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Procedia Computer Science 76 (2015) 223 – 228

Procedia Computer Science

2015 IEEE International Symposium on Robotics and Intelligent Sensors (IRIS 2015)

Electromyography (EMG) based Classification of Neuromuscular Disorders using Multi-Layer Perceptron

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Abstract

Electromyography (EMG) signals are the measure of activity in the muscles. The aim of this study is to identify the neuromuscular disease based on EMG signals by means of classification. The neuromuscular diseases that have been identified are myopathy and neuropathy. The classification was carried out using Artificial Neural Network (ANN). There are five feature extraction techniques that were used to extract the signals such as Autoregressive (AR), Root Mean Square (RMS), Zero Crossing (ZC), Waveform length (WL) and Mean Absolute Value (MAV). A comparative analysis of these different techniques were carried out based on the results. The Multilayer Perceptron (MLP) was used for carrying out the classification.

Peer-review under responsibility of organizing committee of the 2015 IEEE International Symposium on Robotics and Intelligent Sensors (IRIS 2015)

Keywords: Electromyography (EMG); Neuromuscular Disease; Feature Extraction; Classification; Autoregressive method (AR); Root mean square (RMS); Zero Crossing (ZC); Waveform length (WL) and Mean Absolute Value (MAV); Multilayer Perceptron (MLP)

1. Introduction

An electromyography (EMG) is a measurement of the electrical activity in muscles as a byproduct of contraction.

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Peer-review under responsibility of organizing committee of the 2015 IEEE International Symposium on Robotics and Intelligent Sensors (IRIS 2015)
doi:10.1016/j.procs.2015.12.346

An EMG is the summation of action potentials from the muscle fibers under the electrodes placed on the skin. The more muscles that fire, the greater the amount of action potentials recorded and the greater the EMG reading. The acquisition of Motor Unit Action Potentials (MUAPs) during EMG examination would help to provide the important information for the estimation of neuromuscular disorders[1].

The parametric extraction that used from EMG signals is one of the important steps to determine the feature vector. Feature selection provides the indications for choosing the best feature for classification based on several criteria. This is the reason why feature extraction plays an important role in artificial neural network systems for the classification purpose.

ANNs have gained a lot of success over the previous years as a powerful technique to solve many real world problems[2]. Although there are various types of ANNs like Multilayer Perceptron (MLP), Radial Basic Function (RBF) and Kohonen network[3], but, the most widely used learning algorithm in ANN is the Back-propagation algorithm. The application of ANNs can be used for forecasting and prediction, classification and diagnostic, pattern recognition and estimation and control, system identification, parameter estimation and optimization[4].

In this paper, the use of MLP for classifying the neuromuscular disorders based on Electromyography (EMG) is presented. Section 2 presents the materials and methods and followed by results and discussion in section 3. Finally, section 4 presents the conclusion.

2. Materials and Methods

2.1 Types of Neuromuscular Disorders

In this research, there are two types of neuromuscular disorders are classified separately as myopathy and neuropathy with healthy subjects used as control. They are described in the following:

- Healthy: a person who is not affected by a disease nor damaged muscle so that he or she is able to move freely at any time.
- Myopathy: is a muscular disease in which the muscle fibres do not function for many reasons, resulting in muscular weakness. Other symptoms of myopathies can include as muscle cramps, stiffness, and spasm.
- Neuropathy: is damage to a single nerve or nerve group, which results in loss of movement, sensation, or other functions of nerve[5].

2.2 Database

All the EMG data were obtained from an EMG lab database[6]. The EMG signals were obtained from many subjects (healthy subjects and subjects suffering from neuropathy and myopathy) with different of mean age. In this research, Myopathy/Neuropathy data has been simulated for 25% fibre/motor unit involvement signals that are used for feature extraction and classification. There are 5 patients for each group that are divided into 100 samples as shown in Table 1.

Table 1. Table of different type of EMG signal taken from patients

Group	Fibre/motor unit	Type of Muscle	Number of patients	Number of samples
Healthy	25 %	Bicep	5	100
Myopathy	25 %	Bicep	5	100
Neuropathy	25 %	Bicep	5	100

2.3 Development of Classification

The development of classification involved steps such as EMG signal acquisition, filtering, feature extraction and classification. The EMG signals were obtained from many subjects (healthy subjects, subjects suffering from neuropathy, subjects suffering from myopathy) with different mean age that was saved in a database. The signal is then filtered by using the filter such as high-pass filter, low-pass filter and notch filtering[7]. Thereafter, features were extracted using several feature extraction techniques such as autoregressive coefficient, root mean square, mean absolute value, zero crossing, etc.

