Discriminant Analysis Based EMG Pattern Recognition for Hand Function Rehabilitation

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Abstract. Electromyographic (EMG) signal is playing an important role on hand function training as a neuromuscular rehabilitation tool. Various pattern recognition algorithms (PRAs) have been compared and evaluated in previous research, and Linear Discriminant Analysis (LDA) showed the higher offline accuracy for motion classification. However, it is rarely of comparison for different types of Discriminant Analysis (DA), and the surface electrodes are common methods for signal acquisition. This paper proposes to evaluate the offline performance of LDA and other types of DA, and using Myo armband for recording signals. The offline data was acquired by Myo armband, processing recognizing the data in BioPatRec, an open source platform for motion classification and hand prosthetics control. From the results of average offline accuracy, training time, and testing time of the five types, LDA and Quadratic Discriminant Analysis (QDA) have the better performance than others, and LDA is the fastest algorithm with simple computing.

Keywords: Electromyographic (EMG) signal
Linear Discriminant Analysis (LDA) · Myo armband
Hand function rehabilitation

1 Introduction

Electromyographic (EMG) signal is produced by skeletal muscles, and be displayed with action potentials by recording electrodes, like surface or intramuscular electrodes [1, 2]. The EMG signal which includes a large of neural information could be applied to motion classification, hand control or hand function rehabilitation for amputees. Stroke is a chronic disease, and the hand function by post-stroke is very difficult to recover, and the rehabilitation robots are the most common method to train hand function [3]. Furthermore, EMG-driven systems are more effective than the continuous passive mode [4].

There are many algorithms for pattern recognition such as Linear Discriminant Analysis (LDA) [5], Multi-Layer Perception (MLP) [6], Artificial Neural Networks

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(ANN) [7, 8], and Support Vector Machine (SVM) [9]. The performance of motion classification depends on the classification accuracy, misclassification rate and the time, etc. LDA, a statistical classification method, is the fastest algorithm with low complexity and quick training than other types of the algorithms [5, 10]. The procedures of pattern recognition consist of signal recordings, signal treatment, feature extraction, and pattern recognition. BioPatRec [11] is a modular open source research platform based on MATLAB for prosthetic control.

In BioPatRec, there are friendly GUIs for users to make experiments, and the implementation of algorithms consist of recording signal, signal treatment, feature extraction, motion classification and hand control. LDA has the higher offline accuracy, and most of researches had evaluated the performance of LDA and other PRAs. However, it is rarely used for the evaluation of different types of DA. The surface and intramuscular electrodes are considered as the common tools for acquiring signals [12]. In this study, Myo armband was used to collect EMG signals. Myo armband is a wearable gesture control and motion control device for you to control your mobile phone, computer, and so much more, touch-free by Thalmic Labs [13].

The aim of this work was to evaluate the offline performance of LDA and other types of DA from accuracy, training and testing time of them, especially with QDA, and using Myo armband to acquire the EMG signals.

2 Method

2.1 Signal Acquisition and Processing

BioPatRec provides the offline data from the data repository, which was acquired by the disposable Ag/AgCl bipolar electrodes and NI acquisition hardware board. In this paper, Myo armband was used to acquiring EMG signals. The Myo armband is composed of 8 parts connected together with the expandable flex inside the electrical sensors (Fig. 1 [13]) (e.g. medical grade stainless EMG sensors, highly sensitive nine-axis IMU containing three-axis gyroscope, three-axis accelerometer, and three-axis magnetometer) for every part, and could recognize 20 motions. The armband is connected to a device (e.g. phone, computer or tablet and supported for most of systems) through Bluetooth 4.0 Low Energy.

Fig. 1. Myo armband [13]

The placement of the Myo armband was around the forearm proximal third of the forearm, and the part with status LED was placed along the extensor carpi ulnaris. Then a program was developed under Microsoft Visual Studio 2012 environment to read the EMG data saved in csv file, and a creat_recS.m file was developed to save the row data in the structure array recSession which can be later loaded and displayed in BioPatRec GUI. Ten non-amputee subjects participated in this study (six men and four women) with the age of (23 ± 1.25). The sampling rate was set at 200 Hz.

