35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Muscle Force Estimation with Surface EMG during Dynamic Muscle Contractions: A Wavelet and ANN based Approach

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Abstract— **Human muscle force estimation is important in biomechanics studies, sports and assistive devices fields. Therefore, it is essential to develop an efficient algorithm to estimate force exerted by muscles. The purpose of this study is to predict force/torque exerted by muscles under dynamic muscle contractions based on continuous wavelet transform (CWT) and artificial neural networks (ANN) approaches. Mean frequency (MF) of the surface electromyography (EMG) signals power spectrum was calculated from CWT. ANN models were trained to derive the MF-force relationships from the subset of EMG signals and the measured forces. Then we use the networks to predict the individual muscle forces for different muscle groups. Fourteen healthy subjects (10 males and 4 females) were voluntarily recruited in this study. EMG signals were collected from the biceps brachii, triceps, hamstring and quadriceps femoris muscles to evaluate the proposed method. Root mean square errors (RMSE) and correlation coefficients between the predicted forces and measured actual forces were calculated.**

I. Introduction

Walking, squatting and lifting heavy load are accomplished by contracting skeletal muscles. It is important and a great interest to find approaches to determine the forces produced by muscles under dynamic muscle contractions in biomechanical research. Especially, in the application fields such as rehabilitation, human-machine interface or sports, it is essential to estimate the muscle forces performed on the human movement control system. For assistive devices, estimated forces are commonly used to trigger the movement and drive the motor to assist the users intuitively. However, to record forces produced by muscles during various activities directly is currently infeasible. Some current methods for the measurement of individual forces exerted by muscles require special force sensors. In addition, most of the commercial force or torque sensors are bulky, expensive, inconvenient and not user friendly.

Typically, current approaches for predicting human limb movement and the amount of force required to accomplish a task have been studied using surface Electromyography (EMG) signals. An EMG signal is the direct reflection of muscle activities. It is the action potential generated in a muscle as the command signal from motion control system of human [1]. Therefore, before muscles contract, the EMG signals will be generated to command the action. Hence, EMG signals can be used as a predictor of force exerted by muscles. Extracting EMG signals features to predict muscle forces was studied by some research studies. These features such as mean absolute value (MAV), averaged rectified value (ARV), integrated EMG (iEMG), smoothed value or low-pass filters and root mean square (RMS) of EMG signals are commonly used to estimate force/torque. Several studies attempted to find the optimal low-pass filter of the rectified EMG signal for muscle force prediction [2-4].

Linear or non-linear relationships have been found between EMG signal characteristics and muscle forces under isometric muscle contractions by recent studies, which is one of the essential steps of muscle force estimation [2, 3, 5, 6]. However, for muscles under dynamic contractions, the relationship between EMG and muscle force is much more complicated due to the muscular properties, such as the varying muscle lengths, muscle contraction velocity, electrodes locations [7]. Some studies have been made to investigate the EMG-force relationship and estimate muscle forces by using a musculoskeletal models [8]. The results showed that muscle models were a good way to estimate muscle forces during movement tasks. However, developing muscle models requires some external kinematic or dynamic data measured by dynamometers or other sensors. Additionally, these models may induce problems by making assumptions about some unknown nonlinear parameters which cannot be measured experimentally [9].

Artificial neural networks (ANN) has been used to approach complicated relationships successfully in biomechanics research [10-12]. As ANN is able to extract features from complicated signals and acts as a black box model to approximate complex nonlinear mappings directly from the input signals, it is commonly used for muscle force estimation. In addition, no detailed information such as the mathematical expression that relates the EMG signals to the muscle force is involved when using ANN.

When muscles contract under a varying force, the EMG signals cannot be assumed to be stationary, which implies the traditional signal processing approaches may not be suitable. Under such circumstances, time-frequency analysis is more appropriate as it would provide direct information about the frequency components occurring at any given time. In order to estimate muscle force with time-frequency analysis, continuous wavelet transform (CWT) theory [13] was applied to EMG signals recorded during dynamic muscle contractions. This transform was derived as an extension of the short time Fourier transforms, which is used in signal processing with time-frequency analysis.

The purpose of this study was to predict force/torque exerted by muscles under dynamic muscle contractions based on CWT and ANN approach. Mean frequency (MF) of EMG signal power spectrum was calculated from CWT to extract time-frequency features. An ANN was implemented to derive the MF-force relationships from a subset of EMG signals and

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measured forces. Then we use the relationships to predict the individual muscle forces for different muscle groups. Experiments were conducted to collect EMG signals from biceps brachii, triceps, hamstring and quadriceps femoris muscles to validate the proposed methods.

