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# Prediction of Wrist Angle from Sonomyography Signals with Artificial Neural Networks Technique

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*Abstract*—**Surface electromyography (SEMG) is widely used for the functional assessment of skeletal muscles, while sonography has been commonly used to detect its morphological information. We defined the signal about the continuous change of the morphological parameters of muscles detected by ultrasound as sonomyography (SMG). In this study, we continuously sampled the ultrasound image, SEMG signals on the extensor carpi radialis muscle together with the wrist angle simultaneously during the whole process of wrist extension and flexion from 7 normal subjects. A three-layer feed-forward artificial neural network with BP learning algorithm was used to predict the wrist angle with the muscle deformation SMG and root mean square of SEMG signals as inputs. The overall mean $R^2$ value was 0.96 ± 0.02, the mean standard root mean square error was 7.26 ± 1.98, and the mean relative root mean square errors was 0.160 ± 0.037. The results demonstrated that the wrist angle could be well predicted by combining the SMG and SEMG signals with ANN. Our result suggested that the combination of the information of SMG and SEMG could provide more comprehensive assessment of the skeletal muscle.**

## I. Introduction

SURFACE electromyography (SEMG) is commonly used to measure muscle activity. There has been a large volume of literatures reporting the relationships between SEMG and muscle force, length, muscle fiber conduction velocity, angle of elbow, knee, etc. Though SEMG signal contain a plenty of information, it is very complex and difficult to analyze, and also has some disadvantages. For example, it is sensitively affected by many factors, such as muscle cross-talking, electrode location, etc. In addition, it is difficult for SEMG signals to differentiate the effects of neighboring muscles, particularly for deep muscles.

Sonography has been widely used to study human nerve and muscles in both static and dynamic conditions. In recent years, sonography has been used to measure the changes in muscle thickness[1][1], muscle fascicle length[2], muscle fiber pennation angle[2], muscle size[3] and so on during isometric and dynamic contractions. In fact, the muscle architecture is a primary determination of muscle function, and the architectural changes of skeletal muscle are always relative to the muscle activities[4]. Therefore, it could potentially provide a noninvasive method of recording activities from deep muscles without cross-talk from adjacent muscles[1]. However, there are few researches on using both ultrasound and EMG signals to study the skeletal muscle. Only recently, some researchers began to investigate the relationship between the ultrasound parameters and the EMG activities in a quasi-static way[1][6].

Since McCulloch and Pitts[6] developed the first neural model, artificial neural networks (ANN) has been quickly developed and successfully applied in many different fields. ANN offers successful strategies for data analysis in multidimensional feature spaces, and has been widely used in biomedical engineering. For the SEMG signal processing, neural networks also has been successfully adopted to predict muscle force[7], joint moments[8], estimate joint torques and trajectory[9], et al.

The aim of this study was to predict the wrist angle from the ultrasound image combined with SEMG using ANN technique. During the whole wrist extension and flexion process, we continuously acquired the ultrasound image, wrist angle, and SEMG signals simultaneously on the extensor carpi radialis muscle from 7 young adult subjects. We named the signal about muscle morphological changes derived from ultrasound images as sonomyography (SMG)[1][10]. The SMG signal combined with SEMG signal by ANN technique could be potentially used for the control of prosthesis.

## II. Methods

### A. Experiment

Seven healthy male subjects (six males and one female) participated in this study (age: 26 ± 3 years; height: 170 ± 3.5 cm; weight: 62 ± 4.7 kg). None of them had any previous history of neuromuscular disorder and each gave written informed consent prior to the experiment.

The subject was seated in a chair with his forearm on the table, and asked to perform wrist extension and flexion repeatedly. Three separate trials were conducted for each subject with a rest of approximately 2 min between two adjacent trials. The subject was asked to perform more than three cycles of wrist flexion-extension in each trial. The sonography of a cross-sectional area of the extensor carpi radialis muscle was recorded using a portable B-mode

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ultrasound scanner (180 Plus, Sonosite Inc., Washington, USA) with a 7.5 MHz 38mm linear probe. The probe was fixed by a custom-made bracket, and its surface had a distance from the skin surface to avoid any compression on the tissue during the whole wrist extension and flexion period. Hence, the change of the muscle thickness was only contributed by the muscle behaviors. Ultrasound gel was used to fill the gap between the probe and the skin to maintain a good coupling during the test. The video output of B-mode ultrasound scanner was digitized by a video captured card (NI PCI-1411, National Instruments, Autstin, USA) with a sample rate of 12 Hz. The images were saved frame by frame together with other signals for subsequent analysis and total 200 frames were saved for every trial. The diagram of the experiment setup is shown in Fig 1.

