Multiclass Classification and Regression Analysis of Muscle Fatigue Using Wrist EMG

Misato Matsushita* Momoyo Ito+ Shin-ichi Ito* Minoru Fukumi+
Department of Systems Innovation Engineering, Intelligent Information System Engineering Course,
Tokushima University, 2-1, Minami-Josanjima, Tokushima, 770-8506, Japan
*{c501937017, s.ito}@tokushima − u.ac.jp
+{momoito, fukumi}@is.tokushima-u.ac.jp

ABSTRACT

Muscles can cause injury by training to improve physical performance. However, there are few ways to assess muscle fatigue currently.

Therefore, in this paper, muscle fatigue is evaluated using surface EMG(ElectroMyoGram). The proposed method in this research consists of 4 parts: Measurement, Pre-processing, Feature extraction, and Learning identification parts. The effectiveness of the proposed method is demonstrated in two ways, classification and regression analysis, and comparative verification is conducted.

KEYWORDS

Biometrics, Wrist EMG, SVM, CNN, Deep learning, Regression analysis, Multiclass classification

1 INTRODUCTION

Athlete and student club activities train to improve physical performance almost every day. Meanwhile, excessive strain can cause injury and as a result poor performance.

Presently, evaluation of muscle fatigue is made by subjective evaluation using visual analog scale (VAS) and questionnaires[1]. Several methods for objectively evaluating muscle fatigue were presented[2]. These methods were based on physiological evaluation such as activity amount and reaction time, sleep and wakefulness rhythm, biochemical evaluation by brain function and blood test, functional analysis of autonomic nervous system and so on. However, it is considered that those evaluation methods are not easy to use because they require medical specialized knowledge or need to visit a specialized institution.

Therefore, in this paper, a method is proposed to evaluate muscle fatigue easily in any environment with personal computers. This paper focuses on muscle action potentials that are easy to handle as a method of evaluation and could be handled anywhere. Most of the previous researches on muscle fatigue using EMG measured it by attaching myoelectric sensors to the parts with much muscle mass such as upper arms, thigh muscles, and abdomen. However, measurement in a location with a large amount of muscle, burdens subjects and is contrary to the purpose of facilitating measurement. EMG measurement is therefore carried out using myoelectric potential of the wrist in this paper.

2 PROPOSED METHOD

2.1 Measurement

The measurement part measures the EMG(ElectroMyoGram) data used in the learning identification part. We use P-EMG plus and dry type sensors for measurement of EMG[3],[4]. The reason why dry type sensors are used instead of wet type sensors is that dry type sensors are less expensive to run.

Figure 1. P-EMG plus

Figure 2. Dry type sensor

The methods of examination of EMG are roughly divided into needle EMG and surface EMG. The reason for using surface EMG of those two is that it does not require medical expertise and does not place a burden on subjects. As for measurement, sensors at the time of measurement are prevented from being dislocated by attaching around the wrist like a wristwatch.

2.2 Pre-processing

In this paper dry type sensors are used, but their characteristics are low in stability and preprocessing is therefore required.

2.2.1 Data extraction

About 3 seconds data are manually cut out of the part where EMG signals are stable state. The stable state indicates that the hand is bent and the movement is stable state. Thereafter, 512 points before and after the center point of the cut out data, which are a total of 1 second (1024 points) data, are used as raw data.

2.2.2 Noise removal

In this paper, noise removal is necessary because dry type sensors are used. Hum noise and drift noise were observed from EMG signals. Hum noise is mainly caused by electromagnetic induction, electrostatic induction, and leakage current. As a method of removing the hum noise, the power supply frequency band affected by the hum noise is the removal target. The value to be substituted for the value to be removed by the following formula is calculated. Let x(i) be the value to be removed.

$$\begin{aligned} sum = x(i-5) + x(i-4) + x(i-3) \\ +x(i+3) + x(i+4) + x(i+5) \end{aligned} \quad (1)$$

$$x(i) = sum/6 \quad (2)$$

Therefore, we remove clearly large values, which are a commercial frequency and its multiples.

