INVESTIGATION OF THE RELATIONSHIP BETWEEN EMG SIGNALS AND THE FORCES APPLIED TO HUMAN ARMS

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ABSTRACT

In this paper, a signal processing method is proposed to establish the EMG signal—force relationship. Higher order frequency moments calculated from the power spectra of short-time signals are used as the characterizing features. An artificial neural network is trained for the estimation of the forces as a function of time. Validation results of the predicted muscle forces compared to the actual forces presented very encouraging performance.

I. INTRODUCTION

In this study a new signal processing technique is developed for establishing the EMG signal—force relationship. Because of the technical, anatomical and physiological factors that effect the electromyoraphy (EMG) signals, it is a challenging study to derive a relationship between EMG signals and force [1].

There have been many researches on biomechanical and neuro-physiological properties of muscle systems, in order to define the relationship between the electromyography (EMG) signals, generated during muscular contraction, and variable dynamic movements [1,2,3,4]. However the relationship between the EMG signals and muscle contraction forces have not yet been fully described. Liu *et al* [1] were able to determine the muscle forces recorded from the cat soleus for a variety of locomotor conditions with an error rate of < 15 %, by using EMG signals. Kent *et al.* [2], investigated the relation between EMG signal and foot wrist joint moment of a subject lying down by using artificial neural networks. Luh *et al* [3] achieved to estimate the joint moments, generated at elbows on isokinetic state. Wang and Buchanan [4] studied the estimation of joint moments from EMG signals using artificial neural network model.

The need for the determination of a distinct relationship between EMG signals and force arises from the desire for improving the life conditions of patients who need artificial hand, arm, etc. Today, widely used hand prosthesis display some restrictions on open/grasp movement properties. Besides, many studies on designing artificial hands that are more flexible, and functional are still under investigation [5,6,7]. There are two main problems to be solved for construction of highly advanced hand prosthesis. First one is the mechanical design that will allow sufficient freedom of movement. The second one is the robust electronics that can handle a more complicated mechanical design. It is almost impossible to discuss a “dexterous prosthesis” without the solution of the above second problem.

In our work, the signal–force relation is investigated by analyzing the EMG signals measured from the pectorialis major muscle under the effect of forces acquired from three subjects. To acquire data from both right and left arms simultaneously, a bi-manual manipulation of an object is considered. Surface EMG signals are recorded during anisometric and quasi-isotonic (slowly force-varying) contractions of muscle. EMG signals are analyzed in a short-time manner to reveal their time-varying characteristics. Higher order frequency moments calculated from the power spectra of short-time EMG segments are used as the characterizing features. The back-propagation, feed-forward artificial neural network is trained for the estimation of the force acting on human arm tip. Validation results of the predicted muscle forces compared to the actual forces presented very encouraging performance with an average of root mean square difference (RMSD) error of < 15 %.

II. MATERIAL AND METHOD

The set-up used for carrying out the experiments during bi-manual manipulation of an object is shown in Fig. 1. The experimental set-up consists of a direct drive SCARA type robot manipulator and a handle-bar (Fig. 1). The robot manipulator consists of three links, all connected by rotational joints, is located on the table aligned with the subject. The distance between the robot base and the subject is set to 0.75 m, a distance enough for a comfortable workspace both for the subject and the robot manipulator. The robot arm tip is connected to a 40 cm handlebar at its center by a revolute joint. In this way the handlebar is coupled to the robot arm and becomes its actively controlled third link.

Experiments were carried out by two right-handed healthy male subjects in age 25 and 35. The subjects were given sufficient information about the experiment and their consent were taken.

