Estimation of triceps muscle strength based on Mechanomyography

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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. Ibitoye 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.

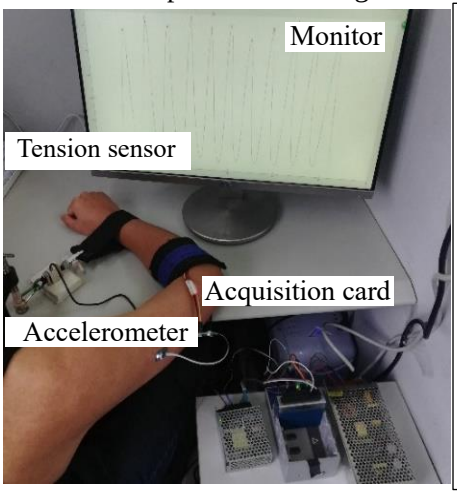

Figure 1. Experimental setup. During the experiment, the subject was required to sit on a non-slip chair with the upper body in an upright position, and both the angle between the forearm and the body and the angle between the forearm and the forearm were90°. To avoid force on the wrist, the tension sensor is fixed at the end of the forearm, the monitor in front of the subject will show the measured MS curve, providing visual feedback to the subject to ensure that the contraction is accurate.

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

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

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:

$$R = 1 - \left(\frac{\sum (\tilde{y}_i - y_i)^2}{\sum y_i^{\,2}} \right)^{1/2} \quad (1)$$

$$\mathrm{NRMSE} = \frac{\left(\sum (y_i - \tilde{y}_i)^2 / N \right)^{1/2}}{y_{\max} - y_{\min}} \quad (2)$$

where y_i is the actual MS value, $\tilde{y}_i$ 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.

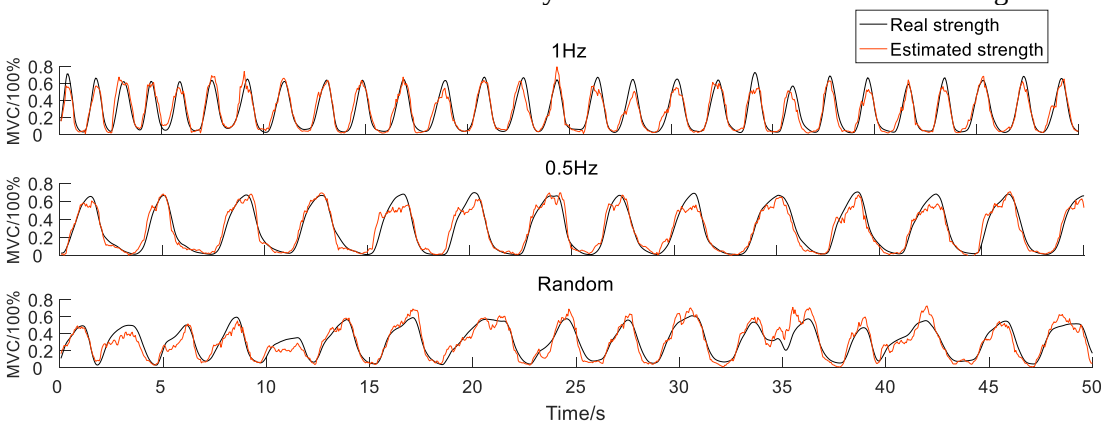

Figure 2. MS curve estimated by QP model

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.

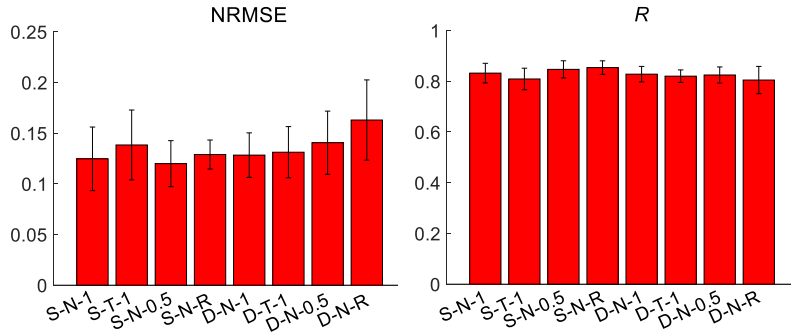

Figure 3. NRMSE, R between estimated and measured MS

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.

Table 3. Statistical *t* value for NRMSE difference and *R* difference

Data pair	S-N-1/S-T-1	S-N-1/S-N-0.5	S-N-1/S-N-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.

References

[1] Ibitoye, Morufu, Olusola, et al. (2016) Estimation of Electrically-Evoked Knee Torque from Mechanomyography Using Support Vector Regression. J. Sensors, 16: 1115.

[2] Kasuya M, Seki M, Kawamura K, Fujie MG. (2011) Subtle grip force estimation from EMG and muscle stiffness - Relationship between muscle character frequency and grip force. In: Annual International Conference. Boston. pp. 4116-4119.

[3] Meng W, Ding B, Zhou Z, et al. (2014) An EMG-based force prediction and control approach for robot-assisted lower limb rehabilitation. In: IEEE International Conference on Systems. San Diego. pp. 2198-2203.

