International Journal of Enhanced Research in Science Technology & Engineering, ISSN: 2319-7463
Vol. 2 Issue 5, May-2013, pp: (6-11), Available online at: www.erpublications.com

Analysis of Best fit Mathematical Model Using Genetic Algorithm for the Implementation of Electromyography (EMG) in the study of Human Lower extremities

M. K. A. Ahamed khan[1], Tan Chee Wei[2], S. Parasuraman[3], I. Elamvazhuti[4], M. Amudha[5]
[1]Faculty of Engineering, University Selangor, Malaysia
[2, 3]School of Engineering, Monash University Sunway Campus, Bandar Sunway, Malaysia
[4]Electrical and Electronics Engineering, University Teknologi PETRONOS, Malaysia
[5]KLMU Wisma sachdev, Jalan raja laut, Kualalumpur, Malaysia

Abstract. The biomechanical analysis assists to provide evidences in the performance of the system used for stroke rehabilitation of lower and upper limb of human body. This could be done by providing a better understanding of human lower extremities movement through implementation of electromyography (EMG). As human body is a complex biomechanical machine, conducting analysis using only EMG is not sufficient in representing muscle coordination pattern for functional task (i.e. walking). For that, Genetic Algorithm (GA) is implemented in the selection process of best fit mathematical model and its parameters used in conversion of EMG signal into estimated torque. Several experiments are conducted to validate the proposed method. The field of management and rehabilitation of motor disability is identified as one important application area. On the basis of relevant literature, the present paper asserts that scientific analysis of human movement patterns can materially affect patient treatment. It provides evidence that patient management and rehabilitation processes in central neurological disorders can be improved through EMG techniques. The use of electromyography for clinical planning in the treatment process of patients helps providing future directions in research, development and applications of scientific analysis of human movement.

Keywords: Biomechanical analysis, functional task, Electromyography (EMG), Genetic Algorithm (GA), Rehabilitation, Movement analysis.

I. INTRODUCTION

Cerebrovascular accident (CVA) also known as stroke is being the major cause of long term disabilities. The only way to aid stroke patient is restoring loss through rehabilitation training, which can be enhanced using rehabilitation device [5]. As referred in [2, 6], the training can be enhanced using exoskeleton systems by guiding patients in relearning motions on correct trajectories, or by giving them force support to perform certain motions. However, mathematical representation of human lower extremities is required in order to build the device. From the past studies, it is clear that EMG system [3, 4] provide changes of neuromuscular system while the muscles experiencing fatigue. Nevertheless, relationship between EMG signal and human movement in most studies is just approximation, which is not practical for kinematic analysis. Therefore, a more practical method is required to select the best fit mathematical model.

Based on D.G Lloyd’s model [8] the reliability of EMG system in estimating knee joint moments are proved and to be validated by experimental studies. In this study, comparison of moment are made between results obtain from EMG and inverse dynamic model.

On the other hand D. Shin et al [7] proposed a mathematical model, which is used to estimate joint torque of human arm based on EMG system. The authors suggest that alternative methods for estimating joint torque using neural network and GA may further enhance the EMG versus Joint torques relationship. The main objective of this project is to provide a plan in the development of biomechanical approach towards understanding of human lower limb movement patterns.

This can be achieved by measuring and comparing muscle activities using EMG and best fit model identified by GA for torque conversion. In this study, special focus is given to walking motion. Based on various literatures such as [1], the most basic technique to obtain muscle coordination pattern for specific given task is by assuming that muscles are in steady state condition during recording raw EMG signal while the most basic method for signal processing is Smooth Rectified EMG (SRE) processing.

2 METHODOLOGY

The experiment is conducted in two (2) stages, which include actual joint data and EMG signal acquisition. Oqus motion cameras and surface EMG (sEMG) are used in the experimental studies. Various mathematical models are suggested as discussed in [9] and 7 of them are tested in the proposed system for torque estimation.

Qualisys Track Manager (QTM): In this section, Surface marker, which is used to track the human motion are placed on lower limbs of the subjects and captured motion by QTM. Meanwhile, the acquisition of EMG signal from the right muscle group are recorded separately.

