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Determination of Mathematical Model and Torque Estimation of s-EMG Signals based on Genetic Algorithm

[1]Ku Nurhanim, [2]I. Elamvazuthi, [3]P. Vasant, [4]S. Parasuraman

Abstract—This paper discusses the conversion of surface electromyography signals (s-EMG) to torque for robotic rehabilitation. Genetic algorithm (GA) has been applied as control algorithm for a number of selected mathematical models. s-EMG signals was treated as input to the mathematical model where pararameters of the mathematicl model were optimized using GA. Hence, the estimated torque is considered as output data of mathematical model.

Index Terms— Electromyography, estimation torque,mathematical model,biomechanics human motion,muscle contraction,robot rehabilitation,feature extraction,genetic algorithm.

1 Introduction

In United States, about 795,000 people suffer from stroke which is the third ranking disease where one quarter of the patients are dependent on assisted activities for daily life [1]. Every year about 130,000 people in United Kingdom have stroke with 13,000 people under retirement age where over one third from 65% of the stroke survivors having disabilities of hand and upper limb. Muscular dystrophy, arthritis and regional pain syndrome are also major cause of disabilities of stroke patients [2].

Task oriented stroke rehabilitation promote the motor recovery and cerebral organisation of patient after stroke [3,4]. However the availability of such training session are limited in hospital and rehabilitation centre. There are constrained number of patients for rehabilitation program, number of facilities and required long duration time, and the ability of therapist to control and repeat the assistance for each training session [5]. Every year, with grossly higher demand for rehabilitation, the implementation of robotic rehabilitation may assist to reduce the dependency on therapist and provide a consistent training exercise. Robotic rehabilitation also provides intensive training without tiring and possible to enhance the therapy beyond the abilities of therapist [6].

The robotic rehabilitation utilizes the surface electromyography signals (s-EMG) as control input to estimate the magnitude and direction of torque for the robotic joint of exoskeleton. Researchers have done several works on mathematical model and black box model to estimate torque based on force produce of the muscle contraction. Biomechanical model has been use to convert s-EMG signals to torque to maintain the posture of arm [7]. Hill-Based model, also known as model-based approach, acts as input, and the output depend on the muscle activation [8] level and musculoskeletal kinematics to generate torque [9]. Fleisher et al, used Hill-muscle model to predict the joint torques for controlling the leg of exoskeleton [10]. Menegaldo et al, estimate the torque of ankle by applying muscle model which summation each individual muscle and compare with torque measure [11]. Hill-based muscle model parameters matched the human ankle for torque and angle walking to control powered ankle prosthesis device [12]. Cavallaro et al, has done research on joint torques prediction for arm power exoskeleton application with and without GA optimization parameters [13].

Clancy et al, have used polynomial equation as a mathematical model for estimation joint torques in isometric and quasi-isometric contractions. Least square method has been used to to minimize the torque error [14]. S. Parasuraman et al, has used mathematical model with SA algorithm and GA optimization with least square method as cost/fitness function to get the best fit model of torque conversion [15]. Khalid et al, introduced new mathematical model using nonlinear regression to estimate joint torques. This new mathematical model has been compared with other mathematical model and neural network and proven to be the best fit model for online processing and real-time processing [16].

Neural-network also recognized as black box model does not require knowledge of physiology and joint dynamics for torque conversion. Neural network model was also used for prediction of joint moments [17], muscle force [18]. Neural network can be trained using different load and frequency to estimate the joint torques [19].Micheal E.Hahn, found that neural network model allow a greater accuracy joint torques prediction but as error goal set to lower, convergence is not achieved 100% [20].The selection of number of hidden unit neural network model was not the main problem to allow accuracy of s-EMG to joint torques conversion [21]. This model was also applied for prediction of output mapping between s-EMG signals and joints angles and joint moments. The result from this study has demonstrated that is has good potential for biomechanical and simulation in human gait [22]. The processed data of s-EMG signals could be converted to estimation torque based on human movement. This estimation torque is important to control the motion of robots for rehabilitation. Mathematical model is used to convert the s-EMG signals to torque for estimation torque value. This estimation torque will be determined by optimizing the parameters of the mathematical model to the nearest value of actual torque. Artificial intelligence algorithms are used to optimize the internal parameters of the mathematical model to find the best fit mathematical model and minimize the error between estimated torque and actual torque. The aim of this paper is to establish mathematical models for s-EMG signals conversion to estimated torque using genetic algorithm.

