the signal is called EMG signal (Roberto and Philip, 2004).

The EMG signal is random, continuous and nonlinear in nature (Hogan and Mann, 1980; Siegler et al., 1985). These properties of EMG signal reveal that it should be processed in order to get a simple model for its amplitude and then map this amplitude to joint torques. Some of the models that map the EMG to joint torque assume that the EMG signal is a band limited white noise modulated by the level of muscle contraction thus joint torque can be derived from this signal by controlling muscle length (Rack and Westbury, 1969). According to these assumptions,

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mapping EMG signal to joint torque requires pre-processing the raw EMG signal. Numerous attempts have been made by researchers to mathematically model the joint moments and torques using EMG signal. In some of these models, first the muscle force is calculated and then joint torque is estimated. In one of these models torque is calculated on basis of response from a single motor (Fuglevand et al., 1993). Herbert and Gandevia (1999) improved this system by providing an accurate single motor response. Statistical optimization methods are also used by researcher to extract the joint torque and muscle tension from EMG signals, but these statistical methods are not robust because they use too many parameters (Hof and Van der Berg, 1981). Some researchers tried to get a signal and to extract torque for each joint of the body from this single EMG signal using low pass filtering. Low pass filtering is the easiest way to get EMG amplitude, and then using it for torque prediction. However if it is used for controlling the whole body skeleton then it is very difficult to get such set of EMG signals that will result in torque for whole body joints (Zajac, 1993). Some researchers have used Artificial Neural Networks (ANN) for estimating joint torque from EMG signal. It has been shown that ANN yield good results if it is trained for limited values of EMG and torque (Fausett, 1993). If there is large data set of EMG and torque, then ANN results are random and not well-correlated with the measured torque.

Most of these models have established a successful relationship between EMG signal and joint torque. However, the muscle fatigue is caused if the force is applied repeatedly and the contractions of muscles are sustained. This fatigue affects the capability of applying force (McComas et al., 1995). Similarly joint angular velocity and cross-talk also have effect on the EMG signal and thus affecting the EMG to torque processing. The previously mentioned models did not consider these cases of muscle fatigue, joint velocity and cross-talk, while modelling the muscle force and joint movements on the basis of EMG signal. Some of the models like Reiner and Quintern (1997) and Gait's et al. (1993) models use more than 25 parameters, making them very complex and it is very difficult to adjust these parameters for different muscle contractions and joint torques. Another major disadvantage of these models is that they use too many assumptions so they are not robust.

One of the solutions to model joint torque on the basis of EMG signal is to use a new mathematical model, which can predict joint torque from EMG signals at both the conditions of muscle fatigue and varying joint velocity. So in this study we present a new mathematical (nonlinear) model using nonlinear regression. Nonlinear

regression enables us to fit a set of data to a mathematical model which represent the data in a compact form (Douglas et al., 1988). The model considers a few parameters, whose values are found and then updated until the difference between the model data and actual data is minimized. Thus, we get a single equation which represents the EMG to torque relation using a single function (Gallant, 1975). In our non-linear regression model Levenberg-Marquardt method is used for finding and adjusting value of the parameters as explained by Marquardt (1963) and Levmar (2005). The pre-processed EMG signal, recorded from the bicep muscle of the human arm, and the joint torque are used as input to our model. Then a merit function is minimized by adjusting the parameter's values until there is no more improvement in the merit function. The joint torque estimated by our model is highly correlated with the measured torque.

MODEL DEVELOPMENT METHODOLOGY

Basic physiology of motor control, muscle contraction and EMG generation

The motor unit is an important functional unit of muscle. It has motor neurons and muscle fibers which are innervated by motor neurons. This is shown in Figure 1. When a muscle fibre of a motor unit is activated an electrical potential is generated called fibre's potential. This potential spreads into the muscle fibre through the transverse tubules. In response to this action potential, the stored calcium is released that binds with troponin, altering the location of tropomyosin. This frees the active site on the actin, allowing a muscle contraction to take place (Roberto and Philip, 2004). The sum these electric potentials in a motor unit are called motor unit action potential (MUAP). Sum of these motor unit action potentials is called electromyographic signal. This signal can be acquired by either placing electrodes on the surface of human's muscle (Non-invasio), or by inserting needle electrode into the muscle (Invasio).

Experimental setup and data collection

The robotic exoskeleton arm that was used in this experiment (Figure 2) had a link and joint corresponding to the human elbow joint. The length of the link was adjustable for different lengths of the arm. Also there was another mechanism that was fastened to the arm as shown in Figure 2. It had a potentiometer at the elbow joint. This was used to record the elbow joint angle when the subject was performing the contractions.