Visual 3D (V3D): The coordinates of tracking markers obtained from QTM are processed through V3D to get the actual joint parameters of the subjects such as displacemnet, velocity and acceleration. The anatomical model is built based on data obtained from V3D and this enables for non-expert to visualize musculoskeletal motion of the subjects.

MATLAB: MATLAB is used for processing the EMG data where the signal is rectified and filtered before the conversion process.

2.1 Experimental Setup

Subject Selection: Four (4) healthy male subjects ranges from 21 to 22 years and one female with osteoarthritis (above 60 years) are selected for the experimental studies. The elderly female subject is used as a mean of EMG signal comparison. As shown in TABLE I, the subjects have mean height of 166.4cm and mean weight of 69.2kg.

Table 1: Subject Profile

	Age (years)	Gender	Height (cm)	Weight (kg)	BMI	Status
Subject 1	22	male	175	60	19.6	Normal
Subject 2	21	male	167	80	28.7	Overweight
Subject 3	22	male	167	66	23.7	Normal
Subject 4	21	male	170	76	26.3	Overweight
Subject 5	62	Female	153	64	27.3	Overweight
Mean	29.6	-	166.4	69.2	-	-
Standard Deviation	16.2062	-	7.3103	7.5472	-	-

Data Acquisition: Six (6) motion cameras interfaced to QTM, which enable time-distance parameters (i.e. position, velocity and acceleration) for lower limb of the subjects to be detected and record coordinate data of the markers. Readings are sampled at a frequency of 100 frames/s.

System Calibration: Before the experiment, the system need to be calibrated to ensure correctness of axis, workspace and frame of origin in a global coordinate [10]. During experiment, subjects are asked to remain idle for at least 2s until static data is recorded and later perform walking motion to record dynamic data.

Marker placement: Since the research is focused on lower extremities of human movements, the markers were attached only on lower body of the subjects. Based on V3D guideline, pelvis, thigh, shank and foot segments are included. Placement of the markers is as shown in Fig. 1.

International Journal of Enhanced Research in Science Technology & Engineering, ISSN: 2319-7463
Vol. 2 Issue 5, May-2013, pp: (6-11), Available online at: www.erpublications.com

Sensor Position: EMG sensors are also placed only on major muscles of lower limb, which include Quadriceps, Hamstrings, Tibialis Anterior and Calves. These are the muscles responsible for flexion and extension of knee and ankle, essential motions during walking. According to [11], the sensor should be placed along longitudinal midline centre of muscle between motor point and tendon insertion. Sensor placement on one (1) of the subjects during experiment is shown in Fig. 1(b).

Signal Processing: Under this step, both actual joint torque and EMG are rectified and filtered for simplification. Rectification is done using MATLAB by taking only absolute values of the raw data into consideration while filtration is done by reading only signal at cut off frequency defined.

In the proposed system GA is employed to find a mathematical model that best map EMG signal into joint torque. GA will find the best mathematical model that translates the recorded EMG into the related joint torque. Processed EMG signal were then converted into estimated torque using mathematical models (1) to (7).

$$\tau_{est} = x_1 E_i + x_2 E_i^{1/2} \quad (1)$$

$$\tau_{est} = x_1 + x_2 E_i^{\,2} + x_3 e^{E_i} \quad (2)$$

$$\tau_{est} = x_1 + x_2 \cos E_i + x_3 \sin E_i \quad (3)$$

$$\tau_{est} = x_1 E_i^{\,x_2} \quad (4)$$

$$\tau_{est} = x_1 + x_2 e^{E_i} + x_3 e^{-E_i} \quad (5)$$

$$\tau_{est} = x_1 E_i^{\,x_2} + x_3 E_i^{\,x_4} \quad (6)$$

$$\tau_{est} = x_1 E_i^{\,4} + x_2 E_i^{\,3} + x_3 E_i^{\,2} + x_4 E_i^{\,1} + x_5 E_i^{\,0} \quad (7)$$

where x_i is the model parameter and E_i is the EMG signal voltage.