A pair of SEMG biploar Ag-Agcl electrodes (Axon Systems, Inc., New York, USA) was placed near the ultrasound probe along the orientation of the extensor carpi radialis muscle. The distance between the pairs of surface electrodes was 20 mm. The SEMG reference electrode was placed on the proximal head of the ulna. The SEMG signal was amplified and filtered by a custom-made device with a gain of 10 and bandwidth of 10-800Hz before being digitized by the A/D card (NI PCI-6024E National Instruments, Austin, USA). The sample rate for EMG data collection was 4 kHz.

An electronic goniometer was attached on the surface of skin and through the wrist section to monitoring the wrist angle. The wrist angle signal from the goniometer was digitized by the data acquisition card (NI PCI-6024E, National Instruments, Austin, USA) installed in the PC, where it was synchronized with the ultrasound images and SEMG signals.

The data acquisition was controlled by custom-developed software for the ultrasonic measurement of motion and elasticity (UMME) in the platform of Visual C++ 6.0 (Microsoft, Washington, USA). Multithread technology was applied in UMME Software to insure the synchronization among the ultrasound image, wrist angle, and SEMG. Ultrasound image was sampled frame by frame, and each frame was accompanied by a SEMG epoch of 64 ms and a value of the wrist angle.

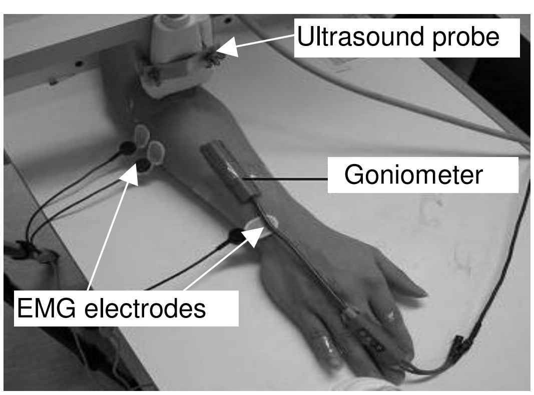



Fig. 1 The diagram of the experiment setup

*B. Data processing*

All the ultrasound, SEMG and wrist angle signals were processed off-line with UMME software and another program written in MATLAB (Version 6.5, MathWorks, Inc., Massachusetts, USA). The ultrasound images were imported to UMME software and displayed and analyzed frame by frame. A cross-correlation algorithm was used in UMME software to track the displacements of the interested tissue regions in the images[10]. Two rectangular blocks were manually selected for the upper and lower boundaries of the cross-sectional image of the extensor carpi radialis muscle in the first frame of the image sequences. The images defined by these two blocks were regarded as two templates for the subsequent automatic tracking. The centers of the upper and lower blocks were placed at the subcutaneous fat-muscle interface and the upper boundary of the radius, respectively. The sizes of the blocks were selected to include enough features for a reliable tracking with a cross-correlation coefficient larger than 0.9 between two conjunctive frames. The equation used to calculate the normalized two-dimensional cross-correlation is as follow:

$$R(i,j)=\frac{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}[x(m,n)-\bar{X}][y(m,n)-\bar{Y}]}{\sqrt{\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}[x(m,n)-\bar{X}]^2\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}[y(m+i,n+j)-\bar{Y}]^2}} \quad (1)$$

where $\bar{X}$ and $\bar{Y}$ represent the means of pixel density for the image blocks *x(m,n)* and *y(m+i,n+j)*, respectively. The best matched image block of the template can then be located according to the peak value of the correlation coefficients. When finishing the matching for one frame, the templates were automatically updated using the most similar image blocks in the current frame. After the initial template was manually selected, the above process would be automatically performed for each subsequent image frame until the last one and the positions of matched image blocks were recorded.

The distance between the centers of the two selected blocks was calculated for each frame, which represented the muscle thickness at each frame. The percentage deformation of the muscle was defined as:

$$\rho=\frac{(d-d_0)}{d}\times 100\% \quad (2)$$

where $d_0$ is the initial muscle thickness when subject relaxed his hand on the table, $d$ is the muscle thickness at each frame.

The root mean square (RMS) of amplitude of SEMG signals was calculated for each epoch. A wavelet algorithm was applied to the RMS result to get rid of the fluctuations.