The subjects performed the motion for 3 s, and the relax time was 3 s between each contraction. Repeat each movement for 3 times of 10 movements, including agree (AG), close hand (CH), open hand (OH), extend hand (EH), flex hand (FH), pointer (PT), supination (SP), pronation (PR), side grip (SG), and fine grip (FG), shown in Fig. 2.

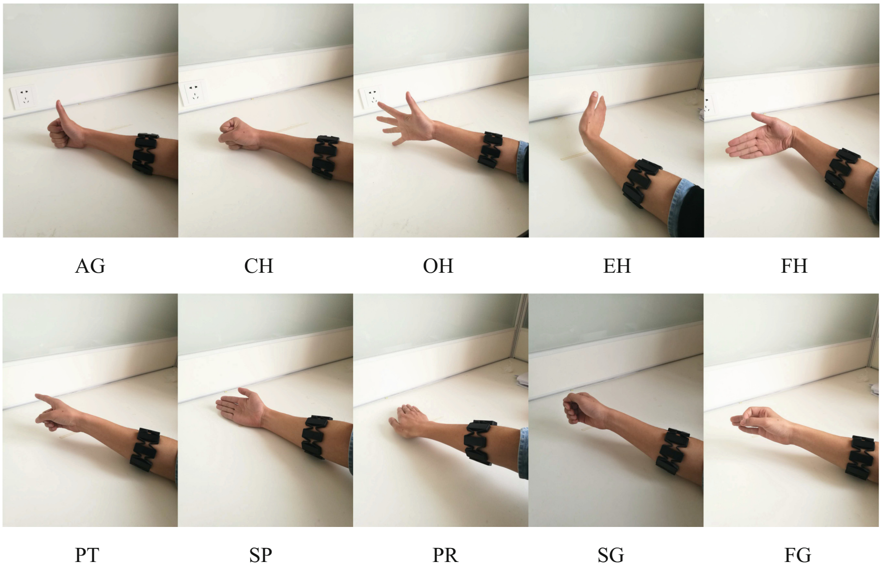

Fig. 2. The ten movements

In order to get the effective information and remain the isotonic contraction, we removed the 15% of the contraction time at the beginning and end of the recording data, which means the contraction percentage (cTp) was 0.7. The acquired data was segmented into 121 time windows of 200 ms with a 50 ms increment. In BioPatRec, there are 4 groups of feature vectors, and we chose the Top 4: mean absolute value, zero crossings, slope sign changes, and wave length time-domain features.

2.2 Offline Pattern Recognition Procedures

Processing the data through applying filters (frequency or spatial), configuring time windows, and selecting the proportion of data sets, mostly is 40%, 20%, and 40% for training, validation and test. Normalization is necessary to unite the weight of standard deviations, otherwise, the learning algorithms would not get the accurate results. Different classifier topologies were applied in different types of classes, including Single, Ago/Antagonist-Mixed, One-Vs-All, One-Vs-One, and All-And-One. Single classifier is the simplest and usually used. In this paper, we chose DA as the pattern recognition algorithm, and training the data with five types of DA. The offline pattern recognition procedures are shown in Fig. 3.

