Wavelet Neural Network Based Emg Signal Classifier

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Abstract

Classification of EMG signals is an important area in biomedical signal processing. Several algorithms have been developed for classification of EMG signals. These techniques extract features, which are either temporal or a transformed representation of the EMG waveforms. Artificial Neural Networks (ANN) trained with BP algorithm classifies the applied input EMG to an appropriate class which either normal or abnormal muscular responses.

This paper shows an approach for EMG signal processing based on ANN and transform domain (Discrete Wavelet Transform (DWT) in order to perform automatic analysis using personal computers. The Neural Networks (NN) are introduced to solve different pattern recognition problems associated with EMG analysis. A Multi-Layer Perceptron (MLP) NN is used in the present work with Back Propagation (BP) algorithm to train the proposed network.

1. Introduction

Electromyography is the discipline that deals with the detection, analysis, and use of the electrical signal that emanates from contracting muscles. This signal is referred to as the electromyographic (EMG) signal.

An example of the EMG signal can be seen in Fig. 1. Here the signal begins with a low amplitude, which when expanded reveals the individual action potentials associated with the contractile activity of individual (or a small group) of muscle fibers. As the force output of the muscle contraction increases, more muscle fibers are activated and the firing rate of the fibers increases. Correspondingly, the amplitude of the signal increases taking on the appearance and characteristics of a Gaussian distributed variable [1].

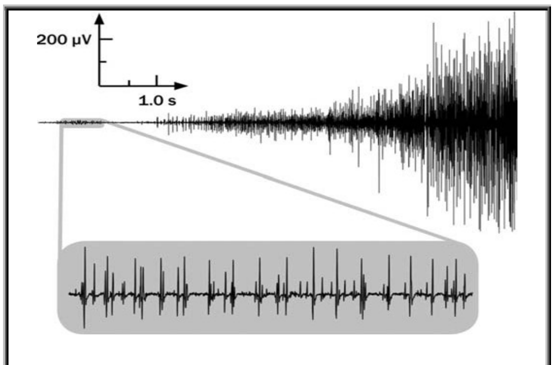

Figure (1). The EMG signal recorded with surface electrodes located on the skin above the first dorsal interosseous.

The nervous system always controls the muscle activity (contraction / relaxation). Hence, the EMG signal is a complicated signal, which is controlled by the nervous system and is dependent on the anatomical and physiological properties of muscles. EMG signal acquires noise while traveling through different tissues. Moreover, the EMG detector, particularly if it is at the surface of the skin, collects signals from different motor units at a time, which may generate interaction of different signals [2].

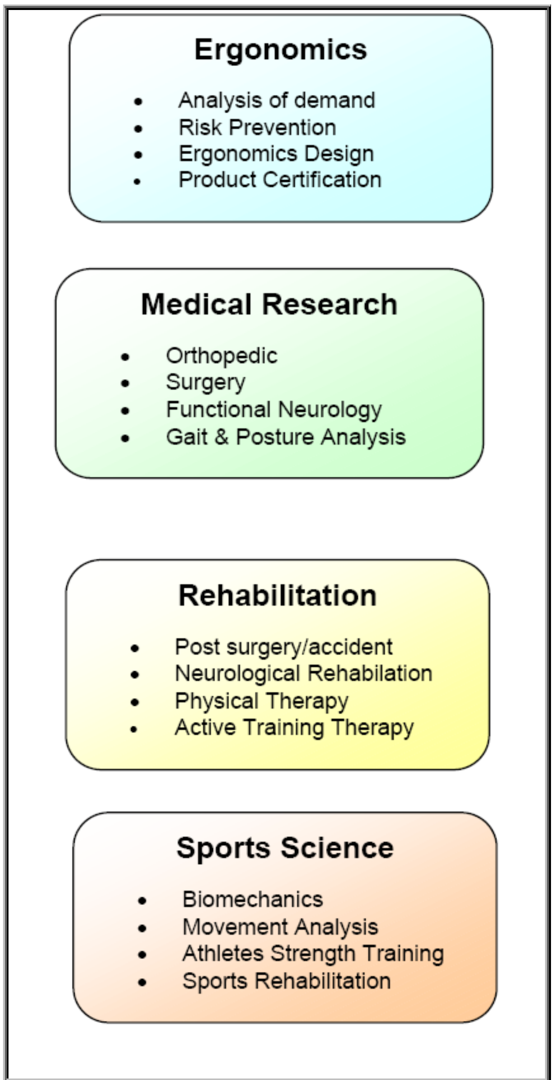

Figure (2). The EMG Aspects.