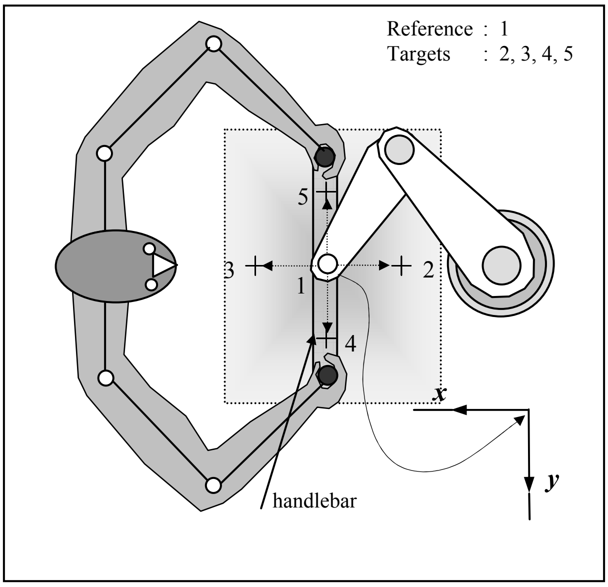

Figure1. Experimental set-up for EMG signals measurements [12]

During the experiment the subject was seated in front of a horizontal table and firmly grasps two handles on the handlebar. Shoulder movement of the subject was restrained, and the wrists were immobilized so that each arm can be treated as a two link manipulator consists of shoulder and elbow. The handlebar has three degrees of motion freedom (two translations and a rotation) and can have a floating motion in the horizontal plane formed by the subject's arms. Four different target sets, and a reference position are specified on the table (Fig. 1). Two of the target sets were used for the motion in sagittal plane and the other two were used for the motion parallel to the frontal plane. These motions are named as;

1→2 : forward, 1→3 : backward,
1→4 : rightward and 1→5 : leftward.

Subject is required to move the handlebar from the reference to the specified target. Each motion from the reference point to the specied target is divided into three phases as shown in Fig. 2; *proceed* phase, *maintain* phase and *retreat* phase. Using a metronome, the subject is instructed by a tone signal (a beep) to make an advancing motion of δ= *50 mm* towards the visually guided desired target, and *maintain* the object there for 4 seconds until the next tone, and then make the retreating motion back to the reference position. In addition to the *maintain* phase, data is also collected for 2 seconds before the *proceed* and after the *retreat* phases during which the subject relaxes. *Proceed* and *retreat* phases of the motion are instantaneous and the time elapsed during these phases is in general very short. These motions are repeated 10 times for each subject.

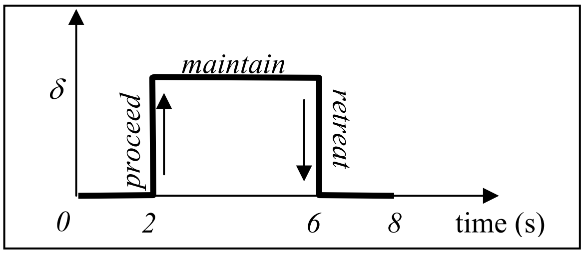

Figure2. Displacement – Time profile [12]

Interaction forces between the human arms and the handlebar and between the manipulator and the handlebar were measured by two six-axis force/torque sensors located on the handlebar. The two EMG amplifiers, used in experiments, has four channels each as input, which enables the record of EMG signals from four seperate muscles. In experiments, EMG signals used for measurement are recorded from biceps, triceps, pectorialis and trapezius muscles which are most actively utilized when the anisometric contraction state of arm, parallel to ground, is considered. While recording EMG signals, in order to achieve a good contact between the electrodes and muscles, which is a must for healthy signal acquisition, a special conducting gel is applied. As it is expected that there are too many parameters to affect the EMG signal behaviours, careful measurement is required. For example, to avoid crosstalk effect, the electrodes must be installed exactly on the center of muscles.

Detected EMG signals are applied to a filter that has 20 Hz lower and 200 Hz upper frequency cut-offs. The sampling frequency of signals is 500 Hz.

III. ANALYSIS OF EMG SIGNALS

In order to characterize and classify EMG signals with non-stationary characteristics, simple time domain methods, such as absolute average value and effective peak value, are proposed in the literature [1]. The reason for using those methods is to be able to extract features that will allow us to classify and characterize EMG signal. However, when using above methods, signal processing operations which can harm/change the features of the

EMG signals that involve the functional properties of corresponding muscle, must be avoided. It is therefore necesseary to employ correct methods for the analysis of EMG signals, in order to relate forces to signal features.

