Modelling of Neuromuscular Interactions with Electromyographic Biofeedback

[1*]Ching-Hua Ting and [2]Szu-Hua Yang

Abstract

The surface electromyography (sEMG) is a useful biofeedback signal for exploring neuromuscular interactions which are important in rehabilitation applications. Thus, a neuromuscular model that correlates muscular force generation and sEMG is developed in this paper. The model was developed based on muscular forces and corresponding sEMG responses measured on 10 volunteers. Linear correlation exists between the two biosignals and generated muscular forces can therefore be easily converted from sEMG measurements with a constant factor. Surface EMG signals were furthered to fit a Hill-type neuromuscular model. The model was validated with the acquired biosignals from 5 volunteers. The prediction error is less than 20%.

Keywords: surface electromyography (sEMG); skeletomuscular system; modelling; Hill model.

1. Introduction

1.1 Background

Body movements are manipulated by the skeletomuscular system which may be dysfunctional because of diseases or hurts [2, 14]. The dysfunction could be recovered through physical rehabilitation practices [1, 4, 10] or partially improved through adequate assistive facilities [3, 9, 11]. However, it may take ages before answering the question whether a therapy is really beneficial to the patients or not [4]. This wastes medical resources, is ineffective in disease remedy, and hence provokes the demand of an integrated rehabilitation system. An integrated rehabilitation system can show the process of rehabilitation and modulate process parameters in a real time fashion through monitoring adequate physiological signals [21, 23, 26].

Figure 1 describes the framework of a conceptual integrated rehabilitation system. The system regulates therapeutic facilities, such as neuromuscular electrical stimulation (NMES) or continuous passive motion machine (CPM), in accordance with feedback signals, normally electromyography (EMG) [12, 15, 23, 27]. The physician knowledgebase and the physiological database are considered in undergoing treatments. To facilitate the design of this rehabilitation system, a neuromuscular model of human body that characterizes the relationship between biofeedback signals and output forces shall be established [5, 24, 28]. A neuromuscular model may consist of a nerve model and a muscle model [2, 6, 7]. The model can predict muscular force generation, based on EMG measurement, for closed-loop skeletomuscular control in rehabilitation [5, 8, 9].

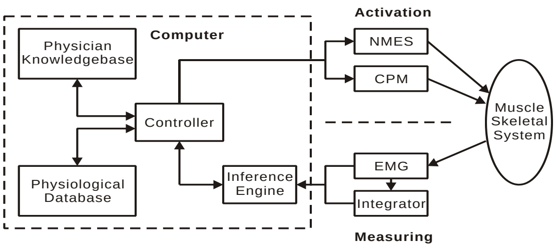


Figure 1: Conceptual integrated rehabilitation system

*Corresponding Author: Chingh- Hua Ting (E-mail:cting@mail.ncyu.edu.tw).
[1]Department of Mechanical and Energy Engineering, National Chiayi University, 300 University Road, Chiayi 60004, Taiwan.
[2]Department of Biomechatronic Engineering, National Chiayi University, 300 University Road, Chiayi 60004, Taiwan.

Figure 2 shows the structure of a closed-loop skeletomuscular control. In systems engineering, a motor (efferent) neuron performs the role of actuator element while a sensory (afferent) neuron as a sensor for system output. Contraction commands from the brain are transmitted in the form of action potentials to skeletal muscles through efferent neurons. At the same time, feedback signals that represent muscular reactions are acquired by afferent neurons and are transmitted back to the brain [14].

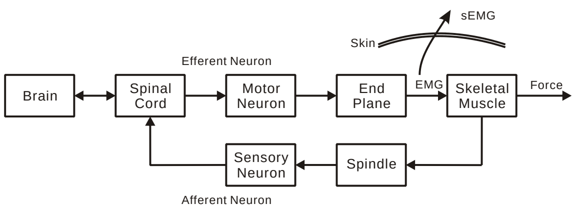


Figure 2: Closed-loop skeletomuscular control

The use of EMG in examining the states of the neuromuscular system has been a long history [20]. There are two kinds of electrodes used to pick EMG signals: surface electrodes (non-invasive) and needle electrodes (invasive) [15, 17]. A needle electrode has a better recording quality. However, a needle intrudes into the target tissue and may cause infection or damage the surrounding tissues [22]. A surface electrode has the advantages of being clean and easy to use, and is widely accepted in clinic applications. EMG signals acquired from the surface of skin using a surface electrode are called surface electromyography (sEMG) [20]. Signal processing must be employed to amplify, isolate, and denoise weak and contaminated sEMG to obtain a useful version [30].

An sEMG, originates from EMG that makes muscle contracting under the skin surface, indicates the resistance properties of the skin. There exists a direct link between EMG and sEMG. Thus, it is possible to predict the force generated by the skeletomuscular system using sEMG. In this study, an experimental scenario was developed to verify a proposed muscle model. Experiments were conducted on 10 male volunteers. Physiological responses correlating with muscle contraction were measured. The acquired data were used to validate the proposed muscle model and to optimize the model for different individualities.

