Estimation of triceps muscle strength based on Mechanomyography

Jiazhi Xie¹, Yue Zhang¹, Ke Yang¹,² and Chunming Xia¹,³ *

¹School of Mechanical and Power Engineering, East China University of Science and Technology, Shanghai, 200237, China
²School of Science and Engineering, University of Dundee, Dundee, DD14HN, UK
³School of Mechanical and Automotive Engineering, Shanghai University of Engineering Science, Shanghai, 201620, China
*Corresponding author’s e-mail: cmxia@ecust.edu.cn

Abstract. The aim of this study is to establish a reliable and widely applicable muscle strength (MS) estimation model based on the Mechanomyography (MMG). Seven healthy male volunteers were recruited to collect MMG and MS during the isometric contraction of their triceps. For MMG, 18 features were extracted. For the extreme gradient boosting (XGBoost) model and the quadratic polynomial (QP) model, the feature combination with the best estimation result was selected. The MS estimation performance of the XGBoost model and the QP model were compared. The performance of the QP model on the estimation of MS in different frequencies, different fatigue states and time periods was evaluated by using t-test. The results showed that when the number of features exceeds three, the model estimation accuracy has not improved significantly; and there was no significant difference in the estimation result of MS between the two models (p < 0.05), though the QP model was slightly better. The normalized root mean square error (NRMSE) and goodness of fit R of the MS estimation by the QP model were: 0.1343 ± 0.0296 and 0.8273 ± 0.0376. There was no significant difference in the MS estimation results in different conditions (p < 0.05).

1. Introduction
Muscle strength (MS) estimation has been widely used in many fields, such as exoskeleton [1], prosthetic control [2], rehabilitation robot [3], and muscle disease research [4]. At present, the biomedical signals used for MS estimation are mainly electromyography (EMG) and Mechanomyography (MMG). MMG is a low frequency signal generated by the lateral vibration of muscle fibers during muscle contraction, which can reflect the mechanical characteristics of muscle contraction. Compared with EMG, MMG has certain advantages: a) due to the propagation characteristics of MMG in muscle tissue, the MMG sensors do not need to be accurately placed [5, 6]; b) MMG is a mechanical signal which will not be influenced by the change of the skin impedance due to sweating [7]. Thus, as a counterpart of EMG, MMG is widely used in the researches of the action pattern recognition [7-9], muscle fatigue [10-12] and so on. Some studies have shown that there is a non-linear relationship between MMG and MS [13, 14], suggesting that MMG could be used for MS estimation. Ibitye et al. [1] selected root mean square (RMS) and peak-to-peak (PP) value as MMG features, and used support vector regression (SVR) model to realize the MS estimation of the quadriceps. Lei et al. [15] selected RMS and spectral variance as MMG features, and find that
artificial neural network (ANN) is superior than linear model in estimating biceps MS. Youn et al. [16] selected mean average value (MAV) and zero crossing (ZC) as MMG features, and find that ANN has better estimation effect on biceps MS than multiple linear regression model.

Extreme gradient boosting (XGBoost) is a decision tree method, which has been widely used in the prediction task. XGBoost has advantages of low computational complexity, and high accuracy [17-19]. Studies have found there is a non-linear relationship between MMG features and MS [13, 20, 21], and the quadratic polynomial (QP) as a simple nonlinear model has been proven available in the study of estimating MS by EMG [22]. Therefore, in this study, XGBoost and QP model are selected for comparative analysis, and the performance of the two models on MS estimation during isometric contraction of the triceps brachii has been compared. 18 types of time-domain, frequency-domain, and time-frequency domain features of MMG were extracted, and the optimal feature combination to estimate MS were selected according to the model. The applicability of the model to MS estimation at different frequencies, different fatigue states, and different periods were validated by hypothesis t-test.

2. Method

2.1. Experiment

In this study, the triceps brachii was selected as the research object. A triaxial accelerometer (ADXL335, Analog Devices, USA) that was fixed at the abdominal position of the triceps brachii was used to collect MMG. A tension sensor (ZNLBS-VI-30KG, Bengbu Chino Sensor, China) was selected to collect the force signal. A data acquisition card (NI9205, National Instruments, USA) was used to acquire the MMG and MS signals with 1000 Hz sampling frequency. The signals were filtered with a digital filter with a bandwidth of 2 ~ 50Hz.