A neural network was used for classification. The algorithm used in this method is back-propagation[8,9]. A commonly used feed-forward network is MLP with popular activation function of sigmoid. From the data that was calculated above after using filter and feature extraction, five different datasets were created and labeled as shown in Table 2.

Table 2. Five different datasets divided into five groups

Group	Description
Group 1	healthy / unhealthy (abnormal)
Group 2	healthy / myopathy
Group 3	healthy / neuropathy
Group 4	myopathy / neuropathy
Group 5	healthy / myopathy / neuropathy

In this classification, 10 input, 50 hidden and 3 output units were chosen based on different groups. Assuming that there are 300 samples with 100 samples from each class, the data is divided into three sets for training, testing and validation. In order to make the neural network training more accurate, the input feature vectors were normalized so that they fall in the range [0.1, 0.9]. The correct category corresponds with variable 0.9 and the other will be variable 0.1, and the output of the training is divided into 3 groups as shown in Table 3.

Table 3. Group of three stages of Healthy, Myopathy and Neuropathy

Group/Types	Healthy (NOR)	Myopathy (MYO)	Neuropathy (NEU)
Healthy	0.9	0.1	0.1
Myopathy	0.1	0.9	0.1
Neuropathy	0.1	0.1	0.9

In this research, EMG signals that were divided into healthy, myopathy and neuropathy and used in order perform the classification using MLP. For developing the classifiers, 300 samples were randomly taken from the database to become a training data (60 samples), validation data (20 samples) and testing data (20 samples) from each group is shown in Table 4.

Table 4. Group of number of Training and validation data

Group/Types	Training data	Validation data	Testing data	Total
Healthy	60	20	20	100
Myopathy	60	20	20	100
Neuropathy	60	20	20	100
Total	180	60	60	300

A training rate of 0.001 and momentum coefficient of 0.95 was found optimum for this training network by using error-backpropagation algorithm training.

3. Result and Discussion

Fig. 1 (a) to (c) show the different EMG signals.

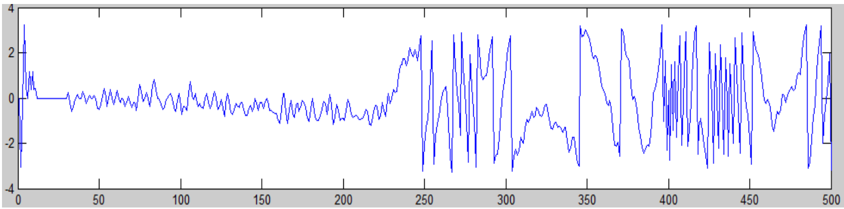

Fig. 1 (a). Myopathy EMG signals

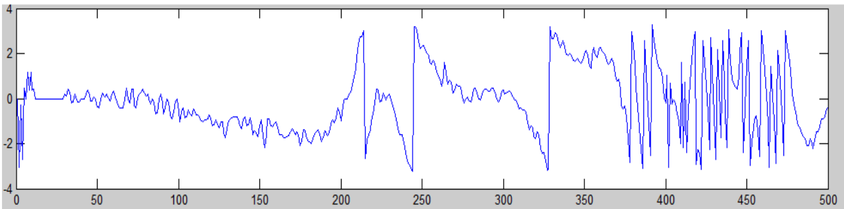

Fig. 1 (b). Neuropathy EMG signals

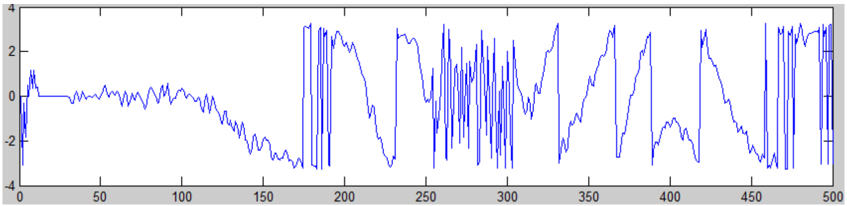

Fig. 1 (c). Healthy EMG signals

To obtain best classification, five different methods from feature extraction were used as the input of the training. They are Autoregressive, Root mean square, Mean absolute value, Zero crossing and Waveform length. The result of accuracy for each testing group based from each feature extraction is used to compare with other results are as shown in Table 5.