2 Theory and Technique

2.1 Mathematical Model of EMG to Torque Conversion

The fitness function to evaluate the performance of each selected mathematical model using genetic algorithm is

$$SSE = \sum_{i=1}^{n} \left(\tau_{act} - \tau_{est(i)} \right)^2 \quad (1)$$

where,

SSE = sum square error as fitness function

τ_{act} = actual torque

$\tau_{est(i)}$ = estimated torque as mathematical model

Mathematical model for estimated torque [15],[16]:

$$\tau_{est(1)} = x_1.u_i + x_2.u_i^{\frac{1}{2}} \quad (2)$$

$$\tau_{est(2)} = x_1.u_i^{x_2} \quad (3)$$

$$\tau_{est(3)} = x_1.u_i^{x_2} + x_3.u_i^{x_4} \quad (4)$$

$$\tau_{est(4)} = x_1 + x_2\sqrt{u_i} \quad (5)$$

$$\tau_{est(5)} = u_i^{x_1}.e^{(x_2 - x_3 * u_i)} \quad (6)$$

where,

$\tau_{est(1)}$ to $\tau_{est(5)}$ = torque estimation mathematical model.
u_i = processed EMG data sample
x_i = where, i=(1,2,3..) as random value parameter associated with selected model.

2.2 Regression analysis

Regression analysis accommodates the fitness function to minimize fitness values and obtain the optimum value of the parameter of selected mathematical model using genetic algorithm(GA).The steps to investigate the best fit mathematical model is identified as the following:

i. Initialize population-start the population by random generation.
ii. Evaluation: The fitness function evaluates each chrosome. The lower fitness value indicates good solution, minimize sum square error.
iii. Selection: To form new population individual from previous population selected according to selection criteria. higher fitness level has higher presumption to be selected.
iv. Genetic operator: crossover and mutation are applied to each selected individual to produce new generation.
v. Termination:
The process from Step i to iv are repeated until one of the condition as following are satisfied:

- A pre-determined number of generations or time has elapsed.
- A satisfactory solution has been achieved.
- No improvement in solution quality has taken place for a pre-determined number of generations.

Evaluate correlation between estimated torque and actual torque using coefficient of determination

$$R^2 = \frac{\sum_{i=1}^{n} (\tau_{est(i)} - mean\_\tau_{act})^2}{\sum_{i=1}^{n} (\tau_{act(i)} - \tau_{est(i)})^2 + \sum_{i=1}^{n} (\tau_{est(i)} - mean\_\tau_{act})^2} \quad (7)$$

where,

τ_{act} = actual torque

τ_{est} = estimated torque

$mean\_\tau_{act}$ = mean of actual torque

3 Experimental method

The surface electromyography (s-EMG) signal acquisition was recorded using surface wireless-trigno sensor acquisition system from Delsys Inc. Boston, M.A, USA [23]. Two channel electrodes are placed on biceps brachii muscle with sampling frequency 1 kHz as shown in Fig.1. The experiments were carried on male healthy subjects. The experiment was conducted after obtaining approval from Ethics Committee of University and the subject. The movement task involved was elbow flexion with 90 degree.

Fig. 1: Delsys wireless sensor placed on bicep brachii muscles.

3.1 Estimated Torque s-EMG signal processing method

The EMG to torque conversion involved a few stages as the following:

A. Raw signal Acqusition

Amplitude of s-EMG signal was measured using surface electrode with built in amplifier circuit for acquiring the s-EMG signals.

B. Filtering

Filtering process will remove unwanted signal and leaving the information signal to be measured and recorded. For elimination of noise signal, the band pass filter are used (low pass and high pass) considered as the cut-off frequency of 20Hz-400Hz.

C. Feature extraction:

The s-EMG signals were analysed by root mean square (RMS) based on square root calculation to obtain the s-EMG input data signal of muscle contraction.

D. Muscle activation:

Detect the time duration of active region of muscle. This will produce post-processed signal which is the product of root mean square signal and muscle activation.

3.2 Actual Torque modeling and preprocessing

A. Human tracking system

Modeling the elbow flexion movement of static and dynamic motion was recorded by using camera of Qualisys Tracking Markers System (QTM) [24]. Marker points were placed on the lower arm and hand as shown in Fig 2.

Fig. 2: Markers point for lower arm and hand

B. Modeling the biomechanical data

The static and dynamic motion data is modeling into body segment parameters using 3D-visual software of C-motion Inc. to get the signal of actual torque [25].

C. Processing the actual torque signal

The raw actual torques signal will be filtered to eliminate noise signal and rectified to obtain the actual torques data.

4 Result and Discussion

The results for each mathematical model for estimated torque using genetic algorithm (GA) for subject 1(S1) and subject 2(S2) are shown in Table 1.0.