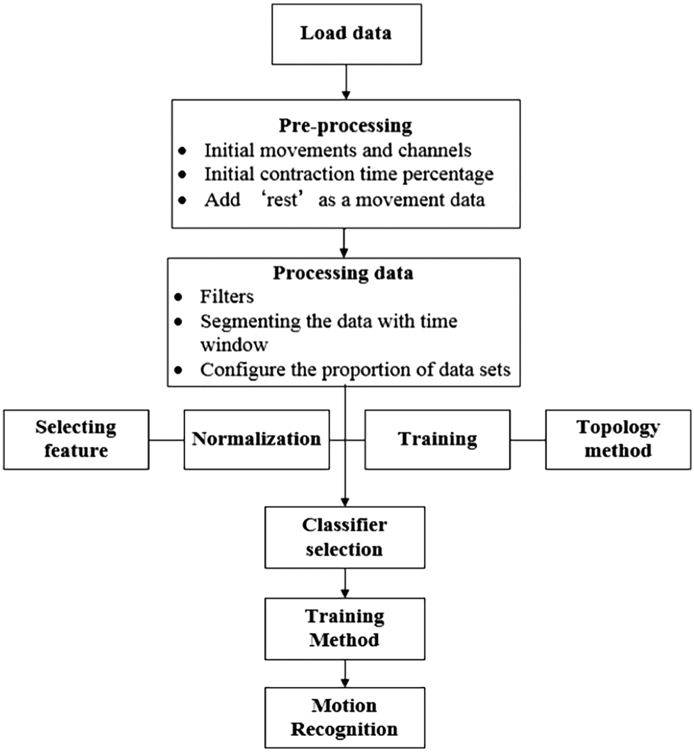

Fig. 3. Offline pattern recognition in BioPatRec

2.3 Pattern Recognition Algorithms

This paper aims to compare the Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) performance for offline performance.

LDA and QDA are both statistic methods Gaussian Maximum-likelihood based on Bayes' rule [14, 15]. LDA is build a linear function to separate the data by minimizing the inter-class distance with linear boundaries and maximizing the intra-class distance, and the all groups have the equal covariance matrices. QDA could learn the quadratic boundaries, and has different covariance matrices with different classes, which is more complicated than LDA.

3 Results

The offline accuracy and training time are shown in the box plots where the central line represents the median value; the edges of the box are the 25th and 75th percentiles; the whiskers give the range of data values; the diamond markers represent the mean values; and there were no outliers located within ±2.7σ in the data.

The average offline accuracy of Linear, Diaglinear, Quadratic, Diaquadratic, and Mahalanobis was 94.4 (±1.0%), 86.5 (±1.6%), and 96.5 (±0.7%), 89.87 (±1.3), and 95.3 (±0.6), respectively, which is illustrated in Fig. 4. The average training time was 0.100 s (±0.006 s), 0.123 s (±0.008 s), 0.115 s (±0.004 s), 0.112 s (±0.013 s), and 0.119 s (±0.011 s) for Linear, Diaglinear, Quadratic, Diaquadratic and Mahalanobis, respectively, shown in Fig. 5.

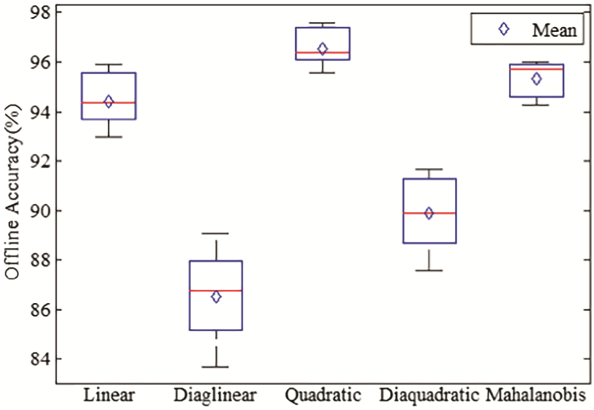

Fig. 4. Offline accuracy for five types of DA

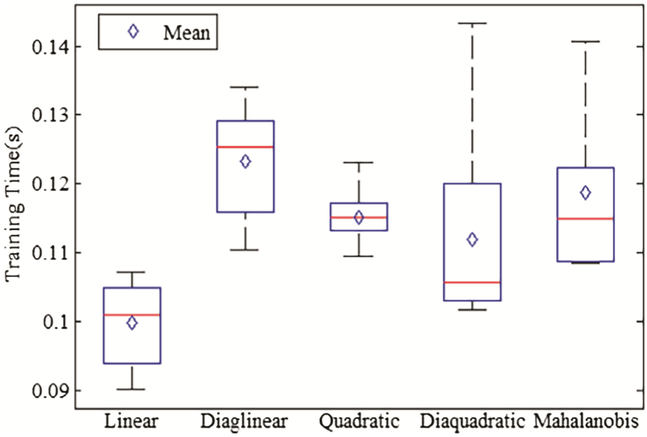

Fig. 5. Training time for five types of DA

The average testing time was 0.629 ms (±0.029 ms), 0.598 ms (±0.005 ms), 1.038 ms (±0.048 ms), 1.007 ms (±0.004 ms), and 1.032 ms (±0.045 ms) for Linear, Diaglinear, Quadratic, Diaquadratic, and Mahalanobis, respectively. The results are illustrated in Fig. 6. The average testing time of LDA is approximately half of the QDA.

