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Frequency Feature for Proportional Myoelectric Control of Robotic Rehabilitation Therapy

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국문초록

- Objective : There have been active movements in developing exoskeletal robot system (ERS) which is electrically powered, especially for after stroke patient's rehabilitation purposes. For the general principle of motor skill rehabilitation, controlling algorithm for ERS should simulate actual tasks based on surface electromyogram (sEMG).
- Methods : In this study, the modified linear regression model based on frequency feature was demonstrated, and compared to conventional method. An electro-goniometer was used to measure a degree of wrist movement, and six channel sEMG device were employed to measure electric activates on the middle of forearm.
- Results : The results show that modified linear regression model has higher accuracy for controlling ERS. According to the results, we assure of the possibility that the suggested model will be used for stroke robot rehabilitation.
- Conclusion : Moreover, these techniques will be used as a prominent tool in making device or finding new therapy approaches in robot assisted rehabilitation for stroke survivors.

주제어 : proportional control, regression model, robot rehabilitation, sEMG

I. Introduction

Surface electromyographic (sEMG) signals recorded from forearm muscles have been widely used as an input parameter to exoskeletal robot system (ERS) for primary rehabilitation, especially for stroke and cerebrovascular disease survivors (Colombo et al., 2005; Rosen, Brand, Fuchs, & Arcan, 2001; Stein, Narendran, McBean, Krebs,

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& Hughes, 2007). So far, most studies regard to myoelectric control have focused on algorithm classification and pattern-recognition approaches that have been succeed to enhance the classification accuracy by classifying the number of EMG pattern (Young, Smith, Rouse, & Hargrove, 2013; Geng, Tao, Chen, & Li, 2011). Especially, current pattern recognition techniques allow discriminating the difference in wrist/hand contractions with higher accuracy (Young, Smith, Rouse, & Hargrove, 2013). However, most of recent classification studies for sEMG control have a crucial limitation related to practical use in which only one degree of freedom (DOF) can be controlled at a time (Jiang, Dosen, Muller, & Farina, 2012).

Recently, a few studies have shown that the regression technique can be applied for proportional and simultaneous myoelectric control in upper-limb prostheses (Hahne, Graimann, & Muller, 2012; Hahne et al., 2014). Actually, the regression technique for controlling ERS has advantages for practical use: 1) the linear regression technique can control multi-DOFs at a time by using sEMG signals measured from electrode array; 2) it is not only simple calculating structure to implement, but also it requires efficient computational load (Hahne et al., 2014). Therefore, the linear regression model for myoelectric control can be prominent tool to implement the portable exoskeletal robot system inrobotic rehabilitation therapy.

In this study, we hypothesized that various frequency features(filter banks) can enhance the accuracy of linear regression model for myoelectric control or rehabilitation robot. The suggested approach was demonstrated and compared to conventional linear regression approaches. The estimated results based on features in frequency-showed higher accuracy for simultaneous and propositional myoelectric control in upper limb rehabilitation therapy.

Ⅱ. Method

1. Participants and Experimental Setup

Two healthy participants (1 male and 1 female) in between 25 to 35 years old were volunteered for this pilot study and went through the simple experimental paradigm. During the experiment, the participants placed their right arm comfortably on the table which is located in front while they were seating on the chair. The electro-goniometer and sEMG device (Biometrics Ltd, USA) were attached on forearm (Figure 1); goniometer was placed on the dorsum of participant's right hand to measure his/her degree of wrist movement angle, and sEMG electro array was put on subjects' forearm to measure the different types of EMG signals that regard to their degree of wrist movement while they were moving.

Figure 1. The experimental set-up. The one electro-goniometer was placed on dorsum of hand and forearm (long green rod). Six sEMG active electrodes were placed around middle forearm.

2. Experimental Procedures

The devices were being adjusted to 0 degree once the experiment setup was ready to be conducted, making the 3rd metacarpals and the radius to be parallel to one another. Then, the participants moved their wrist for 12 directions in total making 30 degree of difference compared to the previous movement angle starting from full wrist extension position to 330 degree in clockwise. Figure 2 was printed and attached to the wall in front of participants and they were asked to match their metacarpophalangeal joint to each dot of the degree lines for their accurate performance in pointing degrees.