Drift noise is caused by the fact that power lead wires shake with operation and electrodes float from the skin. Since this noise is characterized by affecting low frequencies, it is removed using a high pass filter. The high pass filter is a filter that has the function of passing frequencies higher than the cutoff frequency as it is and reducing low frequencies. Removal of frequencies below 20 Hz was carried out to remove drift noise while leaving muscle fatigue features.

2.3 Feature extraction

The pre-processed EMG signal is converted by Fast Fourier transform (FFT) to calculate power spectral values. FFT is a generic term for operations that perform discrete Fourier transform(DFT) processing at high speed. When the values of the data to be used differ significantly, distortion of the high frequency component occurs owing to the rapid change. In order to avoid this phenomenon, after using a Hamming window, frequency analysis by FFT is carried out to calculate power spectra. Characteristics of muscle fatigue usually appear in low frequency components[5]. By using power spectral values, we can confirm features of muscle fatigue that cannot be confirmed in raw EMG data.

2.4 Learning identification

The learning discriminator evaluates the degree of muscle fatigue by using two approaches. We conduct both classification and regression analysis by supervised learning in machine learning.

2.4.1 Classification

we evaluate classification accuracy using a support vector machine (SVM) and a convolutional neural network (CNN).

The SVM is a method for constructing boundaries that separate classes using margin maximization[6]. We performed grid search for hyperparameter search, and accuracy was evaluated using the cross validation method. We used one to another classification method in multiclass classification.

The CNN is composed of many neural network layers including a full connection layer, convolution layers and pooling layers. The network structure used in this paper is as follows.

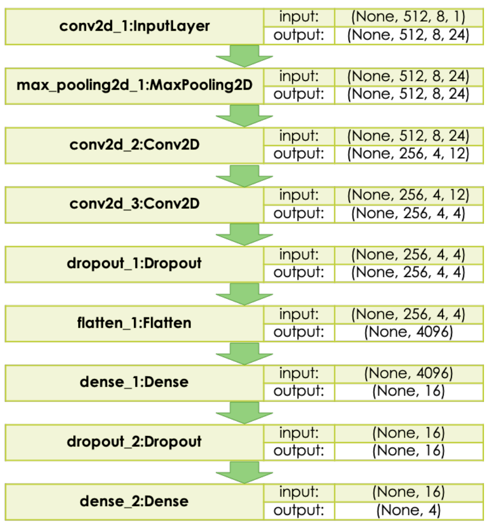

Figure 3. CNN network structure

2.4.2 Regression analysis

Regression analysis is a kind of analysis in statistics. Methods of regression analysis are divided linear analysis and nonlinear analysis. In this paper, we used linear analysis. Linear analysis is a model that predicts the value of objective variables from the explanatory variables. We used a least squares method to predict values. Single regression analysis uses an explanatory variable, and multiple regression analysis uses two or more explanatory variables. In this paper, we used multiple regression analysis. Classification used all of the measured data converted to power spectral values. However, regression analysis used data converted to the average of the power spectrum value. In addition, in the regression analysis, instead of discrete values such as classification, identification was performed by continuous values using the number of muscle trainings.

3 EXPERIMENTS AND RESULTS

3.1 Experiment

Subjects of experiment were three men and a woman in their twenties. We left for more than 2 days so that there was no influence between experiments. Furthermore, we asked subjects if they had fatigue. Below is the experimental design.

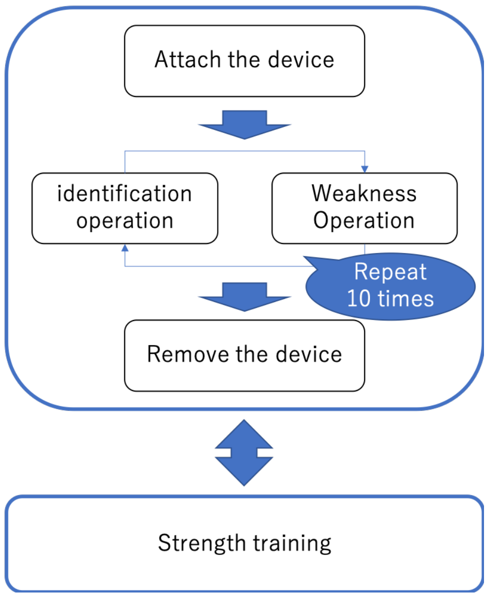

Figure 4. Experimental design

The discrimination operation was measured with the finger bent. Strength training was carried out using a hand grip.