Seven male volunteers (mean±SD, aged = 24.4±1.1 years; mass = 65.6±7.0 kg) were recruited in this experiment. None of them had a history of motor neurological diseases, no sports injuries in the upper limbs, and no intense exercise in the two days before the experiment. The experiment was performed after all volunteers knew the experimental process and signed the informed consent. The experimental setup is shown in Figure 1.

The experiment was conducted in three days in total. On the first day, the subjects were required to familiarize with the experiment process, and to collect data on the second and third days to avoid residual fatigue. During the experiment days, subjects were required to not exercise vigorously. Experiments were divided into two steps: (1) The subject’s Maximum voluntary contraction (MVC) was measured and used as the standard for measuring the strength. To avoid instantaneous abnormal force, the subject was required to slowly improve the force until it could no longer rise. This process was repeated three times, and the subject got fully rest between tests, and the average value of the maximum force achieved three times was taken as the final MVC. (2) According to the prompt sound,
the subjects made sinusoidal contraction with the frequency of 1Hz and 0.5Hz and a random contraction between 0 and 70% MVC.

In the experiment of the first day, the duration of 0.5Hz and random contraction is 60s. The 1Hz contraction needs to be done twice, once for 60s, and the other time until fatigue. The experiment process without the 60s-length 1Hz experiment of the first day was repeated the next day. To avoid residual muscle fatigue, adequate rest was taken between adjacent tests. After the experiment, the subjects' 1Hz data from non-fatigue to fatigue were divided into three sections. The first section was the non-fatigue state, and the third section was the fatigue state. At last received 9 sets of data from each subject, as shown in Table 1.

Table 1. The 9 sets of data from each subject

| Day  | 1Hz non-fatigue×2 | 1Hz fatigue | 0.5Hz non-fatigue | Random non-fatigue |
|------|------------------|-------------|------------------|-------------------|
| Day1 |                  |             |                  |                   |
| Day2 |                  |             |                  |                   |

2.2. Feature extraction and selection
In this study, sliding windows were used for feature extraction of MMG. The window length is 400 data points, and the overlap length is 350 data points.

18 features [23, 24] were extracted in this study, including time domain features: MAV, simple square integral (SSI), variance (VAR), RMS, log root mean square (LRMS), log detector (LOG), waveform length (WL), difference absolute standard deviation value (DASD), zero-crossing rate (ZC); frequency domain characteristics: mean power frequency (MPF), mean frequency (MNF), the 1st, 2nd and 3rd spectrum moment (SM1, SM2, SM3), variance of central frequency (VCF), frequency variance (FVAR), root mean square power spectrum (rmsPS); time-frequency domain characteristics: wavelet packet energy (WPE).

In order to obtain the optimal number of features and feature combinations, this study used a full permutation of a single feature, two features, three features, and four features to train the model.

2.3. Model training methods
In this study, the algorithms were implemented in the platform of Python3.6. The regression module in the XGBoost library was selected as the XGBoost model, and the grid search function of the scikit-learn library was used to optimize the model parameters. LinearRegression module of scikit-learn library was used for training the QP model.

2.4. Evaluation methods
In previous studies, the goodness of fit $R$ [25] and normalized root mean square error (NRMSE) [26] were usually used as the evaluation indexes of the MS estimation effect. The calculation formulas are:

$$R = 1 - \left( \frac{\sum (\hat{y}_i - y_i)^2}{\sum y_i^2} \right)^{1/2}$$  \hspace{1cm} (1)

$$\text{NRMSE} = \frac{\sum (y_i - \bar{y}_i)^2 / N}{\max{y} - \min{y}}$$  \hspace{1cm} (2)

where $y_i$ is the actual MS value, $\hat{y}_i$ is the estimated MS value, $y_{max}$ is the maximum actual MS, $y_{min}$ is the minimum actual MS, and $N$ is the total number of data points.