Ten persons without any physical disorder took part in the experiments in order to collect the EMG signal, joint angle and load data. Before starting the experiment each subject was trained how to operate the load sensor and the potentiometer. Also the skin was prepared by shaving the hair in order to place the surface EMG sensor properly on the bicep brachii muscle. Subjects were asked to stand straight and fasten the exoskeleton robotic arm. They were asked to do non-fatigue MVC and SMVC contractions and the

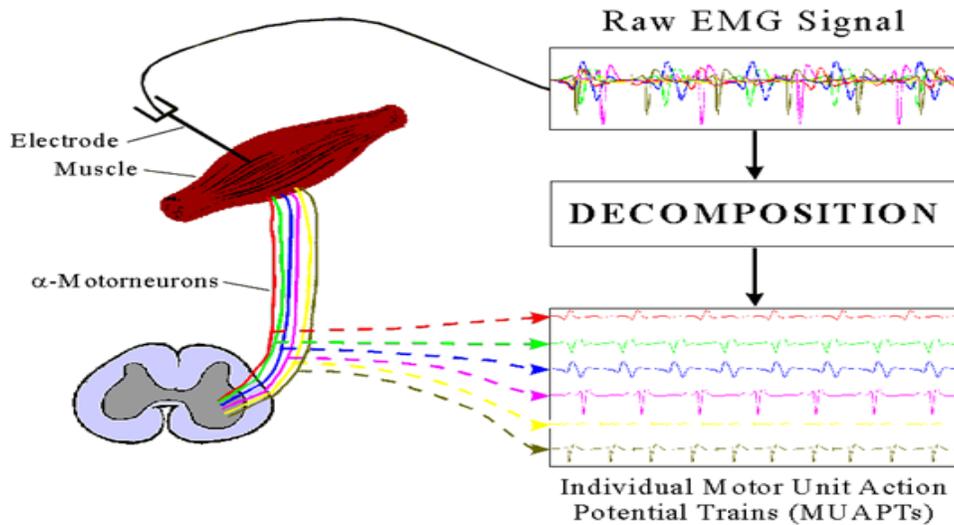


Figure 1. The motor unit, MUAPs and the electromyogram signal.

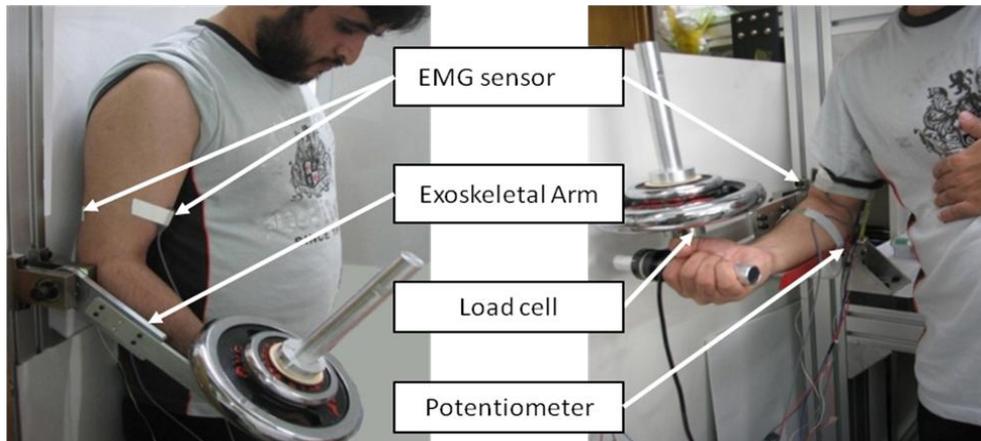


Figure 2. A view of the experimental setup, exoskeletal robotic arm with load cell for measuring load lifted by the subject and a manipulator with potentiometer for measuring joint angles.

corresponding EMG, angle and load data were recorded to a file in computer. The time duration of the experiment for one subject varied between 5 to 15 s for one contraction with rest time 10 min between two contractions. For recording the EMG signal from bicep muscle a DELSYS single differential DE-2.3 sensor was used. This sensor has detection surfaces consisting of two parallel bars. It is a band pass filter with cut-off frequencies 20-500 Hz. MNT-50L miniature load cell was used for measuring the load lifted by a subject. Data from all these sensors was sampled using 1000 Hz sampling frequency and then digitized using a NI USB-6009 A/D converter, in order to feed into the computer for analysis. NI-LabVIEW 8.5 was used for data acquisition and real time processing, while Math works-MATLAB 7.6 and Microsoft Visual

C++ 2005 were used for batch processing.

Data pre-processing

Before inputting the EMG signal to the model it was first pre-processed. DC offset was calculated for 2 s and then removed, this signal was then passed through a 5th ordered notch filter to remove the 60 Hz noise due the power supply, then full-wave rectified and finally the moving average of the EMG (of window size varying from 0.2 to 0.5 s), was found. This moving average EMG is then normalized. The normalized moving average EMG is the estimated amplitude of the EMG signal. Similarly the joint angle and load data