1.2 Objectives

A physiological muscle model with EMG is the essential work in constructing an integrated rehabilitation system. There are two main kinds of modelling techniques, Hill-type model and Huxley-type model [16, 19]. Many derivative models with other biophysical properties involved can be found in the literature [6, 28], but sEMG signals are not considered in existing models. Thus, this study focuses on augmenting the basic skeletal muscle model using sEMG.

The force-velocity relation of muscle contraction is included in the Hill-type model, which becomes the base for many derivative muscle models [6, 24]. The Hill-type model is used as a reference in our modelling. This new muscle model needs several biological parameters and sEMG signals as inputs. The output is predicted force generated in skeletal muscle contraction. Through the assistance of this model, we can investigate how muscular strength is generated with EMGs as biofeedback signal. This allows us to develop a non-invasive diagnosis system for rehabilitation. This model can also be used in other medical or engineering applications to reduce the time in building useful models, to decrease the amount of animal experiments, and hence to reduce the cost.

2. Muscle Physiology

2.1 Physiology for Modelling

The neuromuscular system consists of nervous and muscular systems. In control engineering, the nervous system can be treated as a controller that controls all body organs, and the muscular system can be seen as a combination of many actuators which drives peripheral organs. Skeletal muscles receive action commands from motor nerves. The interactions between muscles and nerves comprise afferent and efferent nerves, as shown in Figure 3(A). The axons of afferent nerves deliver information to the central nervous system. The axons of efferent nerves deliver signals for contraction from the central nervous system to the muscle. A closed-loop control system is constructed by the afferent and efferent nerves. Figure 3(B) illustrates the muscle spindle and its corresponding nerve endings [7]. Figure 3(C) shows a neuromuscular junction which innervates into the muscle fibre but lies entirely outside the muscle fibre plasma membrane. Figure 3(D) sketches a single-branch axon terminal and the muscle fibre membrane

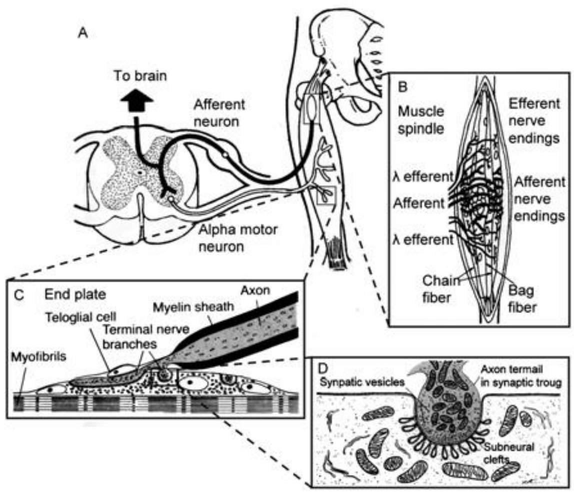


Figure 3: The muscle spindle and the end plate of the neuromuscular system [14]

2.2 Physiology of Electromyography

A motor neuron innervates a number of muscle fibres. This functional unit is called "motor unit", as illustrated in Figure 4. A motor unit is the smallest control unit of a muscle since all fibres belonging to the same motor neuron always contract and relax synchronously.

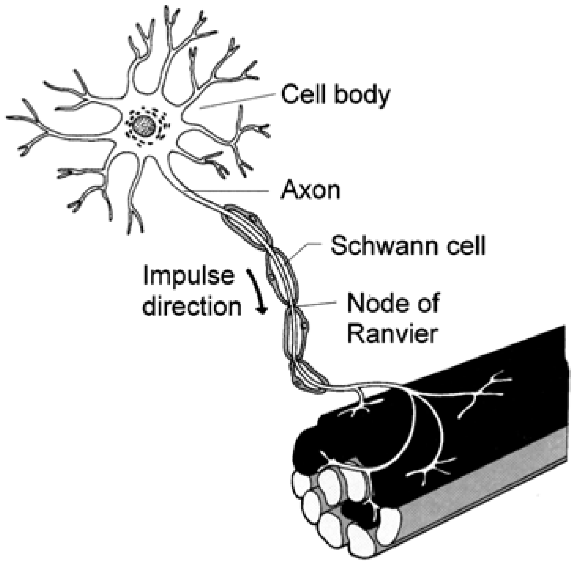


Figure 4: The motor nerve and muscle fibre components of the motor unit [14]

When a nerve impulse reaches the neuromuscular junction, acetylcholine delivered across the junction. Action potentials quickly spread into the muscle fibre to excite myofibrils and hence to produce muscle contraction. For a motor neuron, the acquired signal is the sum of action potentials and is called motor neuron action potential (MUAP). For the sum of action potentials generated from different motor neuron, the acquired signal is called EMG. An EMG signal picked on the skin surface using appropriate instruments is named surface EMG (sEMG) [20]. Because of a highly linear correlation between integrated sEMG (iEMG) and force, integrated sEMG can be used to predict force output [25].

2.3 Properties of Skeletal Muscle

By analysing the above physiological facts, the behaviour of the muscle could be predicted and the mathematical model would be established.

2.3.1 Twitch and summation properties

When a motor unit receives a single action potential pulse from its motor neuron, the corresponding force response is a single twitch. The average period of twitch is approximately 200 ms (5 Hz) in purely slow muscle fibres [14]. When action potentials behave beyond this frequency, the summation property is presented.