3. Results

3.1. Feature selection
The calculation results of the seven subjects were averaged, and the feature with the best estimation effect in each quantitative feature combination was selected. The results are shown in Table 2.
Table 2. Maximum goodness of fit $R$ and corresponding features

|                  | XGBoost model |                  | QP model      |
|------------------|---------------|------------------|---------------|
| **$R$**          | Features      | **$R$**          | Features      |
| A single feature | 0.785 WL      | 0.784 WL         |               |
| Two features     | 0.797 WL+DASD | 0.801 LRMS+WL    |               |
| Three features   | 0.807 RMS+WL+DASD | 0.811 RMS+WL+DASD |               |
| Four features    | 0.808 SSI+WL+DASD+SM2 | 0.812 RMS+WL+DASD+WPE |               |

It could be seen from Table 2 that when the number of features is over two, the optimal fitting goodness $R$ has not significantly improved. And for both two models, the combination of RMS, WL and DASD is the best among the combination of three features. Therefore, this study finally selected RMS, WL, and DASD as the input features.

3.2. Model comparison

In order to compare the performance of the two models on MS estimation, this study used the non-fatigue sinusoidal contraction data (7 persons × 1 group per person) with a frequency of 1 Hz on the first day as the training set, and the remaining data (7 persons × 8 groups per person) as a test set. NRMSE and $R$ were calculated separately for each set of data. The calculated average values of NRMSE and $R$ of XGBoost estimation results were: 0.1412 ± 0.0285, 0.8187 ± 0.0353; and of QP estimation results were: 0.1343 ± 0.0296, 0.8273 ± 0.0376. It could be seen that the performance of the QP estimation was slightly better than that of the XGBoost. As a result, the QP model was finally selected as the model of MS estimation in this study. The estimation effect is shown in Figure 2.

![Figure 2. MS curve estimated by QP model](image)

3.3. Model applicability

In order to verify the applicability of the model, the sinusoidal contraction with a frequency of 1 Hz in the non-fatigue state acquired from the first day was used as training data. The method of controlling variables was used in three variables (frequency, fatigue state, experiment day) to compare and analyze the model applicability. The NRMSE and the $R$ between the estimated MS and the measured value are shown in Figure 3.
Figure 3. NRMSE, R between estimated and measured MS

The three characters of the horizontal axis in Figure 3 indicate whether the test data and the training data on the same day (S is the same day and D is a different day), whether they are fatigued (T is the fatigued state, and N is the non-fatigued state), and the contraction frequency (1 is 1Hz, 0.5 is 0.5Hz, R is random contraction). For example, S-N-1 indicates the muscle strength of 1Hz in the non-fatigue state on the same day.

In order to verify whether the model has significant differences between the estimation results of different data sets, a hypothesis t-test was used. Take the significance level $\alpha = 0.05$, and calculate the statistical $t$ value between the estimated muscle strength values of the model for different frequencies, fatigue states, and periods as shown in Table 3.

| Data pair | S-N-1/S-T-1 | S-N-1/S-N-0.5 | S-N-1/S-R | S-N-1/D-N-1 |
|-----------|-------------|--------------|-----------|-------------|
| $t$ (NRMSE) | 0.7763 | 0.3242 | 0.3266 | 0.2538 |
| $t$ (R) | 1.0638 | 0.7628 | 1.220 | 0.2219 |

The critical value $t_{\alpha/2}(n_1 + n_2 - 2) = t_{0.025}(12) = 2.1788$, which is bigger than all the data in Table 3. Therefore, the QP model trained on the first day of non-fatigue 1Hz data could be used. It is suitable for estimating MS in different fatigue states, different frequencies and different days.

4. Conclusion

In this study, features of MMG were extracted and selected for the XGBoost model and the QP model, and a combination of RMS, WL, and DASD was used to compare the performance of XGBoost model and QP model on MS estimation. Finally, the applicability of the QP model was verified by t-test. The results showed that when the number of features exceeds three, the estimation accuracy of the two models does not improve significantly; the estimation performance of the QP model is slightly better than that of the XGBoost model, but there were no significant difference between the results of two models ($p < 0.05$). Moreover, there was no significant difference among the estimation results of the MS estimation under different conditions by QP model ($p < 0.05$), indicating that QP model could be used for MS estimation based on MMG. This study can provide a reliable model for the MS research in the fields of clinical medicine and rehabilitation engineering.

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