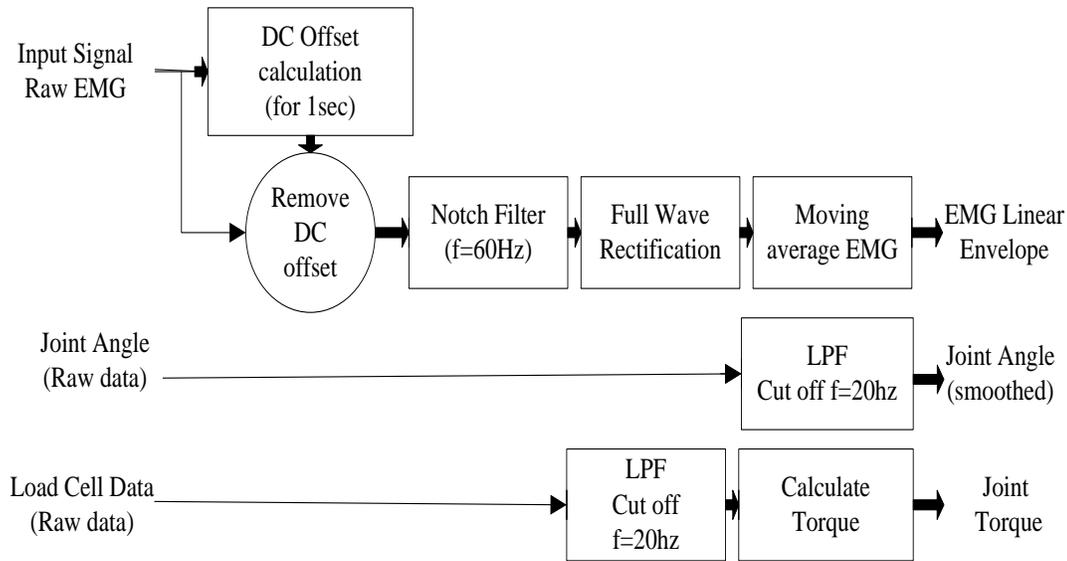


Figure 3. Schematic diagram for EMG signal, joint angle and joint torque pre-processing.

were collected and smoothed and then joint torque was calculated. Now, this torque acted as a control variable for our model because on the basis of this measured torque the parameters of our mathematical model are adjusted. The schematic diagram for pre-processing of the EMG signal, joint angle and load data is shown below in Figure 3. The EMG linear envelope obtained after pre-processing and actual torque was then entered as input to our model. The raw EMG, pre-processed EMG and joint torque data for MVC and .SMVC for two different subjects is shown in Figure 4.

EMG to torque models

In order to model joint torques from EMG signal, it is important to know the nature of the relationship between EMG and joint torque. According to these assumptions to find a best mathematical model for estimating joint torque, EMG linear envelope was plotted against joint torque and it was found that the relation is not linear and is somewhat exponential (Figure 5). Also according to Stephen and Stuart (2008) EMG producing less torque output at higher levels of activation. Due to the nonlinear and exponential nature of the relationship, different exponential models including neural network were introduced and analyzed to get the best model. Each of these models except ANN has unknown parameters, a , b and c . The values of these parameters are obtained using nonlinear regression. The ANN and other models were analysed in two ways, batch processing and real-time processing. In the batch processing the ANN is trained and for the other models both EMG estimated amplitude, and measured joint torque were entered to the model and best fit values were found for the parameters using nonlinear regression. These values were put into the model to calculate the torque for the same EMG signal. While in real-time processing,

another different EMG signal was entered to the model and the joint torque for this new EMG was calculated using the parameters obtained from batch processing.

Table 1 shows the analysis of different candidate models. MSE and correlation coefficient were calculated for each model. The model which has least MSE and greater correlation between measured torque estimated torque in both batch and real-time processing was selected. The comparison of these models is shown in Figure 6. The selected mathematical model and the non-linear regression for finding values of the parameters are discussed in details in the next subsections. Besides the above models polynomial curve fitting was also used. The polynomial gave good results in range of the data but outside the range of the data the results were quite different from measured data. The results of our new selected model were also compared to some existing models developed by Metral and Cassar (1981) and Fleischer (2005).

The selected best mathematical model

As the relationship between EMG and joint torque is non-linear Metral and Cassar (1981). Thus a new mathematical model was introduced to map EMG to joint torque. The model which can best describe the relationship between EMG and joint torque is given in Equation. (1).

$$\tau_{es} = u^a * \exp(b - c * u) \quad (1)$$

Here in Equation 1, τ_{es} is the estimated joint torque, u is the pre-processed EMG signal and a , b , c are the unknown parameters. The problem is to estimate best fit values for these unknown parameters. For this purpose non-linear regression was used,