Detection of EMG signals with powerful and advance methodologies is becoming a very important requirement in biomedical engineering. The main reason for the interest in EMG Besides basic physiological and biomechanical studies, kinesiological EMG is established as an evaluation tool for applied research, physiotherapy / rehabilitation, sports training and interactions of the human body to industrial products and work conditions, Fig. 2 explains the wide spread use of EMG signal [3].

However, a number of problems are associated with the recording and the analysis of the transient EMG signal. A main problem is due to the noisy character of the signal. The noisy character is due to the fact that several muscle activations that occur simultaneously are recorded from the electrode(s) that are attached to the skin. What is actually being recorded is the superposition of several muscle activations filtered through different transfer paths of the surrounding tissues and the skin itself [4].

EMG signals are nonstationary and have highly complex time–frequency characteristics. Consequently, these signals cannot be analyzed using classical methods such as Fourier transform. Although the short time Fourier Transform can be used to satisfy the stationarity condition for such nonstationary signals, it suffers from the fact that the performance depends on choosing an appropriate length of the desired segment of the signal. To overcome such problem, Wavelet Transform has been widely used in signal analysis [5].

An important requirement in this area is to accurately classify different EMG patterns for controlling a prosthetic device. For this reason, effective feature extraction is a crucial step to improve the accuracy of pattern classification; therefore, many signal representations have been suggested.

The wavelet transform have been successfully applied with promising results in EMG pattern recognition by Englehart and others [5,6]. The discrete wavelet transform (DWT) and its generalization, the wavelet packet transform (WPT), were elaborated in (Englehart. These techniques have shown better performance than the others in this area because of its multilevel decomposition with variable trade-off in time and frequency resolution. The WPT generates a full decomposition tree in the transform space in which different wavelet bases can be considered to represent the signal. Amount of coefficients, since the transform space has very large dimension. This fact suggests the system-atic application of feature selection or projection methods and dimensionality reduction techniques to enable the methodology for real time applications. The techniques were applied to feature extraction from surface EMG signals [6].

This paper continues the work described above by taking different families of Wavelet transform and studies the coefficients of them after passing the training and validate in the neural network.

3. Raw EMG signal

An unfiltered (exception: amplifier band pass) and unprocessed signal detecting the superposed Multi Unit Action Potentials (MUAP) is called a raw EMG Signal. As given below (Fig.3), a raw surface EMG recording (sEMG) was done for three static contractions of the biceps brachii muscle:

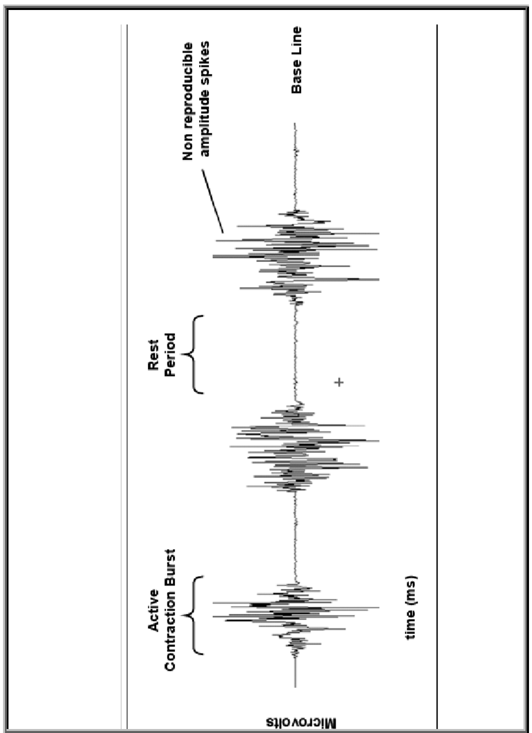

Figure .(3) The raw EMG recording of three contractions the Muscle biceps brachii.