2.3.2 Tetanus

When the action potential pulse frequency is much higher than the presented summation property, continuous contractions fuse together and are indistinguishable. This state is named tetanus, and the lowest frequency of tetanus is called critical frequency.

2.3.3 Force-length property

The force-length property of a skeletal muscle is defined by the maximal concentric contraction force and the length of the muscle. The maximal isometric force is usually calculated with the physiological cross-sectional area and a factor *k*. Equation (1) shows the relation between the force (F_0) and the fibre length:

$$F_0 = k \times \frac{Muscle\ Volume}{Fiber\ Length} \qquad (1)$$

with atypical coefficient k= 20 - 40 N · cm^{-2} .

2.3.4 Force-velocity property.

The force-velocity relation proposed by Hill in 1938 describes the maximal, steady-state force of a skeletal muscle with its contraction velocity [16]. The proposed formula of this property is shown in Equation (2) where F is the steady-state force for shortening muscle length at the velocity v. F_0 is the maximal, isometric force at an optimal sarcomere length, and the constant parameter is symbolized by a and b.

$$(F+a)(v+b)=(F_0+a)=const. \qquad (2)$$

3. Modelling the Skeletal Muscle

3.1 Hill-type Model

The Hill-type model composes three simple mechanical elements that are easy to analyse with fundamental mechanical theories. Figure 5 shows a free body diagram of the Hill-type model. The displacements of the contractile element (E_C) and of the parallel element (E_P) are represented by symbols w and u, respectively. The coefficients of elasticity of the contractile element (E_C), serial element (E_S), and the parallel element (E_P) are indicated by K_P, K_S, and K_P, respectively. In the same way, the lengths and the applied forces of each element are represented by L_C, L_S, L_P and f_C, f_S, f_P, respectively. The overall force output of the model is represented by f.

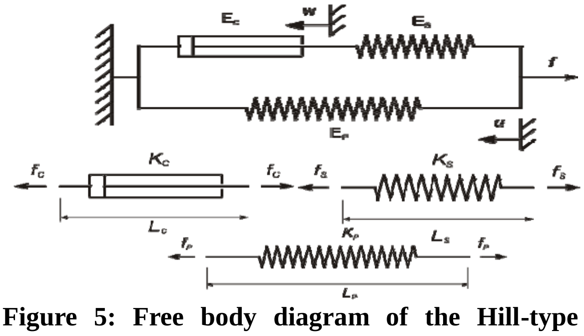
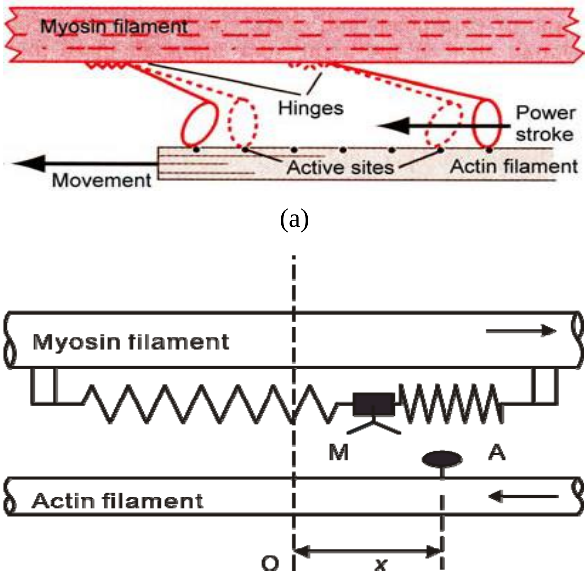


Figure 5: Free body diagram of the Hill-type model win three individual elements [7]

3.2 Huxley-Type Model

The Huxley-type model focusing on the contractile element in the Hill-type model is another famous mathematical muscle model [19]. The Huxley-type model, as shown in Figure 6, simulates the cross-bridge behaviour of the myosin filament.



(a)

(b)

Figure 6. (a) Cross-bridge muscular behaviour and (b) the Huxley-type model [7]

The Huxley-type model behaves mainly dominated by the probability of attachment between receiving site M and attaching site A. An unattached sliding element M may oscillates and hence the probability of attachment per unit time is only related to the distance x between the attaching site A and the equilibrium point O. The relationship between the probability of attachment and un-attachment is formulated as Equation (3), the so-called Huxley's equation [7]:

$$\frac{dn}{dt} = (1-n)f(x) - ng(x) \tag{3}$$

Where x is the displacement between O and A in the Huxley model, n is the proportion of attached pairs which relates only with time alone, $f(x)$ is the probability of attachment, and $g(x)$ is the probability of which the attached connection broken.

3.3 Surface EMG for Modelling

In this paper, a Hill-based neuromuscular model is developed using sEMG for physiological indication. The inclusion of sEMG in modelling is the major difference of this study to existing models. The advantages of using sEMG as input signals are non-invasive and easy-to-use. A block diagram of the modified neuromuscular model containing sEMG module is illustrated in Figure 7. The human body is simulated using a modified neuromuscular model with input to the neuromuscular system replaced with sEMG. Since the Huxley-type neuromuscular model is a derivative of the Hill-type model, the force-length relation is considered in the model and the force-velocity relation is already involved in the Hill-type model. Finally, the predicted force is converted by a simulated skeletal system with the parameters measured on volunteer's arms. Model parameters are hence identified experimentally.