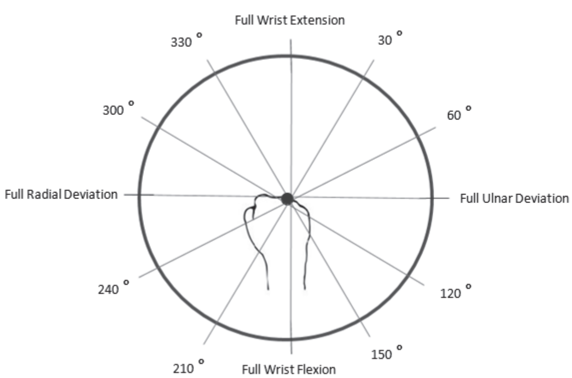

Figure 2. Twelve degree of participant's wrist movements

Starting with the resting time, the participants were asked to make the twelve wrist movements one by one. The resting time was required mandatorily between each movement, (i.e. pointing one degree and come back to natural position, which is 0 degree, and then performing next movement and so on). Figure 3 is scatter plot which shows measured two axes angle information of wrist movement. It is not only explicit enough to tell the difference of the wrist movements, but also most of the movement angles can be handled through the electro-goniometer.

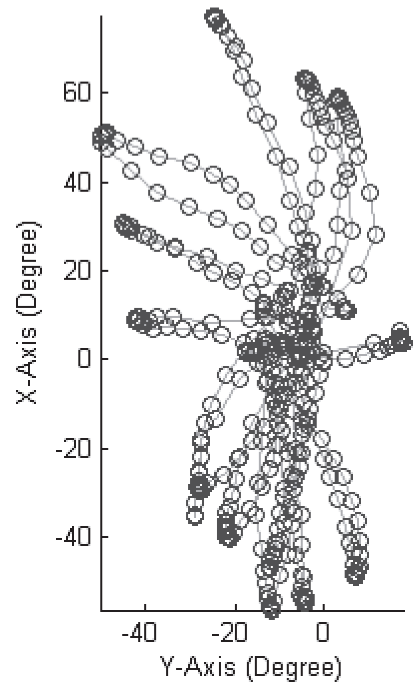

Figure 3. Wrist movements measured from electro-goniometer. The red circle is sampled point and green line is the trajectory line of real wrist movement.

3. Data Analysis

1) Data Acquisition

During the task, the angles between wrist and hand were measured with 50Hz sampling rate from electro-goniometer. The sEMG signals were obtained with 1000 Hz sampling rate using stainless dry electrode. The positive- and negative-electrodes were placed on the middle forearm (Figure 1) to measure the sEMG signals from muscles of wrist flexion/extensors. The measured sEMG signals and angle data were saved as an Ascii format file after experiment.

2) Preprocessing

The digital notching filter (MATLAB function: iircomb) was employed to remove 60Hz noise and its harmonic components that were contaminated by electric power–line. In order to remove motion artifacts, bandpass filter (MATLAB function: iirlpnorm) was used, and extract a primary sEMG signal between 20Hz and 500Hz.

3) Feature Extraction and Linear Regression Model

In this study, three kinds of feature was employed as an input source: 1) Raw signals, 2) 80–120Hz filtered signal, and 3) two filter banks signals (20–260Hz and 260 to 500Hz). Each signal was segmented with 100ms (100 sample) to calculated the RMS value. In addition, logarithm, $f(n) = \log(\sum RMS(X))$, was employed to obtain a reasonable regression performance because the Log–var provides best performance when linear regression model was applied (Brochard, Robertson, Médée, & Remy–Neris, 2010). Figure 4 shows the entire procedure of feature extraction.

Let $\boldsymbol{X} \in R^{C \times T}$ denotes the feature matrix, whose columns contain C dimensional feature vectors for the T–th time instance, and Y is a vector that corresponds to actual wrist angles for each time instance. A linear regression model has the form:

$$\hat{Y} = W^T X + w_O, \tag{1}$$

Where $\hat{Y}$ is the approximation of Y, and W^T is a vector of regression coefficients. For simplicity, the bias w_O is included in W by extending X with the constant 1. To fit the linear model, the most widely used approach is to minimize the sum of squared errors of the linear regression model:

$$\widehat{W} = \operatorname{arg}min \sum (Y - W^T X)(Y - W^T X)^T, \tag{2}$$

Once we obtain the coefficient matrix $\widehat{W}$ using training data set, we can compute a wrist angle at each time instance in real–time (100ms interval):