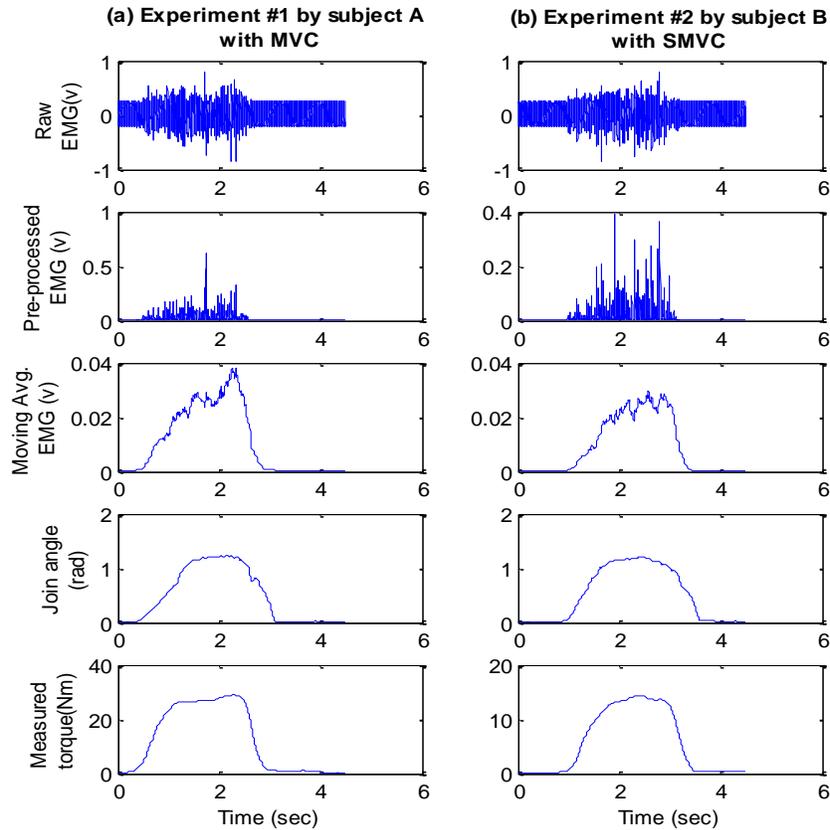


Figure 4. EMG Signals, raw EMG and denoised EMG, normalized moving averaged EMG and the measured joint Torque for two different subjects.

where a merit function was selected and minimized. This is explained in detail in next subsection.

Non-linear regression for finding values of the parameters

Regression analysis is a technique that fits a set of data to a smooth continuous function (Laurene, 1998). Regression has two types, linear and nonlinear. In non-linear regression, large number of iterations are performed to minimize the merit function (*MF*) and the values of the parameters are non-linearly related to the model.

The purpose of nonlinear regression is to determine the best-fit values for the parameters for a model by minimizing the chosen *MF* (Laurene and Fausett, 1998). In this iterative approach first initial values were obtained using least square fitting for the parameters and then the Levenberg-Marquardt Algorithm developed by Marquardt (1963), was used to obtain values of the parameters for next iteration. The newly estimated values now act as the initial values for the following iteration. Adjusting the values of the parameters is continued until no further improvement in the *MF*. Let our model torque is denoted by τ_{es} and τ_{ac} is the actual measured torque. Then our model can be written as follows in Equation 2.

$$\tau_{es} = \tau_{es}(u, a, b, c) \tag{2}$$

The *MF* minimization can be represented by Equationn. 3.

$$MF^2 = \sum_{i=1}^N \left[\frac{\tau_{aci} - \tau_{es}(u_i, a, b, c)}{\sigma_i} \right]^2 \tag{3}$$

The whole algorithm for merit function minimization to find values of parameters is as follows Marquardt (1963):

- (i) Estimate initial values for the unknown parameters using least square fitting.
- (ii) Using these initial values, calculate the merit function by putting values of parameters in Equation 3.
- (iii) Now to minimize the merit function, adjust the values of the parameters using the Levenberg-Marquardt method.
- (iv) Compute the merit function and compare it to its previously obtained value.
- (v) Repeat step 3 and 4 until no further minimization occurs in MF^2

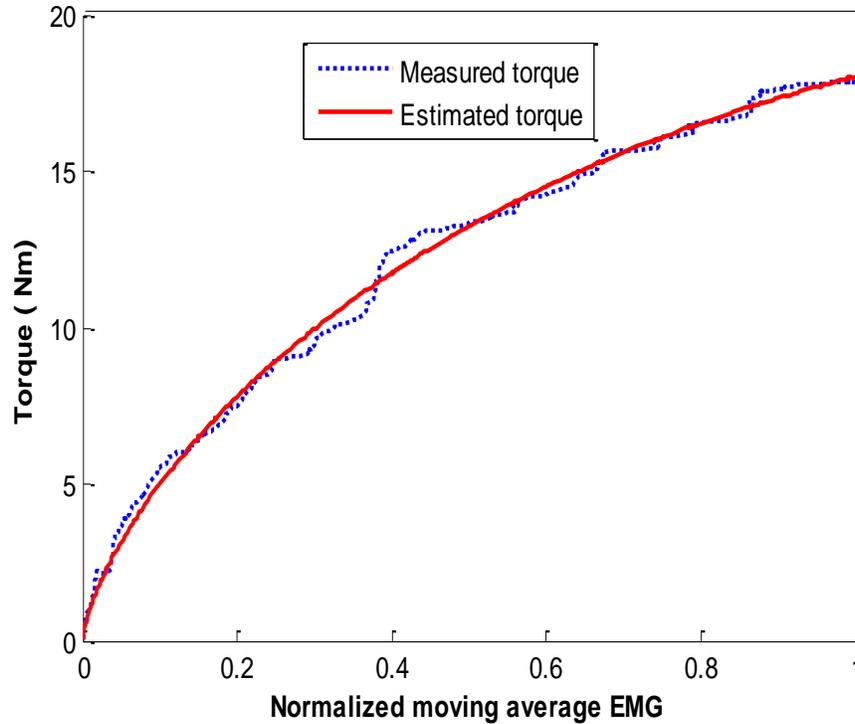


Figure 5. EMG Signal versus Joint Torque plot.

Table 1. Detail of the different models and ANN for estimating joint torque from EMG signal.