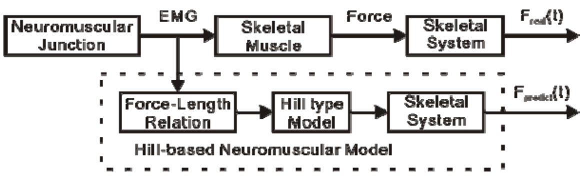
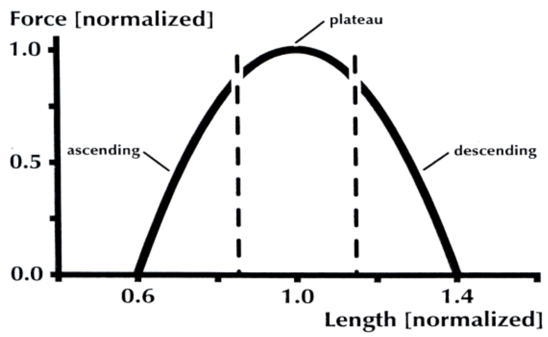


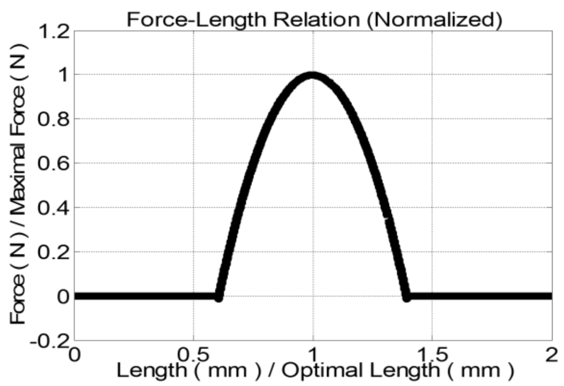
Figure 7: The Hill-based neuromuscular model

3.4 Tentative Model Validation

The force-length and force-velocity relation are applied to validate the modified neuromuscular model [7]. The relative curve between the force output and the fibre length is sketched in Figure 8. Another property is the force-velocity relation that contained in the Hill-type model. The validation is presented by the relative curves between force and contractive velocity that are shown in Figure 9.

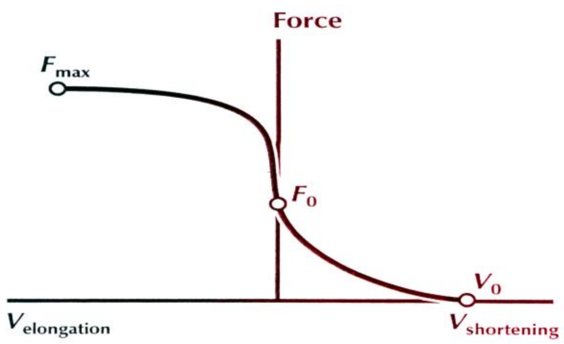


(a)

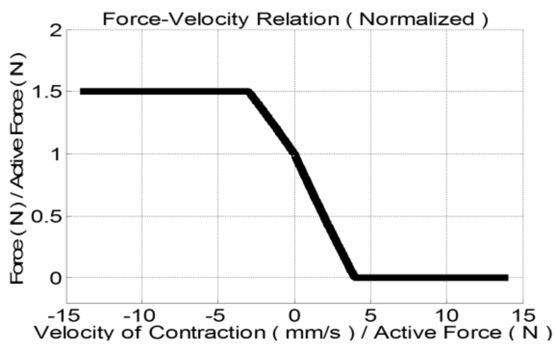


(b)

Figure 8: Force-length relation: (a) experimental data [7] and (b) model prediction



(a)



(b)

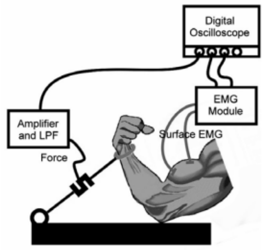
Figure 9: Force-velocity relation: (a) experimental data [7] and (b) model prediction

4. Model Validation

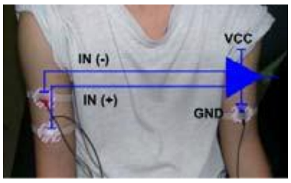
4.1 Experimental Setup

Signals from 10 male volunteers were measured at the same condition and the same method using the experimental rig developed in house, as shown in Figure 10. The biceps of the fore arm is selected as the target skeletal muscle for recording because of less environmental noise contamination. The bicep has uniform skeletal muscle. Hence, it has a better quality of EMG recording than other sites.