Fig.1: (a) Sensor (EMG) placement on lower limb of subject (b) Surface marker placement on lower body

GA codes represented in flowchart shown in Figure 2 are to randomly generate the model parameters (x_1 to x_5) to compute estimated torque along with EMG voltage value at each period. Roulette Wheel Selection will then randomly select pairs of best-fit chromosomes for crossover and mutation process.

$$FS = \Sigma_{k=1}^{N} (\tau_{actual} - MM_i (E_i x_i))^2 \quad (8)$$

Where MM_i is estimated torque from chosen model

During each iteration, fitness function (FS) based on above equation will be calculated, where smaller FS is preferable in order to reduce difference between both actual and estimated torque. Figure 2 and Figure 3 show step by step transformation of EMG on knee and ankle from raw into processed data.

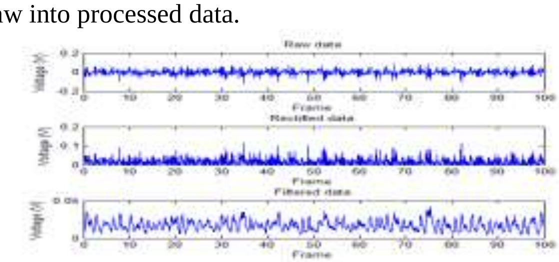

Fig. 2: Raw and processed (rectified and filtered) data on knee of subject 3 (young male, BMI: normal)

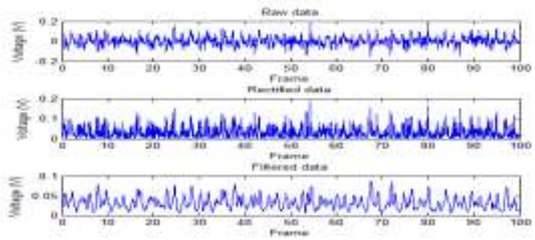

Fig.3: Raw and processed (rectified and filtered) data on ankle of subject 3 (young male, BMI: normal)

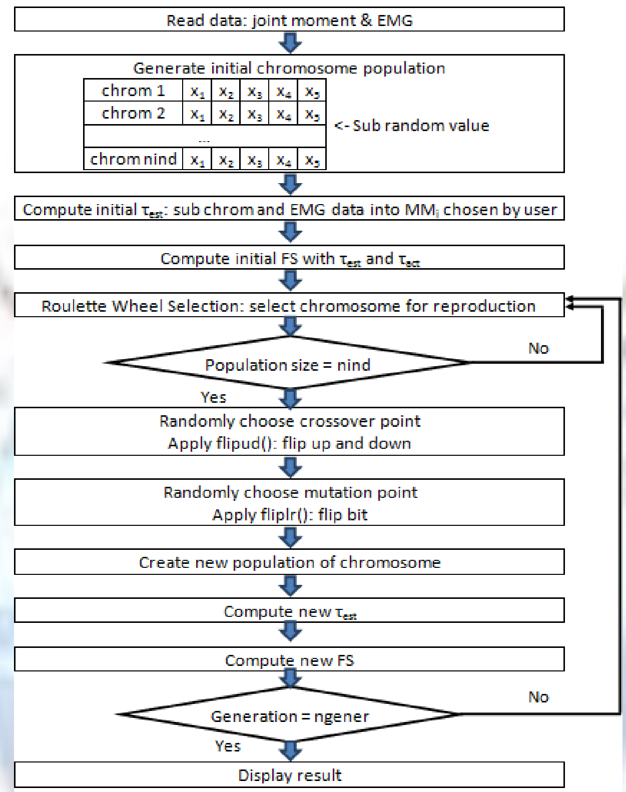

Fig.4: Flow chart showing GA for EMG to torque conversion.

3 Results and Discussions

When comparing both actual estimated torque of knee, slight offset and phase shift could be observed. This might be caused by experiment conducted in different stages instead of both (i.e. actual joint data and EMG signal) at the same instance. On the other hand, unstable fluctuations in addition to slight offset were also can be observed on estimated torque of ankle although both actual and estimated torque still have similar pattern. This might be due to complexity on ankle (3DOF) and knee (1DOF) opposition, since more muscles are involved in its movement.