II. Methods

A. Surface EMG and Force Measurement

Fourteen healthy subjects (10 males and 4 females) were voluntarily participated in this study. The subjects' mean ± standard deviation age, weight and height were 26.3±2.9 years, 65.6±12.3 kg and 170.3±7.0 cm respectively. Each subject agreed and signed the written informed consent documents before participating in the experiments. All the subjects were healthy and none of them reported any neurological disorders or musculoskeletal problems. The experiments were approved by the local institutional review board.

Surface EMG signals were collected from biceps brachii, triceps, hamstring and quadriceps femoris muscles. The signals were recorded using self-adhesive Ag/AgCl surface electrodes (Noraxon USA, Inc.). All electrodes pairs were placed parallel to the general direction of muscle fibers on the selected muscle groups. To reduce the electrical impedance between the targeted skin and the electrodes, skin preparation (removal of excess hair and cleaning the skin with alcohol) was undertaken before electrodes were attached to the skin. Contraction tests were carried out to make sure there was good contact between electrodes and skin. EMG signals were pre-amplified at the electrode site and the common mode rejection ratio of the pre-amplifier was 95 dB. The signal was recorded with a 12 bit analog to digital convertor at a sampling rate of 10K Hz. The recorded signal was subsequently stored in a computer for off-line analysis.

A force-measuring strain gauge setup with handles was used to measure the force exerted by muscles. Force signal from the strain gauge was amplified with a strain gauge amplifier (RS Components Ltd). The force and voltage relationship of the force measurement setup was calibrated using a digital force gauge (IMADA, DS2-50N) before the experiments were conducted. The measured force was used in the ANN training and it is a reference to validate the feasibility of the proposed method. Graphs depicting the target force, actual applied force and EMG signals were displayed real-time on a computer screen facing the subjects to provide a visual biofeedback while they performed their muscle contractions.

B. Experimental Protocol

Subjects sat comfortably in front of the force measurement setup. To help the subjects familiarize with the setup and the experimental tasks, warm-up exercises were performed by slowly doing elbow and knee flexion/extension. A target trajectory of force amplitude in the shape of a dynamic half-sinusoidal was displayed on computer. The subjects exerted muscle contraction forces in accordance to the trajectory by performing their dominant elbow and knee flexion or extension. Each subject performed four trials with the different muscles. Fig.1 shows the experimental setup used in this study. The collected signals were used for off-line analysis by down sampling to 5000 Hz in MATLAB for further signal processing. A sample of the raw EMG signal from one trial is shown in Fig. 2.

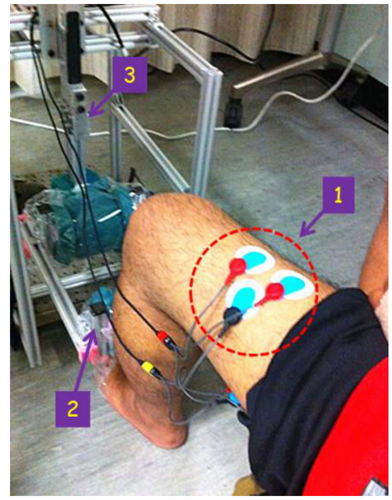

Fig.1. Experiment setup. 1: surface EMG electrodes; 2: handle for legs experiments; 3:force sensor.

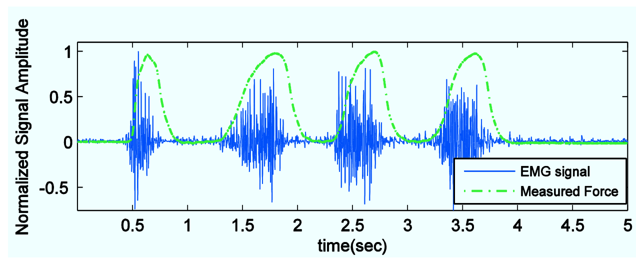

Fig. 2. Sample of raw EMG signal recorded for one trial: Biceps Brachii elbow flexion (EMG signal amplitude and force amplitudes were normalized to be 1).

C. Force Estimation

ANN is a mathematical model inspired by biological neural networks. It consists of interconnection of multiple layers of artificial neurons. The processing units are called "neurons" which are interconnected and distributed in layer. Fig.3 depicts the architectural graph of a multilayer network used in this study. In this figure, the blue circles are the neurons, and every neuron unit receives input from some other units or from an external source. The output of the neurons in each layers are interconnected to the other layer neuron inputs.

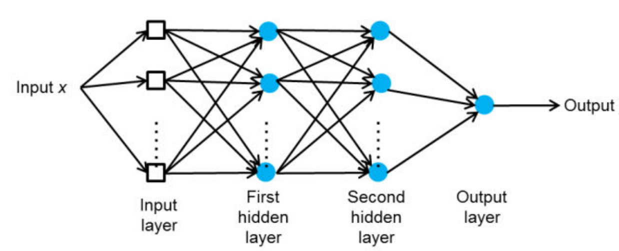

Fig.3. Architectural graph of a multilayer network used in this study.