*C. Neural network model*

The error back-propagation (BP) learning algorithm is one of the most popular training algorithms in the ANN. It is composed of two stages: a feed-forward step, where the neural nodes' output is specified; and a learning stage, where the connection weights and bias terms are updated. The two steps are repeated until the difference between the network predicted output signal (predicted muscle activation) and desired output signal (measured muscle activation) is below a specified tolerance value. In this study, a three-layer feed-forward network with BP learning algorithm was used to construct a model to describe the muscle deformation – angle relationship of wrist, as shown in Fig. 2. This three-layer neural networks has been shown to be sufficient to model problems of any degree of complexity[11].

The first layer, also called input layer, had two neurons, which were the deformation of extensor carpi radialis muscle and one channel RMS of SEMG. The second layer was hidden layer with ten neuron units was used in this study. The third layer, also called the output layer had one neuron, which was the wrist angle. Two transfer functions were used, which were sigmoid activation function and linear activation function. Firstly the sigmoid activation function was used between the input layer and the hidden layer because of its nonlinearity. By using this sigmoid function, the output unit is constrained to generate signals between 0 and 1. Because the wrist angle was not in the range of 0 to 1, thus the linear function was used between the hidden layer and output layer.

In each trial of the experiment, 200 frames of data were save, and the first 100 frames were used as the training data and the remained 100 frames were used to demonstrate the performance of the wrist angle prediction. The training would stop when the learning process was carried out for 2000 iterations or the preset error value was less than 0.10.

Evaluation of the wrist angle predictions from the SMG and SEMG signals was made by calculating the correlation coefficients, standard root mean square error (SRMSE) and the relative root mean square errors (RRMSE) between the predicted and actual values[12][13]. The value of RRMSE was obtained as follow:

$$RRMSE = \sqrt{\frac{\sum_i (\theta(i) - \theta(i)')^2}{\sum_i (\theta(i))^2}} \tag{3}$$

where $\theta(i)$ is the measured wrist angle, and the $\theta(i)'$ is the calculated wrist angle. Predictions were considered excellent if the coefficient of cross-correlation was greater than 0.9 and the relative RMS error was smaller than 15%.

## III. Results

Fig.3 was a typical example that illuminated the original signals including the normalized RMS, muscle deformation SMG and wrist angle (Fig.3a), and the predicted angle compared with the measured angle (Fig. 3b). Fig.3b showed the well fitness between the predicted angle and the measured angle. Table 1 showed the correlation coefficients ($R^2$) SRMSEs and RRMSEs of all the 7 subjects. The overall mean $R^2$ value was 0.96 ± 0.02, the overall mean SRMSE was 7.26 ± 1.98, and the overall mean RRMSE was 0.160 ± 0.037. The result of $R^2$ by ANN was better than the result by linear regression in reference [14], and the SRMSE and RRMSE were also illuminated the well predicted results.

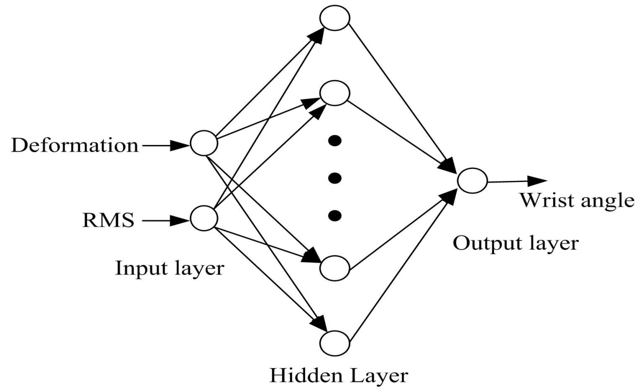
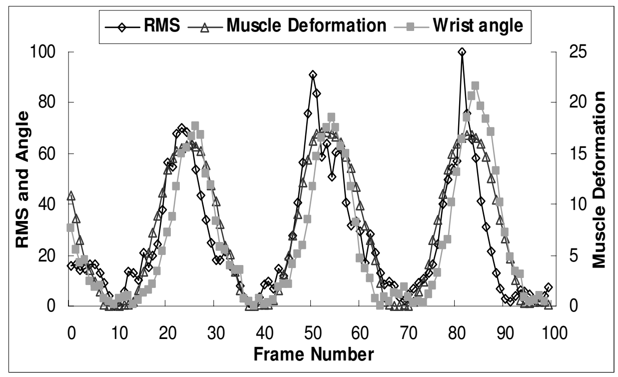
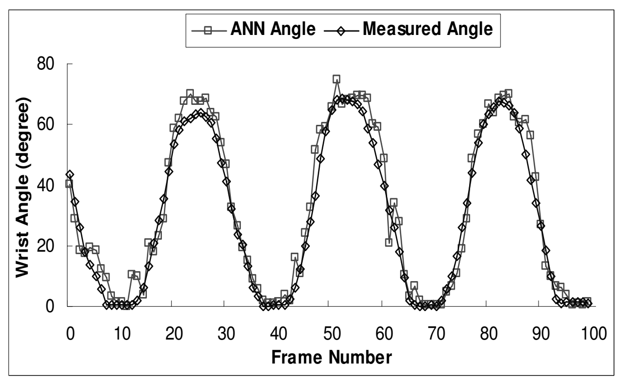



Fig. 2 The BP ANN model used for predicting the wrist angle from the signals of deformation of muscle, RMS of SEMG.