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Figure 5. Discrimination operation

Figure 6. Hand grip

The subject held the handgrip to the limit and recorded the number of times. The discrimination operation was carried out 4 times a day for 3 days. Below is a data used for verification.

days	3 days
stages	4 stages
Number of channels	8 ch
Number of data	120 data (10times * 4stages * 3days)

Figure 7. Experimental data

This paper aims at quantitative assessment of muscles. Below is criteria for quantitative evaluation.

Stage	Criteria for quantitative evaluation
1	Before experiment
2	After first experiment
3	Under (After first experiment) * 80%
4	Under (After first experiment) * 60%

Figure 8. Criteria for quantitative evaluation

3.2 Result

There is a problem with versatility on individual difference in muscle fatigue. Therefore, we made learning identification by each personal model.

3.2.1 Classification

At first, we describe the result obtained by SVM. Below is how to use data for Cross validation.

	Test data	Train data
Dataset1	day1, 2	day3
Dataset2	day2, 3	day1
Dataset3	day1, 3	day2

Figure 9. Cross validation

Below is experimental results.

Table 1. Results obtained by Support Vector Machine (SVM)

subject	A	B	C	D
Dataset1	50.0	17.5	17.5	37.5
Dataset2	27.5	40.0	30.0	25.0
Dataset3	35.0	57.5	42.5	37.5
Avg.	37.5	38.33	30.0	33.33
Hyper Parameter	c=10 γ =0.0001			c=0.0001 γ =0.0001

Second, we describe the results obtained by CNN. The CNN was also evaluated using the cross validation in the same manner as the SVM. Below is experimental results.

Table 2. Results obtained by Convolutional Neural Network (CNN)

subject	A	B	C	D
Dataset1	44.0	29.0	30.5	27.5
Dataset2	31.0	27.5	28.5	28.0
Dataset3	31.5	25.5	35.5	29.5
Average	35.5	27.33	31.5	28.33

3.2.2 Regression analysis

We verified two ways that [Dataset1] was based on criteria for quantitative evaluation and [Dataset2] was based on the number of strength trainings. Below is experimental results.

Table 3. Results obtained by Regression analysis

subject	A	B	C	D	Avg.
Dataset1	26.47	26.1	46.7	16.55	28.96
Dataset2	42.86	30.24	45.01	30.8	37.23

4 CONSIDERATION

In this paper, we verified two ways based on classification and regression analysis.

Table 4. Total result

subject	Avg.
SVM	34.78
CNN	30.67
Regression analysis	37.23

From the above table, as a result, regression analysis obtained better accuracy than classification. Classification average resulted in low accuracy less than 35%, but regression analysis average obtained more than 37% accuracy. From these results, it is suggested that regression analysis is more useful for this paper. It is considered that the reason is that class classification learns and identifies discrete values, while regression analysis largely uses continuous values for learning discrimination. Furthermore, result of regression analysis suggested that the state of muscle fatigue had some correlation with the state of decreasing number of muscle trainings.

However, accuracy obtained using regression was also still low. The cause is that the number of data was insufficient and the subject felt less fatigue. In order to improve the problem of low fatigue, it is necessary to review the experimental design. It is thought that we could improve accuracy of the verification results by performing experiments by other methods instead of amount of muscle training. For the problem of the small number of data, we think that accuracy improvement can be expected by increasing the number of measurements and creating pseudo data.

In this paper, although linear regression was used, there is a possibility of further improvement in accuracy by using nonlinear regression. In the future, this will also be verified.

5 CONCLUSION

In this paper, quantitative assessment of muscle fatigue was carried out. For this purpose, muscular strength training was performed to cause muscle fatigue in a pseudo manner, and surface electromyography was measured. Accuracy of about 30% was obtained by classification, and accuracy of 37% or more was obtained by regression analysis. In the proposed method of this experiment, it is considered that there is a need for improvement in experimental design and learning identification. However, regression analysis was better than classification in learning identification. Furthermore, it is thought that there is a certain correlation between muscle fatigue and myoelectric status.

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