Since the time-frequency analysis provides direct information about the frequency components occurring at any given time, it is much more appropriate for analyzing time-varying EMG signals recorded under dynamic muscle contractions. In time-frequency analysis methods, mean frequency (MF) of the power spectral density is one of the most commonly used characteristics of EMG signals [1, 14]. In this study, CWT was applied to obtain the MF of the EMG signals. CWT is a time-scale representation that is suitable for analyzing non-stationary and time-varying signals. It is an alternative method from short time Fourier transform by replacing the frequency shifting operation with a time scaling operation. CWT has a good frequency resolution for a low-frequency signal and a good time resolution for a high-frequency signal simultaneously. Given the input signal $s(t)$, CWT of the signal $s(t)$ is defined as

$$W_s(a,\tau) = \int_{-\infty}^{\infty} s(t)\,\varphi_{a,\tau}^{*}(t)dt \quad (1)$$

where a>0 represents the scale parameter, τ represents the translation parameter (time shifting), $\varphi_{a,\tau}^{*}(t)$ could be calculated by scaling the mother wavelet $\varphi(t)$ at time τ and scale a,

$$\varphi_{a,\tau}(t) = \frac{1}{\sqrt{a}}\varphi\left(\frac{t-\tau}{a}\right) \quad (2)$$

When scale a becomes large, the basis function $\varphi_{a,\tau}(t)$ will be in a stretched version, which is important to analyze the low-frequency components of the signal. Conversely, when the scale parameter is small, the basis function will be compressed, which is corresponding to the high-frequency of the signal.

The square of the absolute value of the CWT value $E(\omega) = |W_s(a,\tau)|^2$ is called scalogram, which is similar to the spectrogram in Fourier transform. It represents the energy distribution of the EMG signal over the entire time-scale plane. In MATLAB implementation, "Morlet" mother wavelet with a wavelet scale length of 196 was selected to calculate the scalogram. By using the scalogram, the MF represents the EMG signal frequency characteristics, which can be defined as the average frequency of the signal power spectrum,

$$MF = \frac{\int_0^{\infty}\omega E(\omega)d\omega}{\int_0^{\infty}E(\omega)d\omega} \quad (3)$$

where ω is the frequency variable and E(ω) is the power spectrum density (PSD) of the EMG signal. A 4th order low-pass Bessel filter with 5 Hz cut-off frequency was applied to smoothen the MF signal. Afterwards, the filtered MF signal was normalized to the maximum mean frequency of the contraction trial. This normalization procedure could reduce the variability in EMG mean frequency amplitude between subjects, due to differences such as muscle length and fiber conduction velocity.

Fig.4 illustrates the signal flow diagram for the proposed CWT-ANN based approach. The neural networks models were trained using the network input data and the measured force. The input data to the ANN models for training were the normalized MF from each subset. The first one or two contractions of the EMG signals from each trial of each subject were selected as the subset to calculate the MF of signal power spectral. The training target was the normalized measured force correspondingly. For different subjects, the skin impedance at the electrode locations is different. In addition, the muscle lengths during dynamic contractions vary from subject to subject. To avoid the influences from these variable factors as much, the neural works training of each muscle group was carried out for every subject individually. As mentioned in the previous section, four trials were performed by each subject. For each subject, four ANN models were created using four datasets.

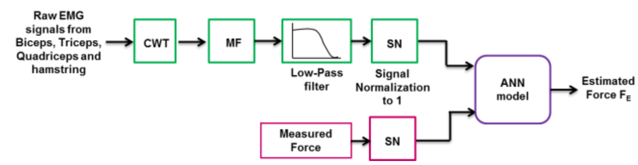

Fig. 4. Signal Flow Diagram for Muscle Force Estimation.

III. Results

A. Network Parameter Settings

In MATLAB implementation, a common method of training ANN models, conjugate gradient back propagation (BP) algorithm, was used to adjust the weights in the ANN models. BP has two steps, a feed-forward stage and a learning stage. The two steps are repeated until the difference between the network predicted output signal and the target signal is below a specified value.

Parameters selection of the ANN model is important for the performance of propose method. Before training the network, the input and the target data in each training set were normalized to [minimum, maximum], which was corresponding to -1 to 1. The networks were trained for 2000 epochs with a very small training performance goal 10^{-15}. In this study, a feed-forward network was created with a hidden layer of 6 neurons.