No	Model	Batch analysis of the models		Real time analysis of the models	
		MSE (Nm)	R ²	MSE (Nm)	R ²
1	$\tau = a + b u^2 + c e^u$	0.094	0.997	0.382	0.993
2	$\tau = a + b \cos(u) + c \sin(u)$	0.167	0.996	0.525	0.990
3	$\tau = a + b e^u + c e^{-u}$	0.116	0.997	0.442	0.992
4	$\tau = a u^b$	0.128	0.997	0.311	0.994
5	$\tau = a + b \sqrt{u}$	0.497	0.988	0.301	0.997
6	Neural network	0.021	0.998	0.415	0.993
7	$\tau = u^a e^{(b-cu)}$	0.049	0.998	0.056	0.997
8	$\tau = a e^{(b/u)}$	0.413	0.981	0.527	0.987
9	$\tau = a / (1 + b e^{(cu)})$	0.145	0.989	0.328	0.988

(vi) Save the final values of the parameters, and now the joint torque is calculated by putting these parameters into Eqn. 1.
 (vi) Finally calculate some performance indexes (MSE, variance and correlation). Once the best fit values for the parameters were

obtained, they were assigned to the parameters of our model. Now in real-time, only the EMG envelope was entered as input to the model, and it generated the estimated joint torque. The schematics for batch and real-time processing are shown in Figure 7.

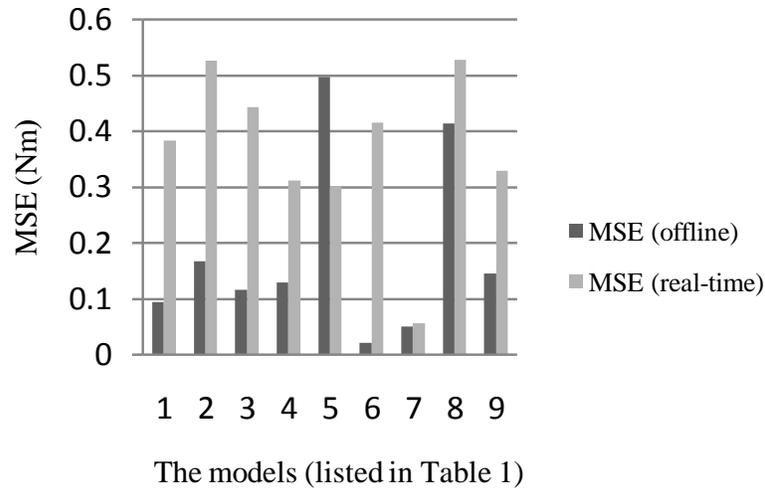


Figure 6. Comparison of the models on basis of MSE in both batch and real-time processing.

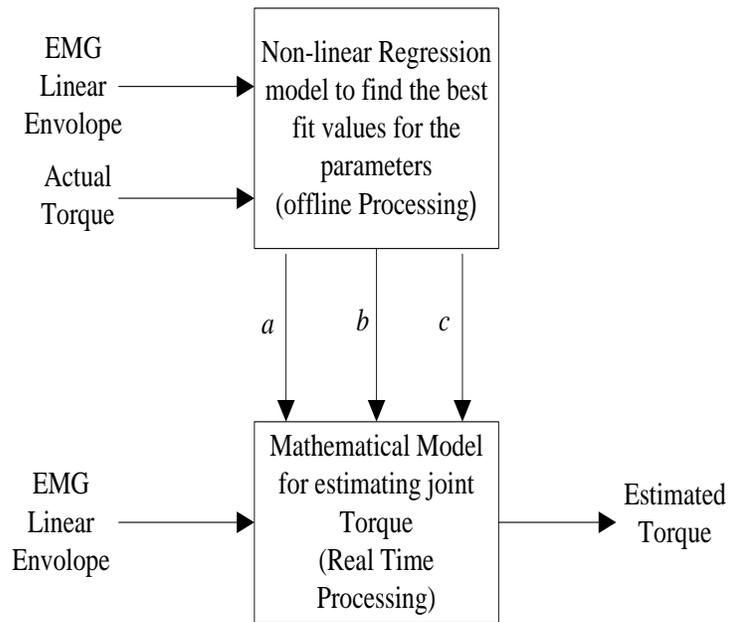


Figure 7. Schematic diagram for batch and real-time processing.

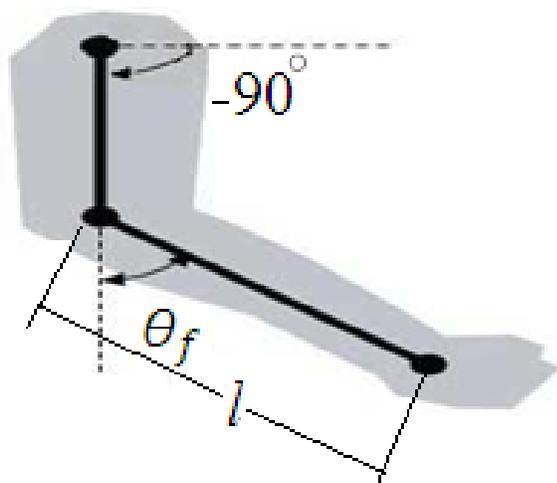
RESULTS OF THE MODEL

To validate the performance of the new model, experiments were performed using the experimental setup discussed in previous section. The experiments were performed in two groups. First group presents

experiments that were performed to obtain best parameter's values. Second group presents experiment in which only EMG signal was entered as input to the model and it generated the required torque. There were several important results derived after completing the described experimental procedure.