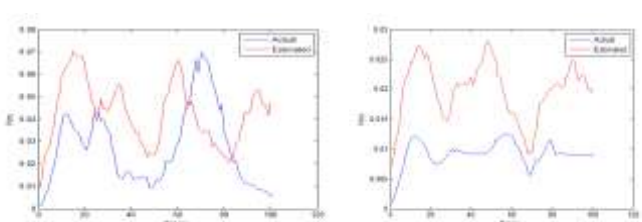

Fig.5: (a) Actual vs. estimated torque on knee of subject 3 (young male, BMI: normal) based on best fit model for knee (7)
(b) Actual vs. estimated torque on ankle of subject 3 (young male, BMI: normal) based on best fit model for ankle (6).

International Journal of Enhanced Research in Science Technology & Engineering, ISSN: 2319-7463
Vol. 2 Issue 5, May-2013, pp: (6-11), Available online at: www.erpublications.com

At the same time, comparison of the results between the subjects in 1 to 5 shows that best fit model selection process is affected by factors such as BMI and health condition of each subject. As observed, subject 3 (young male, BMI: normal,) has most fit result as compared with subject 5 (elderly female, BMI: overweight, osteoarthritis) where estimated torque for both knee and ankle have larger offset and phase shift.

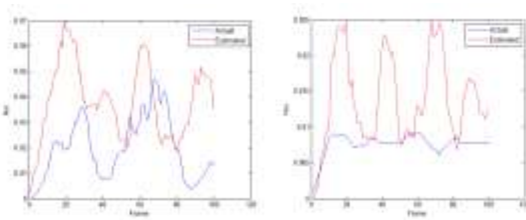

Fig.6: (a) Actual vs. estimated torque on knee of subject 2 (young male, BMI: overweight) based on best fit model for knee (7)
(b) Actual vs. estimated torque on ankle of subject 2 (young male, BMI: overweight) based on best fit model for ankle (6)

4 Clinical Application

The best fit model obtained by the combination of EMG and GA related to human lower limp is sufficient enough to provide a better technique for clinical movement analysis in the management of motor disorders and clinical decision making process [15]. From these contributions, a novel approach for a viable role of movement analysis in clinical routine is obtained [12, 13]. Fig. 7 depicts a simple model of the clinical treatment process which will be used to derive features of movement analysis for routine clinical use. The technological development outlined in the foregoing has created scientific tools for the quantitative description of human movement which can be made in to commercial products today.

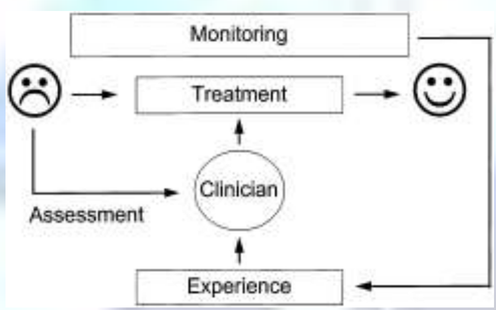

Fig. 7: Simple model to describe the role of movement analysis in the clinical process

Movement analysis tools can provide valuable information in patient assessment and treatment monitoring processes. A patient with a health problem comes to the clinical institute for treatment. Sometime later, when the treatment is completed and the health problem is alleviated, the patient leaves the institute. It is the task of the clinician to select the most suitable treatment for the patient with his individual pattern of pathology. To do so, he needs a reliable patient assessment. This assessment generally comprises an anamnesis, a clinical investigation and if desired, additional special investigations, e.g. an X-ray investigation.

The information collected in this assessment is interpreted on the basis of the clinician's knowledge and experience and this guides him in the choice of the treatment. Conceptually, movement analysis techniques are potentially useful in such a special investigation. During the treatment, the clinician monitors the patient. He continuously checks if the treatment does what it is expected to do. He observes and records the response of the patient to the chosen treatment, watches for unwanted side effects, which should be minimal and keeps track of progress in the treatment process. This scrutiny of the patient during treatment enables him to learn from each individual case. Each patient case provides an update on his clinical experience [15] and in this way contributes to enhancement of the clinician's experience and skills. This monitoring process [16] can be conducted in a rigorous manner as clinical research or it can take place more casually in the form of clinical follow-up. In principle, movement analysis [14] can provide objective and quantitative data which are essential in this monitoring process. The clinician recognizes that technical tools can assist him in this empirical cycle and provide added-value in the collection and management of the information generated in this empirical cycle.