When the muscle is relaxed, a more or less noise–free EMG Baseline can be seen. The raw EMG baseline noise depends on many factors, especially the quality of the EMG amplifier, the environment noise and the quality of the given detection condition. Assuming a state-of-the-art amplifier performance and proper skin preparation, the averaged baseline noise should not be higher than 3 – 5 microvolts, 1 to 2 should be the target. The investigation of the EMG baseline quality is a very important checkpoint of every EMG measurement.

The healthy relaxed muscle shows no significant EMG activity due to lack of depolarization and action potentials! By its nature, raw EMG spikes are of random shape, which means one raw recording burst cannot be precisely reproduced in exact shape. This is due to the fact that the actual set of recruited motor units constantly changes within the matrix / diameter of available motor units: If occasionally two or more motor units fire at the same time and they are located near the electrodes, they produce a strong superposition spike! By applying a smoothing algorithm (e.g. moving average) or selecting a proper amplitude parameter (e.g. area under the rectified curve), the non- reproducible contents of the signal is eliminated or at least minimized.

Raw sEMG can range between +/-5000 microvolts and typically, the frequency contents ranges between 6 and 500 Hz, showing most frequency power between ~20 and 150 Hz [3].

3.1 Factors influencing the EMG signal

On its way from the muscle membrane up to the electrodes, the EMG signal can be influenced by several external factors altering its shape and characteristics. They can be grouped in [3]:

1) Tissue characteristics.
   The human body is a good electrical conductor, but unfortunately, the electrical conductivity varies with tissue type, thickness (Fig. 4), physiological changes and temperature. These conditions can greatly vary from subject to subject (and even within subject) and prohibit a direct quantitative comparison of EMG amplitude parameters calculated on the unprocessed EMG signal.
2) Physiological cross talk.
   Neighboring muscles may produce a significant amount of EMG that is detected by the local electrode site. Typically this “Cross Talk” does not exceed 10%-15% of the overall signal contents or is not available at all. However, care must been taken for narrow arrangements within muscle groups. ECG spikes can interfere with the EMG recording, especially when performed on the upper trunk / shoulder muscles. They are easy to see and new algorithms are developed to eliminate them.
3) Changes in the geometry between muscle belly and electrode Site.
4) External noise.
5) Electrode and amplifiers.

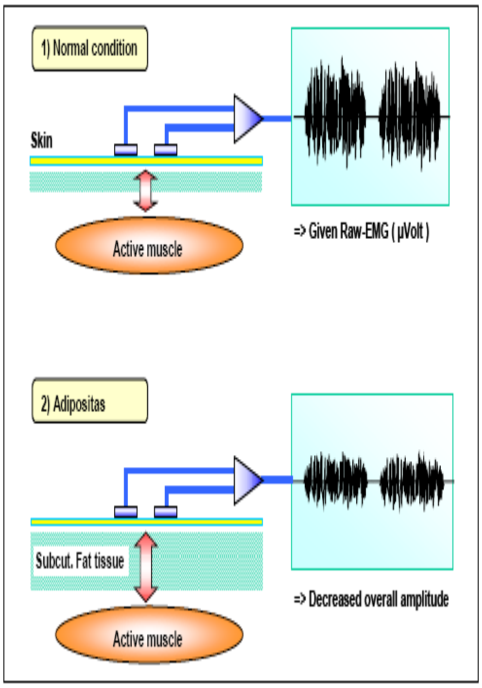

Figure. (4) The influence of varying thickness of tissue layers below the electrodes.

3.2 EMG signal processing

Raw EMG offers us valuable information in a particularly useless form. This information is useful only if it can be quantified. Various signal processing methods are applied on raw EMG to achieve the accurate and actual EMG signal. Reza et al [2] discussed the major EMG signal processing methods used currently.

3.3 Wavelet Transform

Wavelet transforms are used to decompose the original signal into a set of coefficients that describe the signal frequency content at given times. The continuous wavelet transform is defined as [7]:

$$CWT = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t)\, h\left(\frac{t-b}{a}\right) dt \qquad (1)$$

where a and b are the dilation and translation parameter, respectively.