Table 2. Values of the parameters and error analysis for 5 subjects data

No.	Values of the Parameters for model $u^a * \exp(b - c * u)$			Error analysis (Real time)		
	a	b	c	SSE (Nm)	MSE (Nm)	R^2
1	0.815	3.318	0.314	364.4	0.071	0.988
2	0.844	3.450	0.366	285.6	0.056	0.998
3	0.699	3.231	0.348	174.0	0.072	0.987
4	0.784	3.267	0.412	315.0	0.061	0.991
5	0.805	3.336	0.374	321.2	0.062	0.983

**Figure 8.** Shoulder joint angle and elbow joint angle (θ_f) during contractions.

During the first group of experiments, five subjects took part in the experiments. The shoulder joint angle was fixed at -90° w.r.t x-axis as shown in figure. Each subject did isometric flexion on the elbow joint. They flexed the elbow from 0 to 90° (θ_f) w.r.t y-axis as in Figure 8. After flexion, they extended their arms with elbow joint angle decreased from 90 to 0° w.r.t y-axis (Figure 8). During these contractions the subjects applied variable force with maximal and submaximal contractions and the resulted joint torque was entered as input to the model for batch processing. During the batch processing the algorithm found best fit values for the unknown parameters. As the iterations of the *MF* minimization algorithm increased the values of the parameters were adjusted so the estimated torque became closer and closer to the actual torque and thus the mean square

error (MSE) was decreased. The algorithm took 29 iterations to get the best fit values for the parameters for one subject and 24 for the one of the four other subjects. The convergence time for getting best values of the parameters was 31.537 and 21.6 μ for two subject's data respectively. The estimated parameter's values and the error analysis for each of the five subjects (who took part in experiments) are listed in Table 2.

As in batch processing the best values for the parameters are obtained so now in real time processing only EMG signal is entered to the model and torque is obtained for the joint (Figure. 7). The joint torque estimated by our model is highly correlated with measured torque. The mean square error (MSE) and correlation coefficient were 0.056 Nm and 0.998, and for another subject's data were 0.061 Nm, 0.991 respectively. The results for two different subjects that participated in experiments are shown in Figure 9.

Here subject "A" performs maximal voluntary contraction (MVC) and subject "B" performs sub-maximal voluntary contractions (SMVC). Result for another subject, who perform MVC is shown in Figure 10. From Figures 9 and 10, it is clear that our model can successfully map EMG signal to the joint torque in both maximal and sub-maximal voluntary contractions

Factors affecting EMG to torque model

There are a lot of factors which can affect the EMG signal thus can affect EMG to torque model. Due muscle fatigue the EMG envelope is slightly increased. Due to this increase in EMG amplitude the EMG to torque model is affected and the values of the parameters should be adjusted to overcome this change. This change in parameters of the model is shown in Figure 11.

Similarly joint angular velocity also affects the EMG

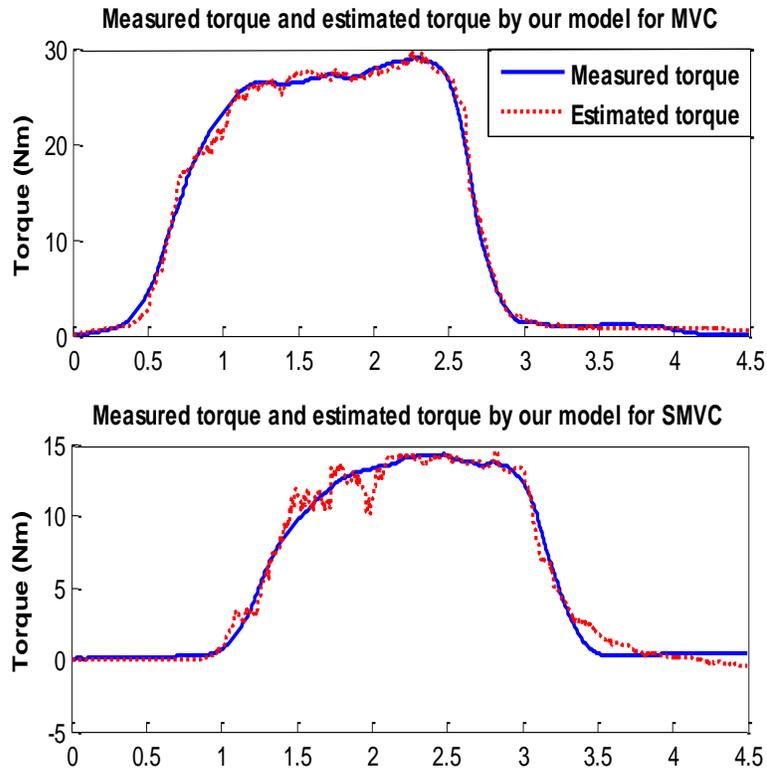


Figure 9. Results of two experiments performed by different subjects (Subject A perform MVC and subject B SMVC).