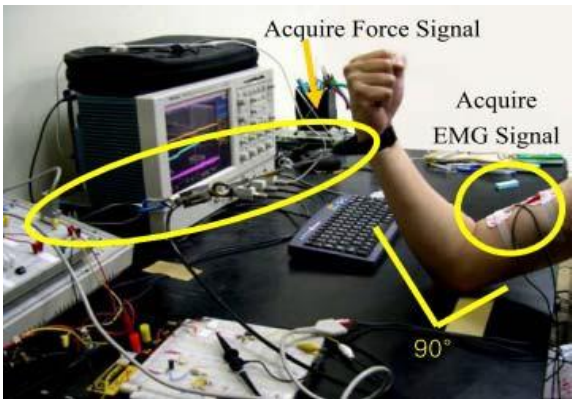
A participant rested for five minute before experimentation, to reduce biased initialization. The target skin surface was cleaned with alcohol solution for better electric conduction. All participants had their right hands as habitual usage hands. As shown in Figure 10(b), two signal electrodes are placed on the right hand and the ground electrode was placed on the left hand [20]. A load cell (5 kg, 3mV/V, Benediction, Taiwan) is used to record force responses from the target skeletomuscular system. Processed sEMG signal and force responses were collected using a digital oscilloscope (TDS5034B, Tektronix, USA) and then saved for subsequently off-line analysis.



(a)



(b)



(c)

Figure 10: The experimental rig: (a) scheme, (b) measuring sites, and (c) setup

Figure 11 shows the structure of the analogue signal processing system developed in house. Implementation of the sEMG signal module is detailed in Figure 12. sEMG signals from the two electrodes are pre-amplified by an instrument amplifier with a gain of 10. Ambient noises are to be effectively removed. The isolator electrically isolates the participant to avoid possible electrical shock. High frequency noises embedded in sEMGs which have frequency components below 350 Hz [18, 29] are rejected using a low-pass filter with a cutoff frequency of 1000Hz. The high-pass filter with a cutoff frequency of 100 Hz removes the 60 Hz power interference. The overall amplification gain is 1000. Peak integrated sEMG represents a high portion of skeletomuscular muscles excited [29], which indicates the rate of the force generated by the contractile elements of the skeletal muscles.

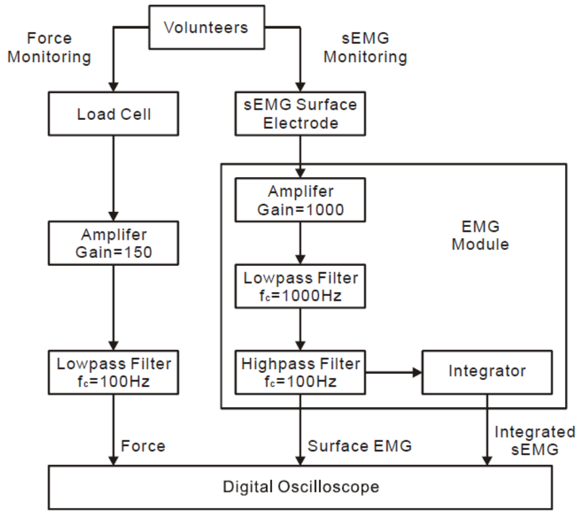


Figure 11: Block diagram of the analogue signal processing system

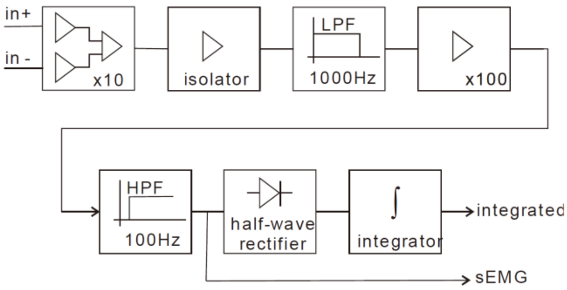


Figure 12: sEMG signal conditioner

4.2 Post Signal Processing

Acquired sEMG signals may be of low signal-to-noise ratio (SNR) because of noise contamination [18] although the analogue signal processor has tried to remove the noises. Hence raw signals were digitally processed for a better quality for analysis and subsequent modelling. The MATLAB DSP toolbox was used for post signal processing. Figure 13 shows the flowchart of the digital signal processing module.

As shown in Figure 14(a), the processed analogue version still has a component at the frequency 60 Hz. This component is further filtered using a third-order digital Butterworth bandstop filter with resultant shown in Figure 14(b). A 120 Hz component was observed in force signals from load cell. It was eliminated using a lowpass Butterworth filter with a cutoff frequency of 120Hz. For the integrated sEMG signals, the mean value filter reduces the influence of the low frequency components in integrated sEMGs. Signals are re-scaled to their original scales for visualisation.