Instead of training time-domain EMG sequences using artificial neural network (ANN) [2,8], here we propose to use higher-order frequency moments derived from power spectrum of EMG signals. First, the power spectra, $P(\omega)$ of overlapping EMG segments are estimated by using periodogram approach [9]. The periodogram estimate of the power spectral density of a random signal $x(t)$ with a time duration of T is given by:

$$P_x(\omega) = \frac{1}{T}\left|X(\omega)^2\right| \qquad (1)$$

where $X(\omega)$ denotes the Forurier transform of $x(t)$. In statistical mean, periodogram estimation converges to signals power spectrum of random process. In our implementation, Discrete Fourier Transform (DFT) is used to calculate periodogram estimate of windowed signals. EMG signal $x(n)$, $0 \le n \le N-1$ is first multiplied by a sliding window to generate overlapping segments of the signal:

$$x_m(n) = x(n)\, w(n - mL) \qquad m = 0,1,2,... \qquad (2)$$

where L is the amount of window shift which is taken as 1/4 of the effective window length. Using short-time overlapping segments to analyze the frequency content of EMG signal allows us to tract the time-variations in the signal due to change of force better than taking the whole spectrum. Then the DFT, $X_m(k)$, of short-time signal $x_m(n)$ is calculated, and the power spectral estimate is obtained:

$$P_m(\omega_k) = \frac{1}{N}\left|X_m(k)^2\right| \qquad (3)$$

$P_x(\omega)$ contains enough information to characterize the EMG signal and it is also used in previous studies [10]. However, for a signal of length N, it is required to calculate an N sample power spectral estimate, which means higher number of features and higher computational burden. Instead of the whole power spectrum, using a few features extracted from it will be a computational advantage [11]. In our proposed method, after power spectrum estimation for the overlapping segments of EMG signal, higher order frequency moments are calculated from and used as the characterizing features. Higher order moments carries the higher order statistical information of a random signal [11] and can be calculated in time and in frequency domain for a signal $x(t)$ as follows:

$$\langle \omega^j \rangle = \int_{-\infty}^{\infty} \omega^j P_x(\omega)\, d\omega \qquad j = 0,1,... \qquad (4)$$

$$\langle t^i \rangle = \int_{-\infty}^{\infty} t^i P_x(t)\, dt \qquad i = 0,1,... \qquad (5)$$

Here, $\langle \omega^j \rangle$ is the jth order higher order frequency moment and $P_x(\omega)$ indicates the density function of $x(t)$ in frequency, $\langle t^i \rangle$ is the i'th order time-moment and finally $P_x(t) = \left| x(t) \right|^2$ is the energy density function of $x(t)$ in time.

IV. ESTIMATION OF FORCES FROM EMG FREQUENCY MOMENTS

In this study, an ANN which has one input layer, two hidden layers, and one output layer was used (Fig. 3). The ANN is trained using spectral moments of the overlapping EMG segments for estimating and tracking the force as a function of time.

In the network model, one input layer, two hidden layers,

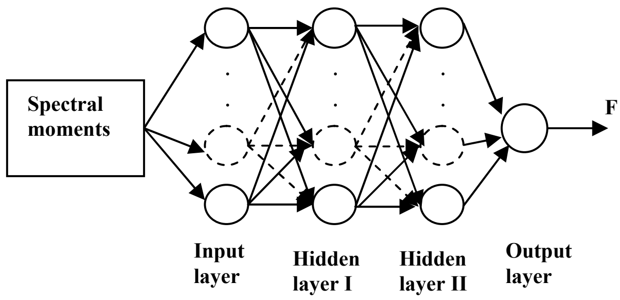

Figure 3. Artificial Neural Network Model

and one output layer have 149, 10 , 5, and 1 neuron, respectively. Log-sigmoid transfer function is used as the transfer function for training.