B. Force Estimation Results

The trained neural networks were implemented into the respective subject's normalized MF signals. Fig. 5 to Fig.8 show the muscle force estimation results for subject 12, 4, 8 and 14 with the four different measured muscle groups, respectively. The green solid line indicates the measured force, and the blue dash-dot line shows the predicted force by the CWT-ANN based method. The muscle force estimation results were quantitatively evaluated against the measured force using the root mean square error (RMSE) and correlation coefficients parameters for every single contraction of each subject. Table 1 tabulates the averaged RMSE and correlation coefficients of the 14 subjects. Evidently, for all the subjects, the average RMSEs are low with 0.1701±0.047. High correlation coefficients were obtained with 0.9398±0.0230 in average.

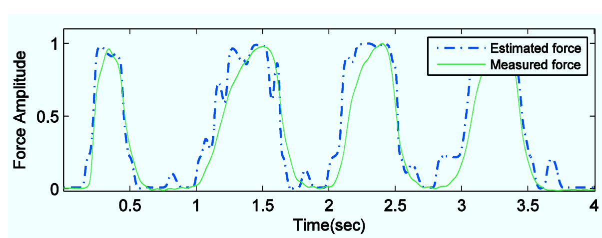

Fig.5. Force estimation results using the proposed CWT-ANN based method (Subject 12, biceps brachii, elbow flexion)

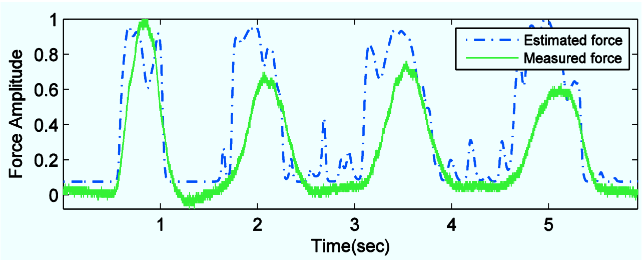

Fig.6. Force estimation results using the proposed CWT-ANN based method (Subject 4, triceps brachii, elbow extention)

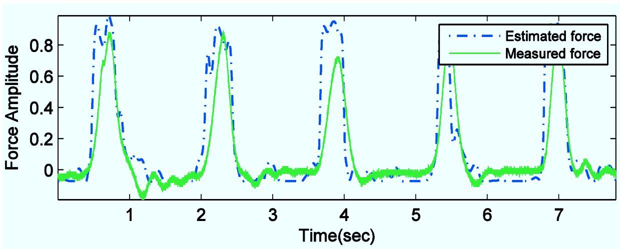

Fig.7. Force estimation results using the proposed CWT-ANN based method (Subject 8, hamstring, knee flexion)

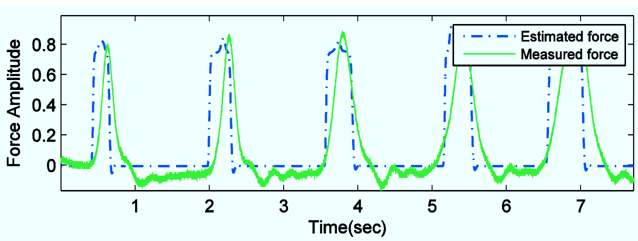

Fig.8. Force estimation results using the proposed CWT-ANN based method (Subject 14, quadriceps femoris, knee extention)

TABLE I. CWT-ANN BASED FORCE ESTIMATION RESULTS (AVERAGE RMS ERROR AND CORRELATION COEFFICIENTS OF EACH SUBJECT)

Subjects	*RMS error*	*Correlation Coefficient*
S1	0.1457	0.9656
S2	0.1727	0.9523
S3	0.1041	0.9627
S4	0.0751	0.9873
S5	0.1532	0.9379
S6	0.1823	0.9417
S7	0.2015	0.9210
S8	0.2447	0.9510
S9	0.1114	0.9410
S10	0.1950	0.9389
S11	0.1907	0.9202
S12	0.1818	0.9066
S13	0.2091	0.9077
S14	0.2121	0.9229
Average±svd	0.1701±0.047	0.9398±0.0230

IV. CONCLUSION

This paper studied the use of CWT and ANN for muscle force/torque estimation during dynamic muscle contractions for predicting human's intention and monitoring their muscle performance. MF of EMG signals in time-frequency analysis was calculated from CWT to extract time-frequency features. ANN models were implemented to derive the MF-force relationships from the subsets of EMG signals and measured forces. Estimated forces were obtained using the trained networks from every subject individually. The RMSE and correlation coefficients between the predicted forces and measured actual forces were also calculated to evaluate the results quantitatively. The results show that the muscle forces were accurately estimated from the EMG signals. Future works should compare this method with a linear regression model. This proposed method will be implemented in real-time on the assistive device [2].

ACKNOWLEDGMENT

This work is under the project of novel rehabilitation device for lower extremities. We acknowledge the financial support from the Singapore Ministry of Education (MOE) Academic Research Fund (AcRF) (Grant No.: R-265-000-419-112). The authors would like to thank the NUS control and mechatronics lab and all the participants in the experiments conducted.

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