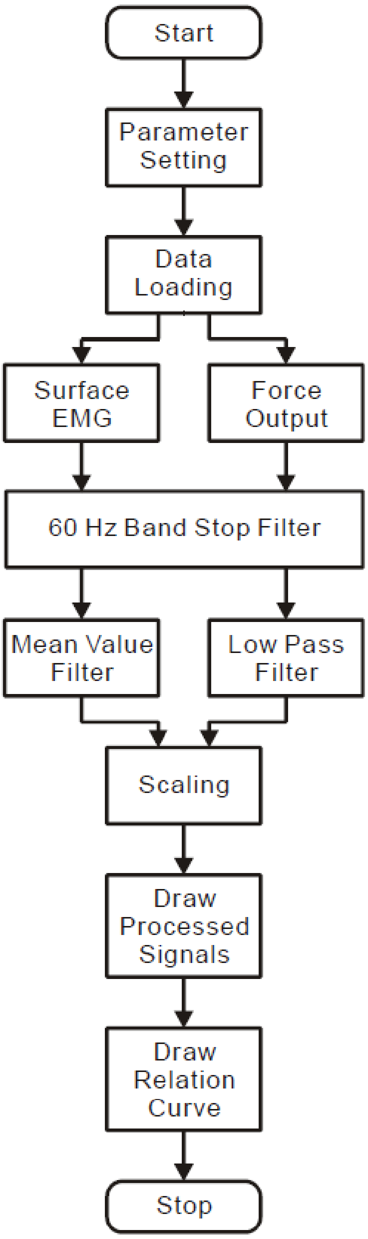


Figure 13: Flowchart of post signal processing

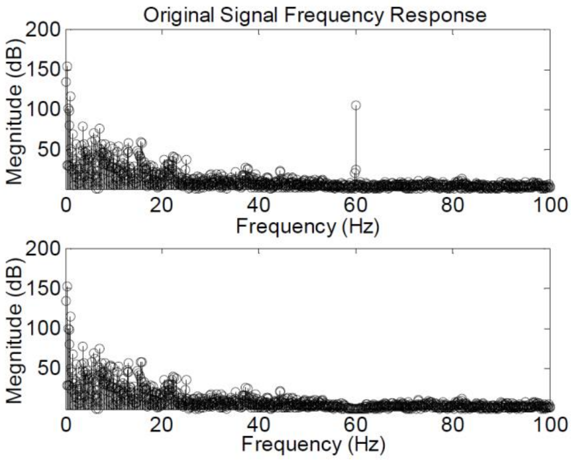


Figure 14: sEMG signals before (top) and after (bottom) processing by a 60 Hz notch filter

Figure 15 shows a sample acquisition. A contraction occurs at time stamp 5 s. Clearly, force responses can be effectively indicated by integrated sEMGs. Hence sEMGs is used in prediction of force generation.

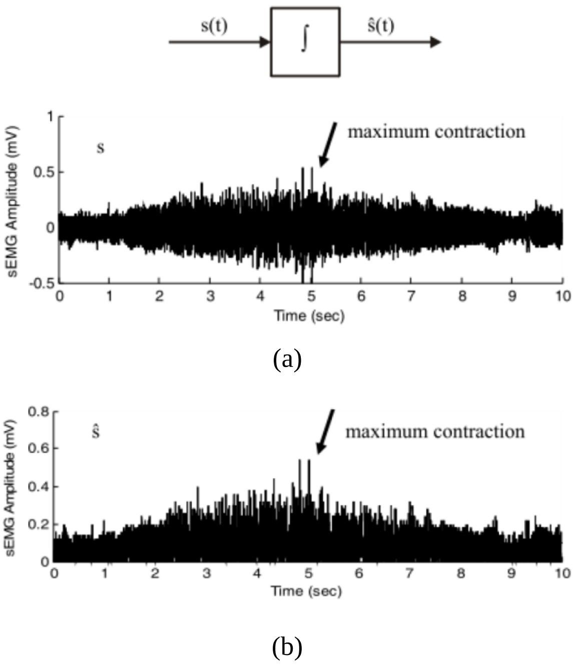


Figure 15: Time responses of a sample sEMG acquisition

4.3 Sample Single Trial

A sample recording from a volunteer is shown in Figure 16. The figure shows sEMG and force responses, before and after signal processing. Correlation between force and sEMG measurements is shown in panel (b). The participant was instructed to gradually increase force application to the maxium and then to release the foce gradually.

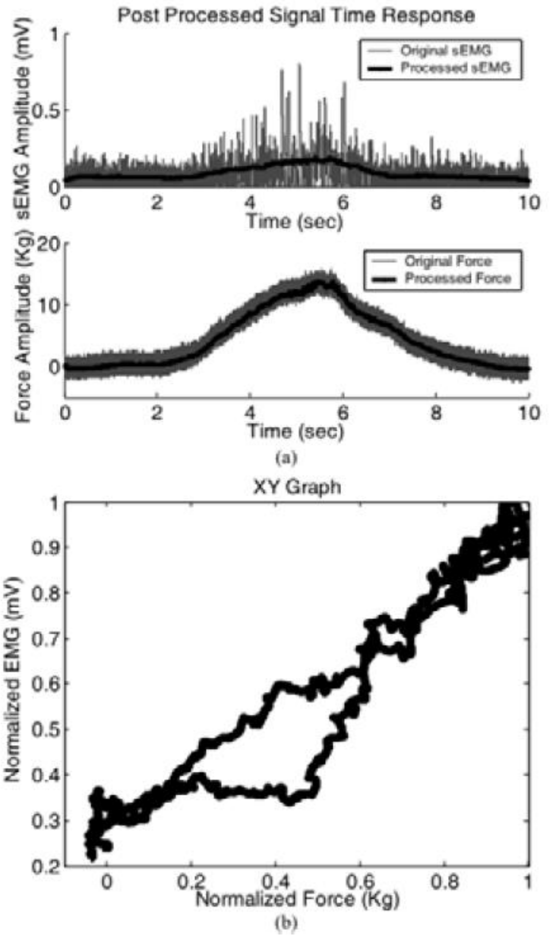


Figure 16: Force and sEMG measurements of a volunteer

Figure 17 shows the mean force-sEMG correlation of recordings from the 10 volunteer. It shows a high linear correlation between integrated sEMG and force response. Accordingly, force generation can be predicted from sEMG measurement by a constant factor, as an alternative to EMG measurement.