[4] Anwar T, Jumaily A A. (2016) ANFIS to estimate damping coefficient from EMG to optimize the interaction force. In: International Conference on Microelectronics, Computing and

Communications (MicroCom). Durgapur. pp. 1-6.
[5] Alves N, Chau T. (2008) Stationarity distributions of mechanomyogram signals from isometric contractions of extrinsic hand muscles during functional grasping. J. Journal of Electromyography and Kinesiology, 18: 509-515.
[6] Silva J, Heim W, Chau T. (2005) A Self-Contained, Mechanomyography-Driven Externally Powered Prosthesis. J. Arch Phys Med Rehabil, 86: 2066-2070.
[7] Xie H B, Zheng Y P, Guo J Y. (2009) Classification of the mechanomyogram signal using a wavelet packet transform and singular value decomposition for multifunction prosthesis control. J. Physiological Measurement, 30: 441-457.
[8] Haifeng W, Daqing W, Lifu G, et al. (2018) A CNN-SVM combined model for pattern recognition of knee motion using mechanomyography signals. J. Journal of electromyography and kinesiology: Official journal of the International Society of Electrophysiological Kinesiology, 42: 136-142.
[9] Yue Z, Jing Y, Chunming X, et al. (2019) Research on GA-SVM based head-motion classification via mechanomyography feature analysis. J. Sensors, 19: 1986.
[10] Cè, Emiliano, Rampichini S, Limonta E, et al. (2013) Torque and mechanomyogram correlations during muscle relaxation: Effects of fatigue and time-course of recovery J. Journal of Electromyography and Kinesiology, 23: 1295-1303.
[11] C. Russel Hendrix, T. J. Housh, C. L. Camic, et al. (2010) Comparing electromyographic and mechanomyographic frequency-based fatigue thresholds to critical torque during isometric forearm flexion. J. Journal of Neuroscience Methods, 194: 64-72.
[12] Wendu J, Chunming X, Yue Z, et al. (2019) Research on muscle fatigue trend via nonlinear dynamic feature analysis of mechanomyography signal. In: International Conference on Signal and Image Processing. Wuxi. pp. 669-673.
[13] Akataki K, Mita K, Watakabe M, et al. (2001) Mechanomyogram and force relationship during voluntary isometric ramp contractions of the biceps brachii muscle. J. European Journal of Applied Physiology, 84: 19-25.
[14] Beck T W, Defreitas J M, Stock M S. (2009) The linearity and reliability of the mechanomyographic amplitude versus submaximal isometric force relationship. J. Physiological Measurement, 30: 1009-1016.
[15] Lei K F, Cheng S C, Lee M Y, et al. (2013) MEASUREMENT AND ESTIMATION OF MUSCLE CONTRACTION STRENGTH USING MECHANOMYOGRAPHY BASED ON ARTIFICIAL NEURAL NETWORK ALGORITHM. J. Biomedical Engineering: Applications, Basis and Communications, 25: 1350020.
[16] Youn W, Kim J. (2010) Estimation of elbow flexion force during isometric muscle contraction from mechanomyography and electromyography. J. MEDICAL & BIOLOGICAL ENGINEERING & COMPUTING, 48: 1149-1157.
[17] Chen T, Guestrin C. (2016) XGBoost: A Scalable Tree Boosting System. In: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM. pp. 785-794.
[18] Zhang D, Qian L, Mao B, et al. (2018) A Data-Driven Design for Fault Detection of Wind Turbines Using Random Forests and XGBoost. J. IEEE Access, 2018: 1-1.
[19] Soram L, Seokho C. (2019) Xgboost application on bridge management systems for proactive damage estimation. J. Advanced Engineering Informatics, 41: 100922.
[20] Defreitas J M, Beck T W, Stock M S. (2012) Effects of strength training on mechanomyographic amplitude. J. Physiological Measurement, 33: 1353-1361.
[21] Akataki K, Mita K, Itoh Y. (1999) Relationship between mechanomyogram and force during voluntary contractions reinvestigated using spectral decomposition. J. European Journal of Applied Physiology & Occupational Physiology, 80: 173-179.
[22] Yu H, Sun Y, Bai F, et al. (2015) A preliminary study of force estimation based on surface EMG: Towards neuromechanically guided soft oral rehabilitation robot. In: IEEE

International Conference on Rehabilitation Robotics. pp. 991-996.
[23] Lei K F, Tsai W W, Lin W Y, et al. (2011) MMG-torque estimation under dynamic contractions. In: IEEE International Conference on Systems. IEEE. pp. 585-590.
[24] Phinyomark A, Phukpattaranont P, Limsakul C. (2012) Feature reduction and selection for EMG signal classification. J. Expert Systems with Applications, 39: 7420-7431.
[25] Kunyi L, Xinhao Z, Jinfan L, et al. (2019) The recognition of grasping force using LDA. J. Biomedical signal processing and control, 47: 393-400.
[26] Youn W, Kim J. (2011) Feasibility of using an artificial neural network model to estimate the elbow flexion force from mechanomyography. J. Neurosci Methods, 194: 386-393.