V. SIMULATION RESULTS

Surface EMG signals recorded from the pectorialis major muscle of three subjects under the effect of different forces recorded during anisometric and quasi-isotonic contractions are used in our experiments. Signals with 8 sec. time duration, sampled at 500 Hz. sampling rate are analyzed using a sliding and overlapping Hamming window for 150 segments. Hence the spectral moments $\langle \omega^j \rangle$ for j=0,1,2,3 of these overlapping segments are calculated and used to train the neural network.

The results from validation were evaluated by RMSD of the actual forces $f_a(n)$ and predicted $f(n)$ forces. The value of RMSD is calculated as follows [13]:

$$RMSD = \sqrt{\frac{\sum_i (f(n) - f_a(n))^2}{\sum_i (f_a(n))^2}} \qquad (6)$$

Validation results of the predicted forces against the actual forces which are measured using force sensors, as explained in section II, presented very successful performance for both subjects as shown in Table I. The values in the table show the average of 10 test results from each arm. The results are obtained to be less than 15 % on the average.

Table I: Mean of the RMS errors

	1→2 forward	1→3 backward	1→4 rightward	1→5 leftward
Subject	RMS error (%)	RMS error (%)	RMS error (%)	RMS error (%)
1	20	20	8.2	12.1
2	10.2	14.4	11.8	13.1

In Figure 4 and Figure 5, examples on the comparison of the predicted and measured forces are presented. It can be observed from the figures that we are able to estimate the actual forces using our proposed method with outstanding performance.

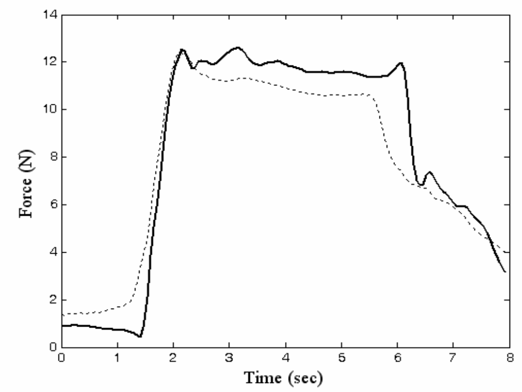

Figure 4-a: 1→2 forward motion

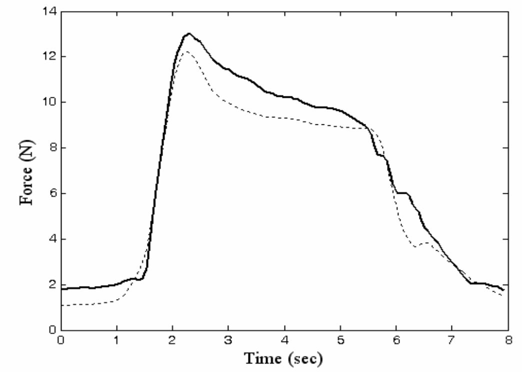

Figure 4-b: 1→3 backward motion

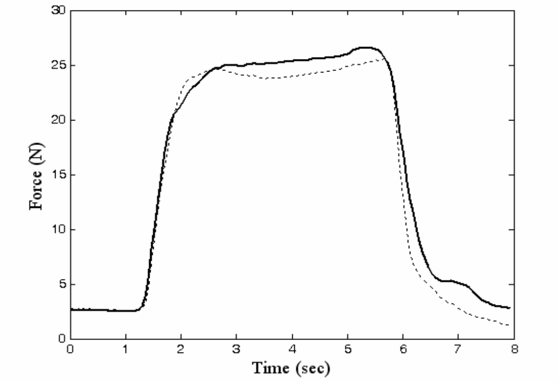

Figure 4-c: 1→4 rightward motion

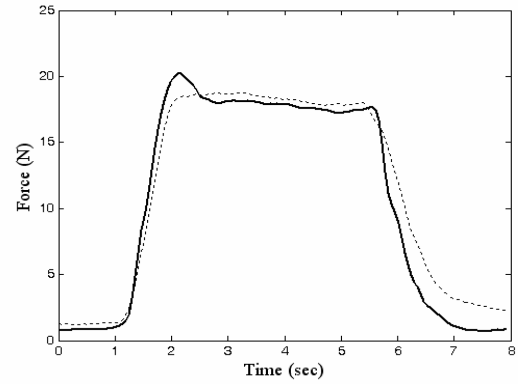

Figure 4-d: 1→5 leftward motion

Figure 4. Subject I tests: comparison of the estimated forces (dashed lines) with the actual forces (solid lines).