$$\hat{Y}(t) = \widehat{W^T} x(t), \tag{3}$$

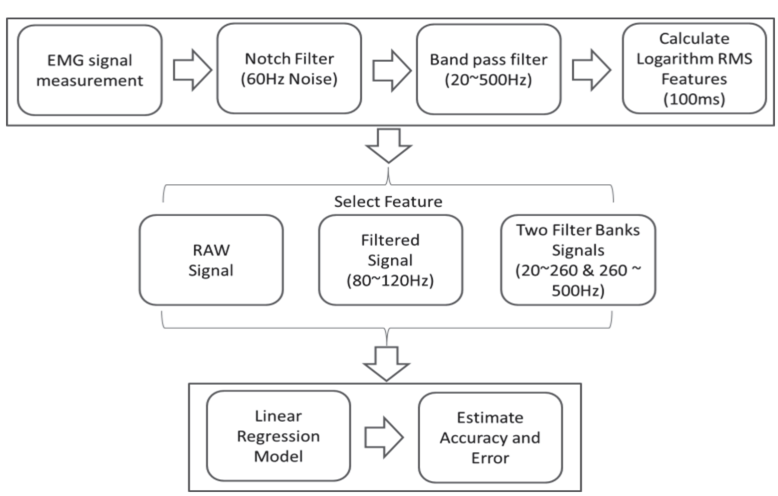

Figure 4. The entire procedure to estimate the accuracy of each feature

III. Result

In order to see the possibility for estimating the wrist movement by using EMG signal, two different types of data were collected; the electro-goniometer, which measures the degree of wrist movement, and EMG data that collects the signal when the wrist is moving. The Figure 5 shows that the combination of collected sEMG signal data by using 6 electrodes are different enough to tell instinctively that different directions of wrist movement have been performed.

The collected EMG signal data, as presented in the above (Figure 6), were analyzed in 2 different ways which were applying one filter bank and two filter banks. As it can be seen from the Figure 6, most of the lines were measured similar to the red line. We identified all the signals in different colors of lines; the red color lines in the above table are direction information from electro-goniometer, the blue dotted lines are raw data, the pink dotted lines are the data that were filtered once in the range of 80 Hz to 120 Hz, and the last green dotted lines are the data that were filtered twice in the range of 20 Hz to 260 Hz and 260 Hz to 500 Hz. According to the result, the signal data which have been filtered twice were most alike to the real-measured value through electro-goniometer.

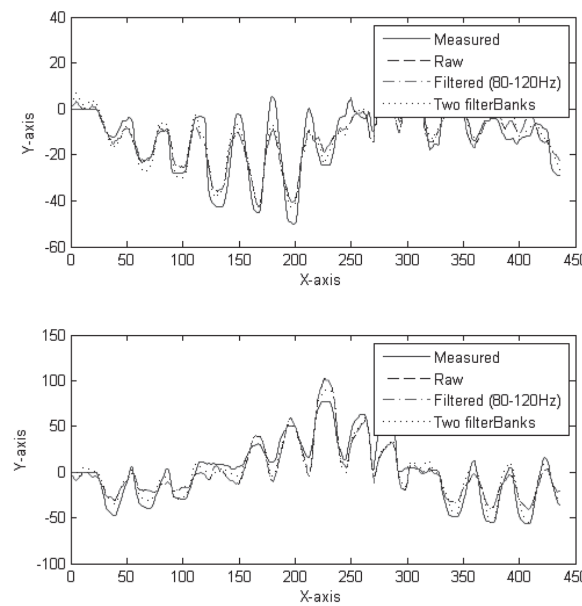

Figure 6. sEMG signal data in the way of conventional linear regression

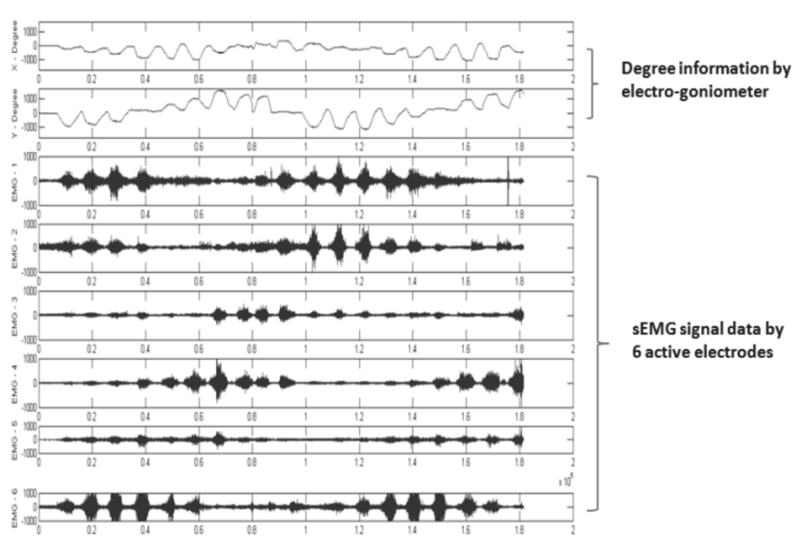

Figure 5. Combination of six EMG signals for wrist movements measured by sEMG active electrodes

The accuracy of the different regression models according to various threshold values (from 0 to 9 degree), was calculated based on the real angle values measured from electrogoniometer. The feature of two filter banks show much higher accuracy result than any others, while the raw data and once filtered data were quite similar to one another (Figure 7).