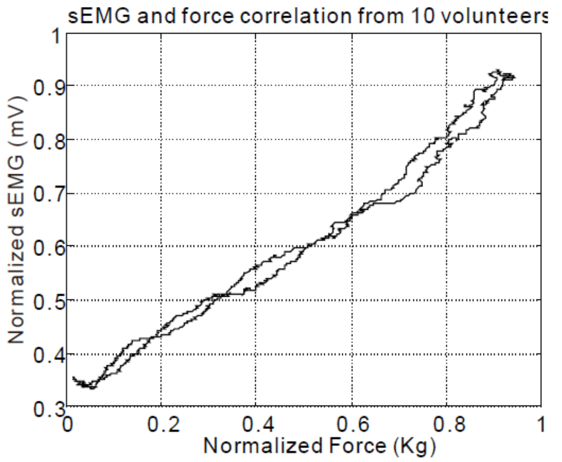


Figure 17: Correlation between sEMG and force measurements

4.4 Force Predictor

A force predictor is realized by applying sEMG to the Hill-type skeletomuscular model. Figure 18 shows the structure of the proposed Hill-type model. The model is validated using the sEMG responses acquired from 5 volunteers. Figure 19 shows the mean value of prediction based on the 5 measurements. The prediction error is within ±20%, quite a promising performance.

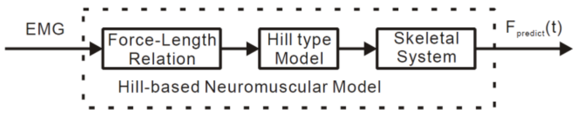


Figure 18: Block diagram of the force predictor

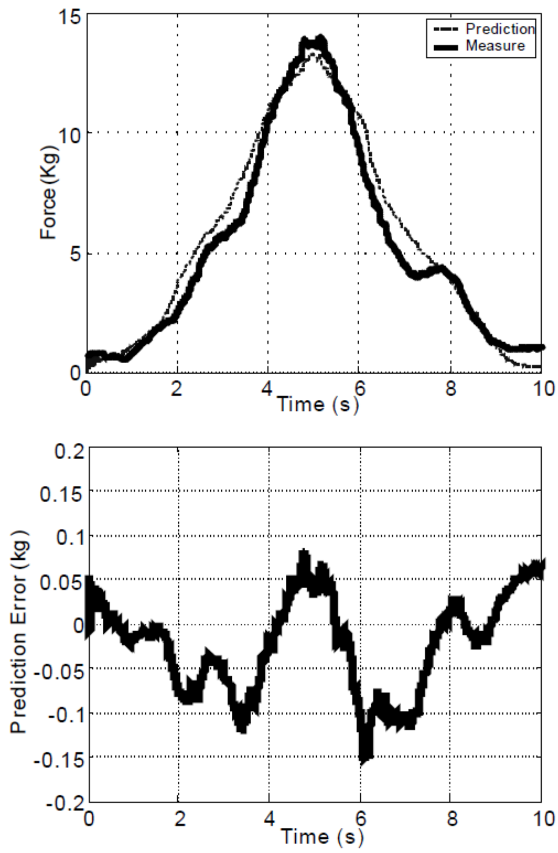


Figure 19: Performance of the force predictor based on responses from 5 volunteers

5. Conclusions

Force generated by the skeletal muscle (biceps) is predicted using a Hill-based neuromuscular model with sEMG as biofeedback. This neuromuscular model is realized by converting theoretical formulas to programs for real-time prediction. A force prediction is built based on sEMGs recorded on 10 volunteers. Validation on recordings from 5 volunteers shows that the model can arrive at a prediction error less than 20%. The prediction is accurate enough in constructing a closed-loop control system for rehabilitation.

Acknowledgments

This study is financially supported by the National Science Council of the Republic of China under a contract number NSC 93-2213-E-415-001.

References

[1] Alon, G., Levitt, A.F., McCarthy P.A., 2007, "Functional Electrical Stimulation Enhancement of Upper Extremity Functional Recovery During Stroke Rehabilitation: A Pilot Study", Neurorehabilitation and Neural Repair, V21, 207.

[2] Beme, R. M., and M. N. Levy, 1998, "Physiology", 4th ed., New York: Oxford University Press.

[3] Braz, G.P., Russold, M. & Davis G.M., 2009, "Functional Electrical Stimulation Control of Standing and Stepping After Spinal Cord Injury: A Review of Technical Characteristics", Neuromodulation, V12, pp.180-190.

[4] Brunnstrom, S., 1970, "Movement therapy in hemiplegia." , New York: Harper & Row.