Table 1.0: Result of GA for elbow flexion.

Mathematical Model	Subjects	SSE	MSE	R^2
$\tau_{est(1)}$	S1	0.002056	3.11595E-05	**0.828343**
	S2	0.008582	0.000130035	0.823165
$\tau_{est(2)}$	S1	0.003208	4.86114E-05	0.818436
	S2	0.002696	4.08529E-05	**0.833655**
$\tau_{est(3)}$	S1	0.001622	2.45867E-05	**0.830217**
	S2	0.005659	8.57461E-05	0.818776
$\tau_{est(4)}$	S1	0.003121	3.85742E-05	**0.841983**
	S2	0.002735	4.14485E-05	0.828200
$\tau_{est(5)}$	S1	0.002909	4.40794E-05	0.862644
	S2	0.001843	2.79371E-05	**0.865148**

It can be seen that the sum square error (SSE) value of the fitness function decreased when the genetic algorithm met the optimum value parameters for each mathematical model. The unknown parameters were adjusted to ensure estimated torque became nearer to actual torque. Correlation between estimated torque and actual torque was found to be good when mean square error (MSE) decreased to small value of error and the coefficient of determination (R^2) increased. From table 1.0, the highest coefficient of determination (R^2) is 0.862644 for S1 and 0.865148 for S2 by mathemathical model $\tau_{est(5)}$.

Fig.3 to Fig.7, show the best correlated graph of the estimated torque that was applied to the mathematical model ($\tau_{est(1)}$ to $\tau_{est(5)}$) with actual torque for S1 and S2 based on table 1.0.