(a)




(b)

Fig. 3 a) Original data include normalized RMS, muscle deformation SMG and wrist angle curves; b) The predicted angle by ANN and the measured angle curves.

TABLE I The Statistic Results

| | A | B | C | D | E | F | G | Me-an |
|---|---|---|---|---|---|---|---|---|
| $R^2$ | 0.98± 0.005 | 0.96± 0.012 | 0.94± 0.021 | 0.97± 0.013 | 0.97± 0.015 | 0.96± 0.019 | 0.93± 0.025 | *0.96± 0.020* |
| SR-MSE | 4.64± 0.74 | 7.96± 1.15 | 10.47 ±0.61 | 5.65± 0.89 | 6.48± 1.59 | 6.81± 1.02 | 8.84± 1.07 | *7.26± 1.98* |
| RR-MSE | 0.09± 0.015 | 0.17± 0.029 | 0.19± 0.023 | 0.13± 0.032 | 0.15± 0.049 | 0.17± 0.051 | 0.20± 0.011 | *0.16± 0.037* |

## IV. Discussion

We described a method to simultaneously collect the wrist angle, SEMG signals and ultrasound images during the process of wrist extension and flexion, and predicted the wrist angle from the deformation of combined with SEMG signal by BP ANN. The overall mean $R^2$ value was 0.96 ± 0.02, the overall mean SRMSE was 7.26 ± 1.98, and the overall mean RRMSE was 0.160 ± 0.037, showing that good correlation could be achieved using this ANN regression.

Though the above result are much better than the previous result in the literature[10] and the mean $R^2$ value was larger than 0.9, the mean RRMSE was a little larger than 15%, which did not reach our expectation. The main reason was that the data set for learning was too small, which resulted in that the trained network was unstable. But this problem is solvable, and we will extend the experimental process and save more data in our future study. It is believed that the result predicted by ANN will better match the experimental data if the training data set is enough.

Though SEMG has been widely used in studying muscle, SEMG signal is very sensitive to external influences, such as the fat and skin impedance, which were also met in our experiments. The architectural changes of skeletal muscle are always relative to the muscle activities, and they could be easily monitored using ultrasound images[1][10]. In our previous study[1][10], high correlation has been found between the deformation of extensor carpi radialis muscle and the wrist angle. But we also noted that the linear regression and the SMG signal along could not well predict the wrist angle. Thus combining the SMG and SEMG signals to predict the wrist angle was more reasonable, and the results in this paper have demonstrated the feasibility to use ANN technique to combine the SMG and SEMG signals. Our results suggested that it was an effective way to study skeletal muscle using biomedical signals obtained by multiple modalities, and more comprehensive information could be provided. Using information related to electrophysiology, mechanics, morphology etc can help us better to understand the relationship between the inner architectural changes and outer behaviors of skeletal muscle. In addition, this kind of combination has the potential feasibility to be used for the better control of prosthesis and other human-machine interfaces. The B-mode ultrasound probe used in this study is too expensive and too large for the used of the prosthesis controlling. Further studies are required to develop low-cost ultrasound devices and low-profile ultrasound transducers for this purpose. Instead of using B-mode ultrasound probe, A-mode ultrasound probe can be adopted in the practical applications and one-dimensional cross-correlation tracking of the A-mode ultrasound signals is much faster than that of the two-dimensional cross-correlation of B-mode ultrasound images. Now we are studying the possibility to use the muscle deformation SMG to control prosthesis based on A-mode ultrasound signals.

## V. Conclusion

In conclusion, we used both SEMG and ultrasound image, i.e. sonomyography (SMG) to predict wrist angle with ANN technique. The results demonstrated that the deformation of muscle and RMS of SEMG could effectively predict the wrist angle with ANN technique. This technique has the potential feasibility to control the prosthesis for amputee. At the same time, it is an efficient way to study skeletal muscle by combining the SMG, SEMG and other signals.

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