CONCLUSION

From a number of literature review and research papers, it was understood that EMG can be used to detect muscle fatigue and in treatment of motor disorder problem. Nonetheless, due to insufficient mathematical model that can fit for general case, more research need to be done for improvement on available model. From the results, it was found that combination of EMG and GA is sufficient for determining best fit model for human lower limb although improvement is still required. The project has provided an enhanced understanding of human movement in walking motion, which is essential for building a stroke rehabilitation device. Clinical use of EMG techniques has primarily focused on interventions at the lower extremities. However, there is a potential application for the upper extremities as well, for instance in the surgical correction of hand dysfunction . The evidence in this research suggests that movement analysis techniques can improve patient treatment. Though an improvement in cost-effectiveness resulting from the use of movement analysis techniques has never been shown until now, this research builds a bridge between the outcome of the treatment decided by the gait laboratory compared to the outcome decided by the clinician without a movement analysis laboratory . There are important challenges ahead. If movement analysis is to become an established element in clinical practice, development of a great body of clinical experience is essential. Without close multidisciplinary cooperation of clinicians, scientists and engineers—even from different institutes—in a clinical environment, it is not possible to develop relevant clinical applications of movement analysis.

REFERENCES

[1]. R.F.M. Kleissen et al. “Electromyography in the Biomechanical Analysis of Human Movement and Its Clinical Application”, Gait and Posture 8, pp.143-158, Jun. 1998.

[2]. Dr. G. Farr, “Electrical Studies / Surface Electromyography.” Internet: http://www.becomehealthynow.com/article/diagelectrical/625/, Apr. 22, 2002 [Oct. 5, 2011].

[3]. Electromyogram (EMG) and Nerve Conduction Studies.” Internet: http://www.webmd.com/brain/electromyogram-emg-and-nerve-conduction-studies, Mar. 01, 2011 [Oct. 5, 2011

[4]. Dr. S. Day, “Important Factors in Surface EMG Measurement”, Bortec Biomedical Ltd.

[5]. Dr. S. Parasuraman, C.Y. Kee. “Bio-Mechanical Analysis of Human Hand” presented at the International Conference on Computer and Automation Engineering, pp. 93-97, 2009.

[6]. I C. Fleischer, G. Hommel. “Torque Control of an Exoskeletal Knee with EMG Signals”.

[7]. D. Shin et al. “A Myokinetic Arm Model for Estimating Joint Torque and Stiffness From EMG Signals During Maintained Posture”, J Neurophysiol, Nov. 2008.

[8]. D.G. Lloyd, T.F. Besier. “An EMG-driven Musculoskeletal Model to Estimate Muscle Forces and Knee Joint Moments in Vivo”, Journal of Biomechanics 36, pp.765-776, Dec. 2002.

[9]. Y Dr. S. Parasuraman et al. “Robot Assisted Upper Arm Rehabilitation: Estimation of Muscle Force/ Joint Moments from EMG using AI Techniques”, M.Eng. thesis, Monash University, Malaysia M. Young, The Technical Writer’s Handbook. Mill Valley, CA: University Science, 1989.

[10]. “Accessories: Qualisys Motion Capture Accessories”, Qualisys AB, ver. 2008-09.

[11]. CJ.D. Luca, “Surface Electromyography: Detection and Recording”, DelSys Incorporated, 2002.:

[12]. Blanc Y. A survey of applications for movement analysis in therapeutic decision making. Invited lecture. Fourth Annual Conference of the European Society for Movement Analysis in Children (ESMAC). The Netherlands: Enschede, October 27–28, 1995.

[13]. Watts HG. Gait laboratory analysis for preoperative decision makingin cerebral palsy: Is it all it’s cracked up to be? J Pediatr Orthop 1994;14:703–4.

[14]. Gage JR. Gait analysis for decision-making in cerebral palsy. BulHosp Jt Dis Orthop Inst 1983;63:147–63.

[15]. Delp SL, Loan P, Hoy MG, Zajac FE, Topp EL, Rosen JM. Ainteractive graphics-based model of the lower extremity to study orthopaedic surgical procedures. IEEE Trans Biomed Eng 1990;37:757–67.