Table 5. Classification result obtained on EMGs signal

Classification of group	Number of class	Number of data sample per class	Classification accuracy (%)				
			Auto regressive (AR)	Root mean square (RMS)	Mean absolute value (MAV)	Zero Crossing (ZC)	Waveform length (WL)
Healthy / unhealthy	2	100/100	81.75%	82.5%	80.5%	81.75%	82.5%
Healthy / myopathy	2	100/100	83%	77.5%	82%	79.5%	81%
Healthy / neuropathy	2	100/100	83.5%	83.5%	75%	82.5%	80.5%
Myopathy/neuropathy	2	100/100	82.5%	78.5%	77.5%	77%	77%
Healthy / myopathy / neuropathy	3	100/100/100	86.3%	78.7%	82%	76.3%	75.7%

Based on Table 5, the classification accuracy results between each different group using different feature extraction are shown clearly with the percentage and the best feature extraction is highlighted to demonstrate the highest accuracy in each group. From the group 1 with healthy and unhealthy subjects, the Root Mean Square (RMS) and Waveform Length (WL) yielded the highest result of classification accuracy (82.5%); for group 2 with healthy and myopathy subjects, the Auto regressive produced the top result with 83%; Similarly, from group 3 with healthy and neuropathy subjects, there are two techniques from feature extraction that produced highest result from classification; they are, Auto regressive (AR) and root mean square (RMS) that produced similar results with 83.5%. And from group 4 and group 5, the highest result comes from Autoregressive also with the percentage is 82.5% (myopathy and neuropathy) from group 4, and 86.3% from group 5 (healthy, myopathy and neuropathy).

Fig. 9 indicates the classification accuracy for five groups. The highest success are from two classes, i.e., from healthy and neuropathy with 83.5%. This shows that healthy and neuropathy groups are the most distinguishable when comparing with the other groups such as healthy / myopathy and myopathy /neuropathy.

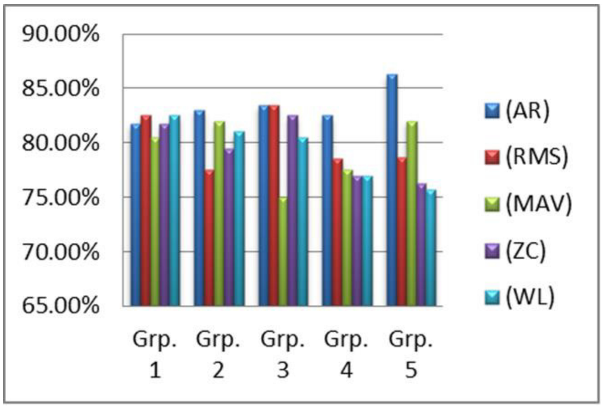

Fig. 2. The classification accuracy for five groups.

Most of the highest result of classification comes from Autoregressive (AR) methods, four over five groups are classified as the best result from feature extraction techniques. The Root mean square (RMS) can get the two over five of highest result. The Mean Absolute Value (MAV) and Zero Crossing (ZC) can show that they are hard to get better result than others. The results are important to determine the best technique used in feature extraction for classification purposes. Autoregressive is still the good method that can be applied in feature extraction to get high accuracy for classification. The other methods such as Root Mean Square, Zero Crossing, Wavelength, Mean Absolute Value are still suitable methods for feature extraction.

4. Conclusion

ANN architecture is successfully developed for identification of EMG signals. Multilayer Perceptron (MLP) is useful tool to classify the EMG signals with three different groups such as healthy, myopathy and neuropathy. The future work could use all these feature extraction technique with other classification methods such as K-nearest neighbor (K-nn) and Support Vector Machine (SVM). Each has different advantage and its limitation. All these techniques can be explored further.

Acknowledgement

The authors would like to thank Ministry of Education (MOE) for sponsoring the project under grant entitled 'Development of EMG-based Decision Support Tool for Diagnosis of Neuromuscular Disorders' (Grant no. 0153AB-I31).

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