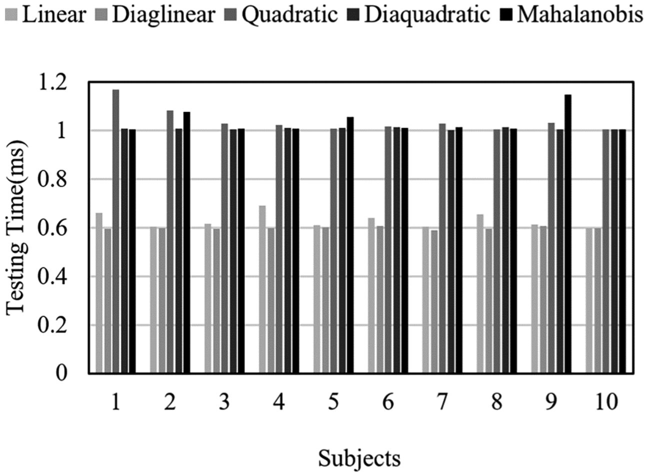

Fig. 6. Testing time for five types of DA

The average accuracy of every movement for the LDA and QDA is shown in Fig. 7. For LDA, the average accuracy was 100%, 100%, 99.8%, 86.5%, 99,8%, 95.7%, 87.3%, 73,7%, 98.2%, and 99.4% for AG, CH, OH, EH, PT, SP, PR, SG, and FG, respectively. For QDA, the average accuracy was 100%, 100%, 99.6%, 98.2%, 99.1%, 98.0%, 86.7%, 100%, and 99.0% for AG, CH, OH, EH, PT, SP, PR, SG, and FG, respectively. The

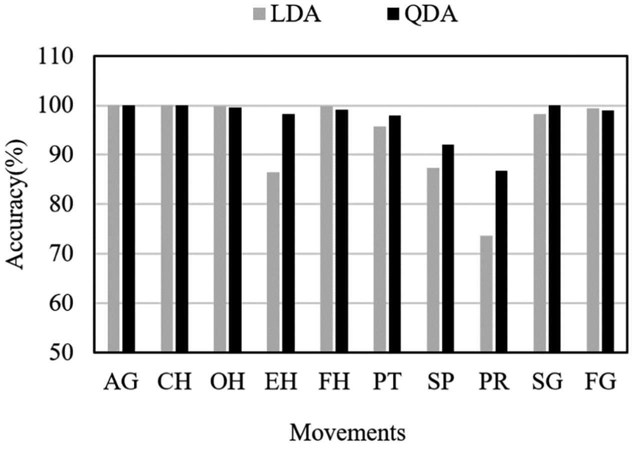

Fig. 7. Offline accuracy of 10 movements for LDA and QDA

lowest accuracy movement of LDA and QDA was both pronation, and the AG, CH, OH, FH, SG, and FG had the extremely high accuracy.

4 Conclusions

The offline results show that LDA and QDA have a better performance for motion classification. The offline average accuracy of them can be higher than 90%, and without statistic difference of the training/validation time between them, but LDA is more stable and lower than QDA. The testing time of LDA is approximately half of the QDA, because the QDA's quadratic boundaries and complicated computing algorithm. LDA finds a linear function, which is more popular and simpler with the fastest training and testing time and used extensively in previous research. QDA could be applied in more complicated classes and massive data. The pronation had the lowest accuracy among the movements for both LDA and QDA. It is likely to be influenced by many factors, such as the placement of the Myo armband, and the subjects' attention and motivation would influence the results. When the amount of training data is relatively small, the LDA is better than QDA. It is necessary to reduce the variance of the QDA model. If the training data contains a large amount of observation data, it will be more likely to use QDA, and the variance of the classifier is no longer a major issue.

In summary, this work aims contribute to the recovery of the post-stroke patients' hand functions. Comparing with motormechanical systems, EMG signals should be seen as the more effective and interactive approach in this aspect. In the future, we could evaluate the real-time classification by the motion test or the Target Achievement Control (TAC) test with Myo armband.

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