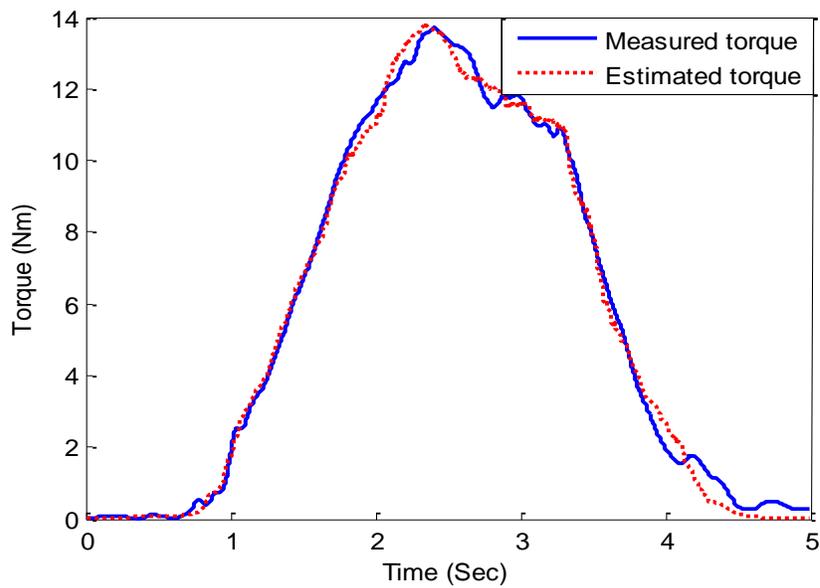


Figure 10. Results of our model for one subject data during MVC.

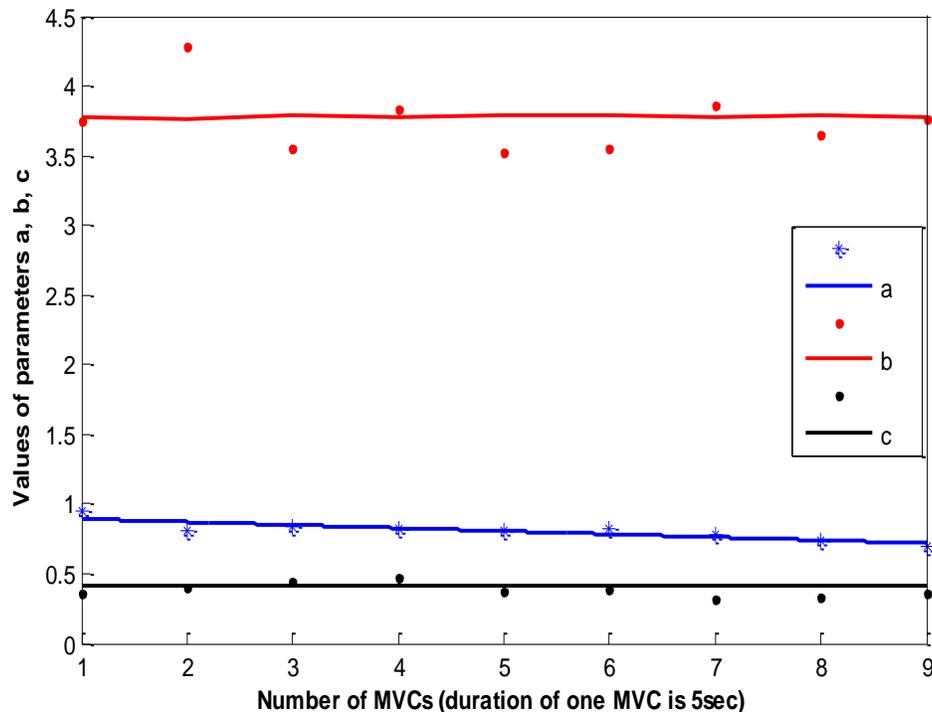


Figure 11. Change in Values of the parameters due to muscle fatigue.

signal and thus affecting the EMG to torque model. A large number of contractions were performed by subjects varying the joint velocity, and it was found during the experiments that the EMG amplitude is increasing linearly in the beginning as the joint velocity increases and after some time it changes very slightly. Now at this stage when EMG amplitude is changing, the values of the parameters were again estimated using the proposed algorithm and it was found that the new values of the parameters are changing. These changes in values of the parameters are shown in Figure 12.

DISCUSSION

In this study a new nonlinear model is introduced and then experiments were performed in order to validate the model. In the creation of the model three parameters (a, b, c) were used. The selection of the number of parameters is very critical and it can affect the predicted output. The robustness of the model is related with the values of the parameters. If optimized values are not obtained for the parameters then there may be larger errors.

In this study a new nonlinear model is introduced and then a number of experiments were performed in order to validate the model. In the creation of the model three parameters (a, b, c) were used. The selection of number of parameters is very critical and it can affect the predicted output. The robustness of the model is related with the values of these parameters. If best fit values are not obtained for the parameters then there may be large errors. As standard method (e.g. Levenberg Marquardt) is used for estimation of the parameters and the correlation coefficient and MSE values show that this model can successfully map EMG to joint torque.