An efficient way to compute the Discrete Wavelet Transform (DWT) is to convolve the signal with a pair of appropriately designed quadrature mirror filters (QMF) and then down sample by a factor of two. The QMF pair which decomposes the signal consists of a low pass filter H and a high pass filter G which split the signal bandwidth to half [8]. In the present work DWT coefficients are used as a features extracted from the EMG to be to the neural networks to classify them into normal and abnormal EMG.

4. PATIENTS AND TOOLS USED

The block diagram of the proposed system is shown in Fig.5. In this work, we tested two cases of EMGs for butterfly exercises one with 5 kg and the other with 10 kg. For each one of the two cases, three different volunteers with three different muscles locations for each one of them have been taken, right pectoralis, right biceps and right triceps. In total, twenty one data files have been collected with sampling frequency 2000 Hz [8], with 4000 samples length for each file.

The analysis of these data files started with converting them to .mat files and then removes any DC offset to be ready for the Wavelet families' analysis.

MATLAB software package version 7 is used to implement the software for the current work.

4.1 Feature extraction

It is basically impossible to apply any classification method directly to the EMG samples, because of the large amount and the high dimension of the examples necessary to describe such a big variety of clinical situations. A set of algorithms from signal conditioning to measurements of average wave amplitudes, durations, and areas, is usually adopted to perform a quantitative description of the signal and a parameter extraction [9].

On this set of extracted EMG parameters, several techniques for medical diagnostic classification are then applied, such as probabilistic approaches, heuristic models, and knowledge-based systems.

The aim of this work is to determine suitable input feature vectors which w discriminate between normal and abnormal EMG signals [10].