[5] Dorgan, S. J. and M. J. O'Malley, 1997, "A Nonlinear Mathematical Model of Electrically Stimulated Skeletal Muscle", IEEE Transactions on Rehabilitation Engineering, V5, pp.179-194.

[6] Dorgan, S. J. and M. J. O'Malley, 1998, "A Mathematical Model for Skeletal Muscle Activated by N-Let Pulse Trains", IEEE Transactions on Rehabilitation Engineering, V6, pp.286-299.

[7] Epstein, M. and W. Herzog, 1998, "Theoretical Models of Skeletal Muscle", 1st ed., New York: John Wiley & Sons.

[8] Farina, D., A. Crosetti, and R. Merletti., 2001, "A Model for the Generation of Synthetic Intramuscular EMG Signals to Test Decomposition Algorithms", IEEE Transactions on Biomedical Engineering, V48, pp.66-77.

[9] Ferrarin, M., Palazzo, F. & Riener R., 2001, "Model-Based Control of FES-Induced Single Joint Movements", IEEE Transactions on Neural Systemsand Rehabilitation Engineering, V9, pp.245-257.

[10] Freeman, C., Hughes, A.M., Burridge, J., Chappell, P., Lewin, P. & Rogers, E., 2009, "Iterative learning control of FES applied to the upper extremity for rehabilitation", Control Engineering Practice, V17, pp.368-381.

[11] Gföhler, M., and Lugner, P., 2000, "Cycling by Means of Functional Electrical Stimulation", IEEE Transaction on Rehabilitation Engineering, V.8, pp.233-243.

[12] Giuffrida, J. P., and Crago, P. E., 2003, "Synergistic EMG Control of FES Elbow Extension after Spinal Cord Injury", 2003 Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, V.2, pp.1515-1518.

[13] Guiraud, D., Stieglitz, T., Koch, K.P., Divoux, J.L. & Rabischong P., 2006, "An implantable neuroprosthesis for standing and walking in paraplegia: 5-year patient follow-up", Journal of Neural Engineering, V3, 268-275.

[14] Guyton, C., and J. E. Hall, 2000, "Textbook of Medical Physiology", 10th ed., Philadelphia: W.B. Saunders.

[15] Hermens, H. J., K. L. Boon, and G. Zilvold, 1984, "The Clinical Use of Surface EMG", Electromyography and Clinical Neurophysiology, V24, pp.243-265.

[16] Hill, A. V., 1938, "The Heat of Shortening and the Dynamic Constants in Muscle", Proceedings of the Royal Society of London. Series B. Biological Sciences, V126, pp. 136-195.

[17] Hogrel, J. Y., 2005, "Clinical Applications of Surface Electromyography in Neuromuscular Disorders.", Clinical Neurophysiology, V24, pp.243-265.

[18] Hu, X., Z. Z. Wang, and X. M. Ren, 2005, "Classification of Surface EMG Signal with Fractal Dimension", Journal of Zhejiang University Science, V6B, pp.844-848.

[19] Huxley, A. F., 1957, "Muscle Structure and Theories of Contraction", Progress in Biophysics and Biophysical Chemistry, V7, pp.255-318.

[20] Jeffery, R. C., S. K. Glenn, and H. Jonathan, 1998, "Introduction to Surface Electromyography", Maryland: Aspen Inc.

[21] Jezernik, S., Wassink, R. G. V., and Keller, T., 2004, "Sliding Mode Closed-Loop Control of FES： controlling the shank movement", IEEE Transaction on Biomedical Engineering, V.51, pp.263-272.

[22] Kimura, J., 2001, "Electrodiagnosis in Diseases of Nerve and Muscle: Principles and Practice", 3rd ed., Philadelphia: Davis.

[23] Kobravi, H.R. & Erfanian, A., 2009, "Decentralized adaptive robust control based on sliding mode and nonlinear compensator for the control of ankle movement using functional electrical stimulation of agonist antagonist muscles", Journal of Neural Engineering, V6, 046007.

[24] Makssoud, H. E., D. Guiraud, and P. Poignet, 2004, "Mathematical Muscle Model for Functional Electrical Stimulation Control Strategies", 2004 IEEE International Conference on Robotics and Automation, V2, pp.1282-1287.

[25] Moritani, T., H. A. DeVries, 1978, "Re-examination of The Relationship Between The Surface Integrated Electromyogram (IEMG) and Force of Isometric Contraction", American Journal of Physical Medicine, V57, pp.263-277.

[26] Mulder, T., Hulstijn, W., and van der Meer, J., 1986, "EMG Feedback and the Restoration of Motor Control: a Controlled Group Study of 12 Hemiparetic Patients", American Journal of Physical Medicine, V.65, pp. 173-188.

[27] Shen, X., 2009, "Nonlinear model-based control of pneumatic artificial muscle servo systems", Control Engineering Practice, V18, pp.311-317.

[28] Wexler, A. S., J. Ding, and S. A. Binder-Macleod, 1997, "A Mathematical Model that Predicts Skeletal Muscle Force", IEEE Transactions on Biomedical Engineering, V44, pp. 337-348.

[29] Xu, Z., and S. Xiao, 2000, "Digital Filter Design for Peak Detection of Surface EMG", Journal of Electromyography and Kinesiology, V10, pp. 275-281.