Another purpose of this study was to examine the estimation of torque from EMG during maximal and submaximal contractions. Previously only torque is estimated from EMG in case of maximal voluntary contractions. As a patient with serious muscle injury can't exert maximum force so the model should be able to estimate the accurate torque from EMG in such case of sub-maximal forces. Hence in our model we calibrate EMG to torque processing for both maximum and also sub-maximal um muscle contractions. The results (Figures 9 and 10) show that our mathematical model is able to map EMG to joint torque for both maximal and

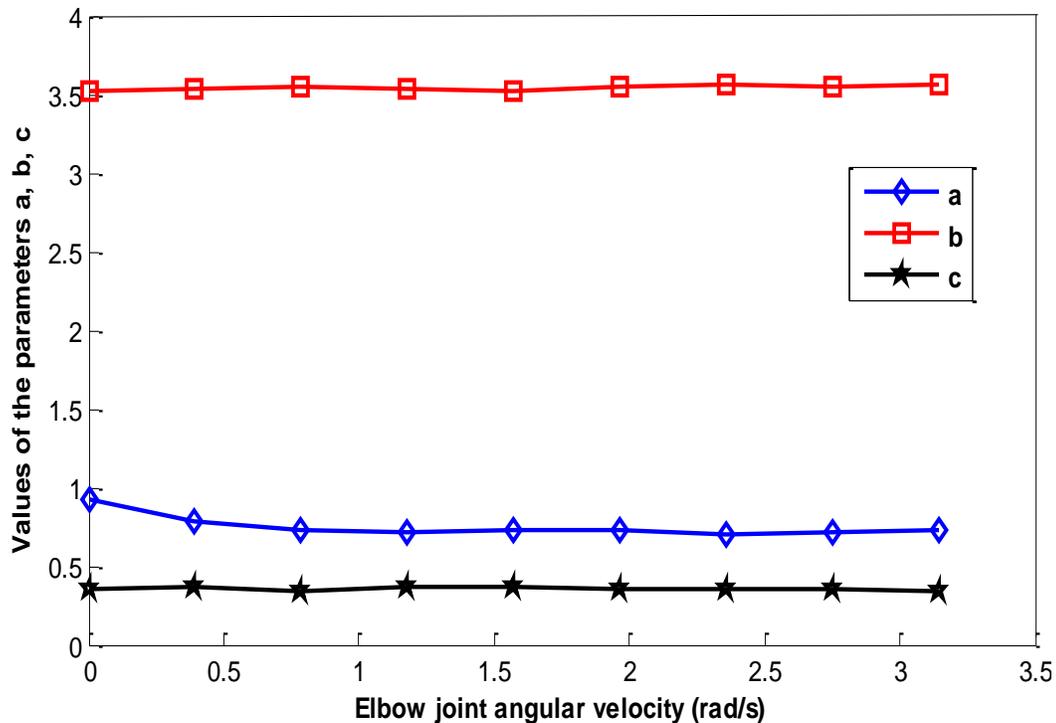


Figure 12. Change in values of the parameters of our model due to change in angular velocity of the joint.

sub- maximal voluntary contractions (Figure 9b).

Although the results of our model are good, still some MSE errors exist between target torque and our estimations. The new model is a simpler model as compare to other existing models because it takes only one EMG signal and only the muscle fatigue and joint velocity are analyzed. The model needs only one EMG signal from the bicep brachii muscle for estimating the joint torque. If torques for the shoulder joint and other joints are to be estimated, then more EMG sensors will be needed, and I hope our model may be successful in this case as well.

This model was refined by studying the EMG signal for muscle fatigue and varying joint velocity. It was found that there are slight changes in parameter's values of the model which should be considered during torque estimation.

Conclusions

This study investigates the relationship between EMG signal and joint torque and presents an EMG-to-torque

model. The main aim of this research was to detect the intended motion of the human arm and then develop an EMG-to-Torque model that will be a basis for controlling the exoskeletons.

For this purpose it was required to find a relationship between the electrical activity (EMG) and joint torque. A nonlinear model which has least MSE and greater correlation with measured torque is selected.

Conceptually this mathematical model has some advantages and disadvantages. As joint torque estimated by this model directly depend on EMG signal so this model is very sensible to EMG recording. Improper placement of sensors and inaccurate experiments may result in wrong estimates, but still this model is more robust because it uses limited number of EMG sensors. From the results of the model, it can be considered that our mathematical model can be used successfully to predict joint torque from EMG signal. A standard method is used for finding parameter's values, which leads to mapping EMG to joint torque. In the experiments only healthy subjects took part due to safety reasons, but we hope that this model can help in controlling assistive devices for disabled people who have some muscular

disorder.

This model will be a basis for controlling exoskeletons. In the future we hope this model can be used successfully to make an interface between human operator and the exoskeleton arm. A device (exoskeleton) and a control system may be developed which will support a human operator with extra force in the elbow joint specially and also for legs and thigh joints. The exoskeleton can be attached with human body and it should increase his or her mobility and strength by supporting the arm, leg and thigh muscles.

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