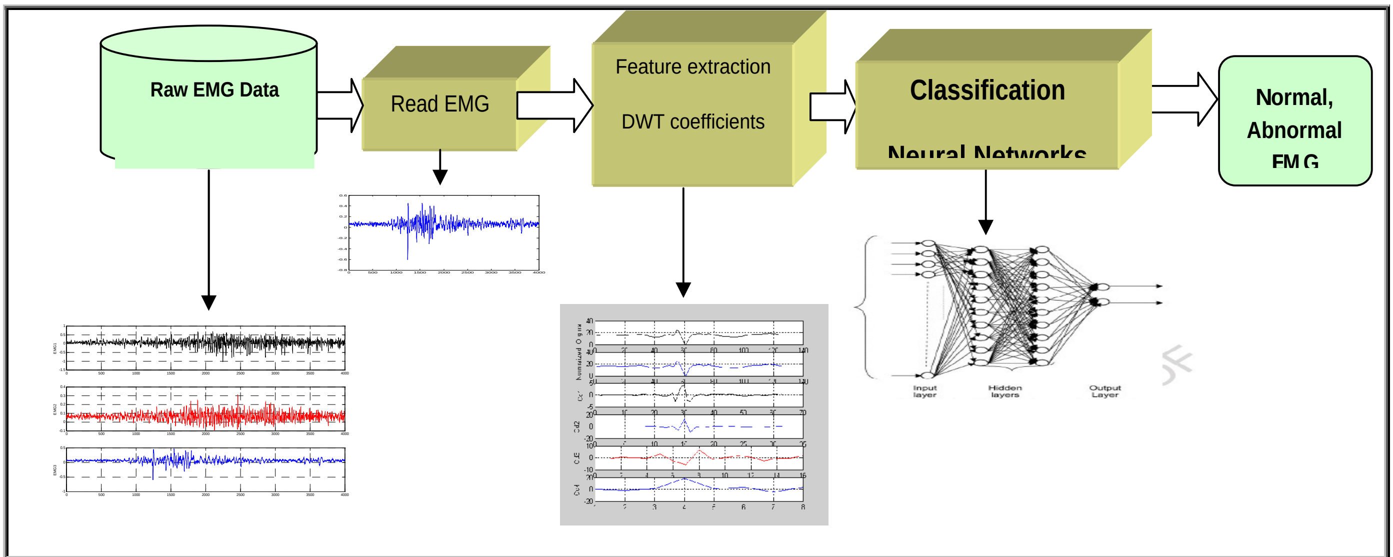

Figure (5). Block diagram of EMG classification system

4.2 DWT coefficients extraction

In the present work Db4 and Haar wavelet have been used as the mother wavelets. MATLAB software package version 7 is used to extract the DWT coefficients. For achieving good time-frequency localization, the preprocessed EMG signal is decomposed by using the DWT up to the fourth level. The smoothing feature of Haar wavelets and Db4 made them more suitable to EMG changes and the feature set is composed of level 1,2,3, 4 coefficients cd1,cd2 cd3,cd3 and ca4. Most of the energy of the EMG signal lies between 0.5 Hz and 40 Hz.

This energy of the wavelet coefficients is concentrated in the lower sub-bands ca4, cd4, and cd3. The level 1, 2 coefficients cd1 and cd2 are the most detail information of the signal and they are discarded. Since the frequency band covered by these levels contains much noise.

It is less necessary for representing the approximate shape of EMG and the frequencies covered by these levels were higher than frequency content of the EMG. Coefficients cd3 and cd4 represent the highest frequency components and ca4 represent the lowest one. For the Db4 wavelets, cd4 having length of 300 coefficients are generated. The DWT coefficients of Haar and Db4 wavelets of EMG signal of sample no. 7 are shown in Fig.6 and Fig.7, respectiveely. For the Haar wavelets, cd4 having length of 250 coefficients are generated.

The obtained feature vectors form Db4 and Haar wavelets decomposition are used as an input to the NN classifier. The above procedure of decomposition is done for the 21 EMG signals for both normal and abnormal muscles with both myopathy and neuropathy.

4.3 Neural networks classifier

In the present work, the neural networks are used for the classification purposes. The neural networks derive their power due to their massively parallel structure, and an ability to learn from experience. They can be used for fairly accurate classification of input data into categories, provided they are previously trained to do so. The accuracy of the classification depends on the efficiency of training. The knowledge gained by the learning experience is stored in the form of connection weights, which are used to make decisions on fresh input.

Three issues need to be settled in designing an ANN for a specific application:

- Topology of the network;
- Training algorithm;
- Neuron activation functions.

In our topology, the number of neurons in the input layer is fixed by the number of elements in the input feature vector. Therefore the input layer has 250 neurons for the first ANN classifiers, 300 neurons for the second using respectively WT (Haar), WT (Db4) methods.

The output layer was determined by the number of classes desired. In our study, the unique neuron of the output layer corresponds to the normal and abnormal muscle. Classification of

EMG is a complicated problem. To solve this two hidden layers are taken in a feed forward neural network. The single hidden layer is set for our two neural classifiers as follows: For the WT (Haar) NN, the hidden layer consists of fifty four neurons. For the WT (Db4) NN, the hidden layer consists of sixty five neurons.