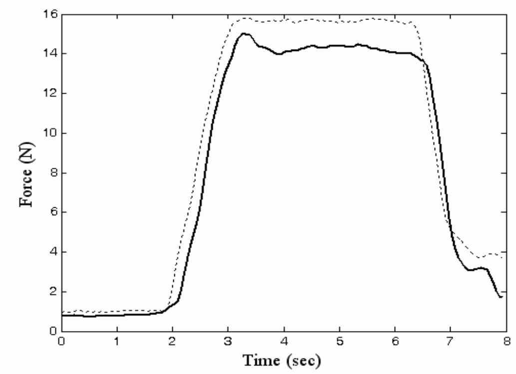

Figure 5-a: 1→2 forward motion

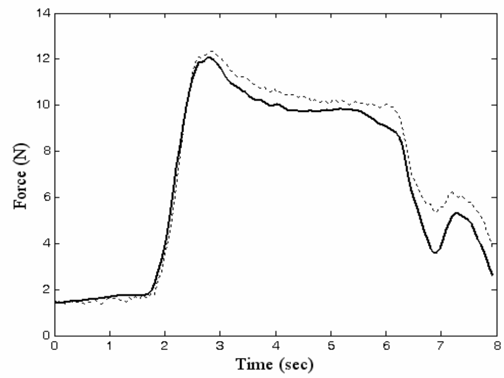

Figure 5-b: 1→3 backward motion

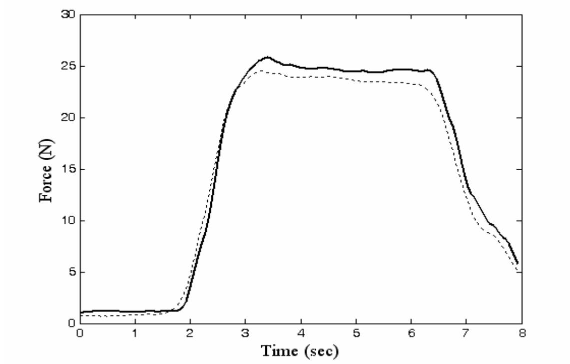

Figure 5-c: 1→4 rightward motion

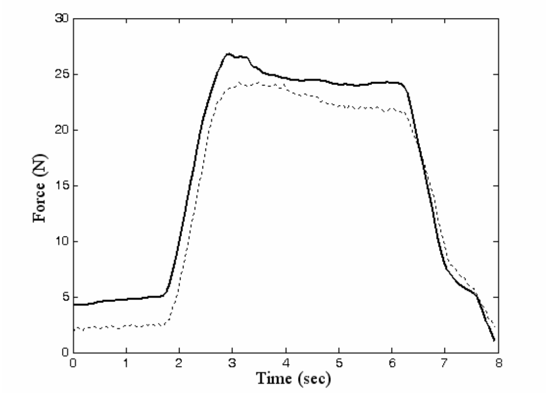

Figure 5-d: 1→5 leftward motion

Figure 5. Subject II tests: comparison of the estimated forces (dashed lines) with the actual forces (solid lines).

VI. CONCLUSIONS

From the results of this study, it can be concluded that spectral moments might be successfully used for characterizing EMG signals and establishing a relation to the force. Our results show that the proposed method is able to predict the applied forces with less than 15 % RMS error which is considered excellent value in the literature [1,14]. Furthermore, the results can be used in the design and control of active arm prosthesis [6,7] for the patients with amputated arms from the elbow.

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