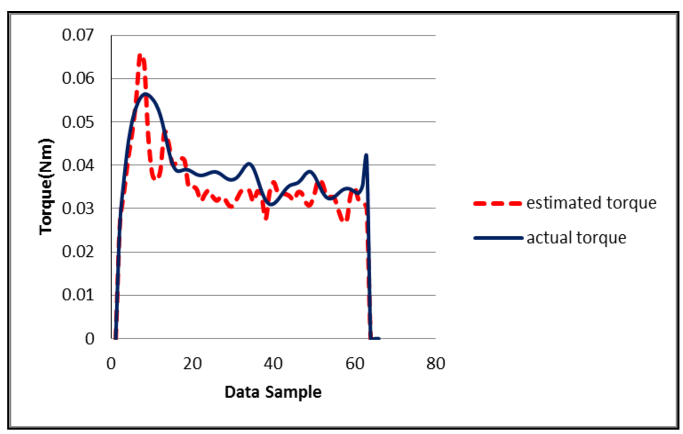

Fig 3: Estimated torque vs actual torque by $\tau_{est(1)}$ for S1

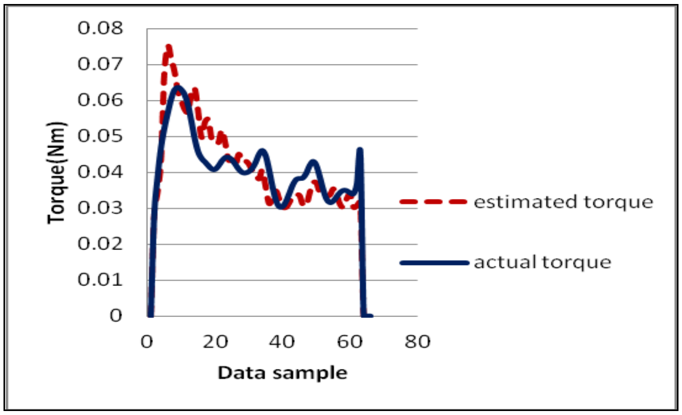

Fig 4: Estimated torque vs actual torque by $\tau_{est(2)}$ for S2

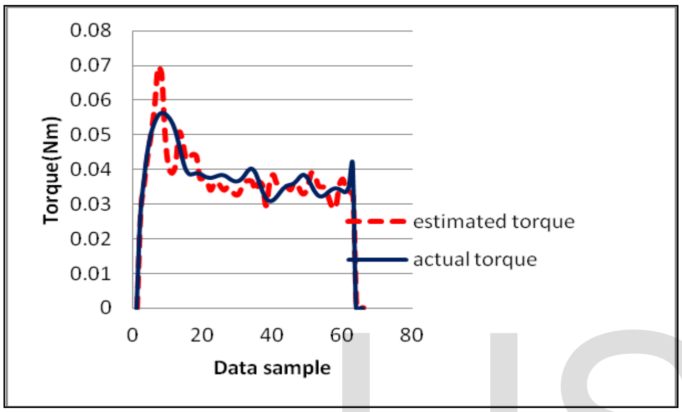

Fig 5: Estimated torque vs actual torque by $\tau_{est(3)}$ for S1

Fig. 3 shows the estimated torque versus actual torque from S1 where the R^2 = 0.828343 is higher than S 2 with R^2= 0.823165 for mathematical model $\tau_{est(1)}$. For mathematical model $\tau_{est(2)}$, S2 obtained R^2=0.833655 as shown Fig.4, estimated torque versus actual torque compared to S1 with R^2 = 0.818436. The coefficient of determination of mathematical model $\tau_{est(3)}$ for S1 are higher than S2, with R^2=0.830217 compared to R^2 = 0.818776 as shown in Fig.5.

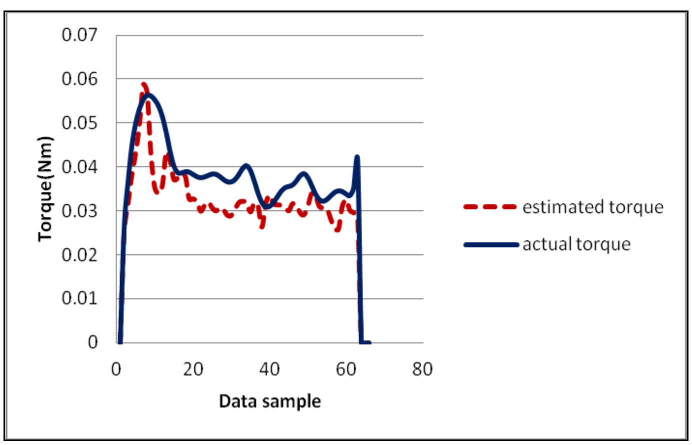

Fig 6: Estimated torque vs actual torque by $\tau_{est(4)}$ for S1

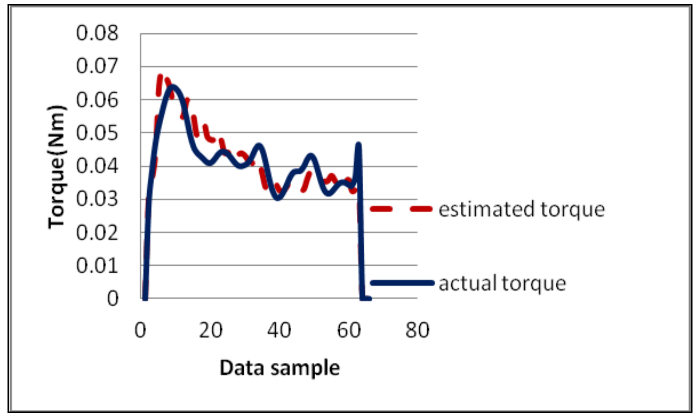

Fig 7: Estimated torque vs actual torque by $\tau_{est(5)}$ for S2

Fig.6 and Fig 7, show the estimated torque versus actual torque for mathematical model $\tau_{est(4)}$ for S1 and mathematical model $\tau_{est(5)}$ for S2. The correlation between estimated torque and actual torque of $\tau_{est(4)}$ indicate that S1 has higher correlation R^2 = 0.841983 than S2 with R^2= 0.828200. Subject 2 has higher correlation R^2= 0.865148 than subject1 R^2= 0.865148 for mathematical model $\tau_{est(5)}$.

Amongst all the mathematical models, mathematical model $\tau_{est(5)}$ is the most suitable model for estimated torque for S1 and S2 which showed higher correlation compared to other models.

5 Conclusions

This paper has discussed the analysis of torque estimation of mathematical model that can be applied to map EMG signal as an input and obtain the output of estimated torque. The actual torque is compared to estimated torque to verify if the estimated values are close to actual torque. It can be deduced that the best mathematical model for estimated torque is the fifth mathematical model ($\tau_{est(5)}$). Estimated torque could be used to control the exoskeleton in various applications such as ergonomics, gait analysis, rehabilitation and also sports exercise.

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[1] *Ku Nurhanim is currently pursuing masters degree program in electrical and electronics , University Technology Petronas, Malaysia, E-mail: hanim.rahim7@gmail.com*

[2] *I.Elamvazuthi,Dept.of Electrical & Electronics,University Tenology Petronas.*

[3] *P.Vasant,Dept. of Fundamental & Applied Science,University Technology Petronas.*

[4] *S.Parasuraman,School of Engineering,University of Monash,Malaysia.*

[2] *Email of Corresponding Author: irraivan_elamvazuthi@petronas.com.my*