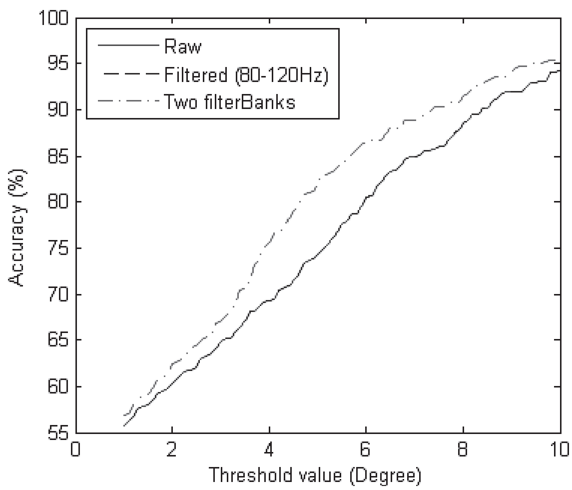

Figure 7. Accuracy of the different regression models corresponding to various threshold values

IV. Discussion

In this study, the different frequency feature was employed and demonstrated to estimate the accuracy of myoelectric control for robotic rehabilitation therapy. The results that use two filter banks signals as an input source show significantly higher accuracy than other features.

According to results, there is no significant difference between feature of filtered signal and feature of raw signal. It describe that frequency feature may not provide meaningful different feature to calculate matrix. In fact, thorough the short time frequency analysis, we can easily understand that there is some significant difference between high and low frequency band according to tasks. However, there is computational issue during calculating matrix because the sEMG signals of different frequency bands is pretty correlated there by causing rank issue. Therefore there is no difference if more than two filter banks are applied. In regard to this issue, further study is necessary (Figure 8).

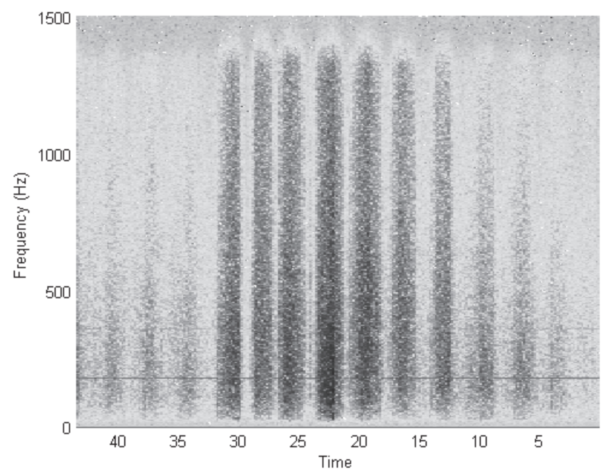

Figure 8. The time frequency analysis of measured sEMG signal

In this study, we demonstrated that difference frequency band feature can be applied to linear regression model separately thereby increase the accuracy of myoelectric control for robotic rehabilitation therapy. We hope that the suggested approach for simultaneous & proportional myoelectric control can be useful tool for practical use of clinical application.

V. Conclusion

In this study, the different frequency features were employed and demonstrated to estimate the accuracy of myoelectric control for robotic rehabilitation therapy. In order to evaluate the control performance, several kinds of frequency features are adopted with regression model for propotional control. the proposed method that is comprised of the two filter-bank features shows better accuracy. The total results that use two filter banks signals as an input source demonstrated significantly higher accuracy than other features. We hope that the suggested approach for simultaneous & proportional myoelectric control can be useful tool for practical use of clinical application.

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Abstract

재활로봇치료의 비례형 근전도기반 제어를 위한 주파수특징

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- **목적** : 본 연구에서는 표전 근전도 신호를 기반으로 기존의 재활로봇 알고리즘의 성능의 개선하기 위한 새로운 특징 요소를 개발 및 검증하였다.
- **연구방법** : 기존의 선형 재귀 모델을 기반으로 한 실시간 로봇 제어 알고리즘을 수정하여, 2개 이상의 주파수 특징을 가지는 근 전도신호에 그 특징의 수에 맞추어 주파수 영역을 다르게 한 모델을 개발하였다.
- **결과** : 측정된 결과 개선된 알고리즘의 모델이 기존 모델대비 높은 정확도가 나옴을 확인할 수 있었으며, 향후 이를 적용한다면, 근전도 기반 재활로봇의 정확도가 향상될 수 있음을 확인할 수 있었다.
- **결론** : 본 연구에서 제안된 복수의 필터뱅크 특징을 기반으로 한 개선될 선형 재귀알고리즘이 기존 알고리즘보다 높은 성능을 보임을 확인할 수 있었다. 이를 바탕으로 향후 뇌졸중 환자의 치료를 위한 재활 로봇을 제어하는데 활용된다면, 환자의 의지를 더욱 정확히 반영한 재활치료를 통하여 환자의 재활치료효과를 증진시킬 것이라 기대된다.

Key words : 로봇재활, 비례형 제어, 표면 근전도, 회귀모델