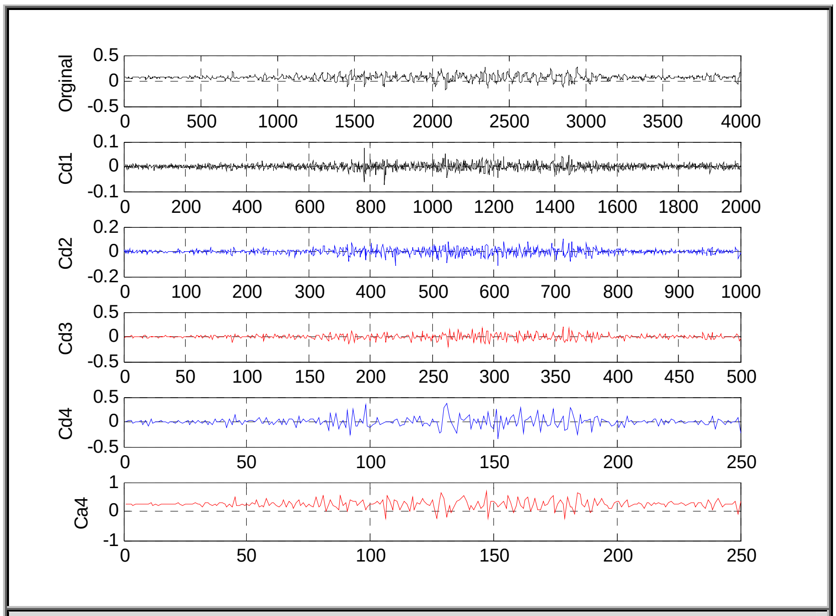

Figure (6). The DWT coefficients of EMG Haar wavelet of level four decomposition

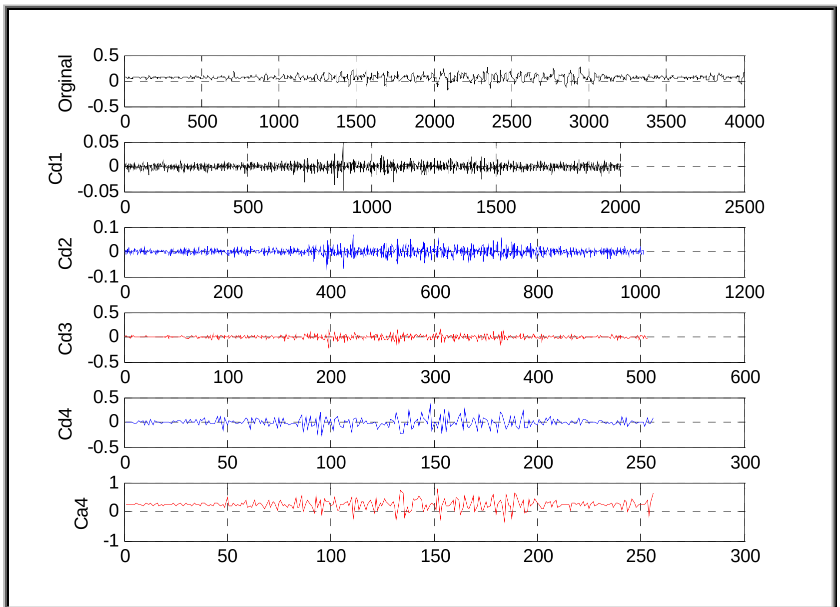

Figure (7). The DWT coefficients of EMG Db4 wavelet of level four decomposition

The BPA is a supervised learning algorithm, which aims at reducing the overall system error to a minimum. The connection weights are randomly assigned at the beginning and progressively modified to reduce the overall mean square system error. The weight updating starts with the output layer, and progresses backwards. The weight update aims at

maximizing the rate of error reduction, and hence, it is termed as 'gradient descent' algorithm. It is desirable that the training data set be large in size, and also uniformly spread throughout the class domains. In the absence of a large training data set, the available data may be used iteratively, until the error function is reduced to an optimum level. For quick and effective training, data are fed from all classes in a routine sequence, so that the right message about the class boundaries is communicated to the ANN.
Before the training process is started, all the weights are initialized to small random numbers. This ensured that the classifier network was not saturated by large values of the weights. In this experiment, the training set was formed by choosing 11 normal and 10 abnormal EMG obtained from the selected cases.
The sigmoid function was used as the neural activation function. The most important reason for choosing the sigmoid as an activation function for our networks is that the sigmoid function f(x) is differentiable for all values of x, which allows the use of the powerful BP learning algorithm.

5. Results and discussion

The performance of the algorithm was evaluated by computing the percentages of Sensitivity (SE), Specificity (SP) and Accuracy of Prediction (AP), the respective definitions are as follows [8]:
Sensitivity: is the fraction of real events that are correctly detected among all real events.

[SE = 100xTP/ (TP+FN)]	2

Specificity: is the fraction of nonevents that has been correctly rejected.

[SP = 100xTN/ (TN+FP)]	3

Accuracy of Prediction: is the prediction rate.

[CP=100x (TP+TN)/ (TN+TP+FN+FP)]	4

where TP was the number of true positives, TN was the number of true negatives, FN was the number of false negatives, and FP was the number of
false positives. Since it is interesting to estimate the performance of classifiers based on the classification of normal and abnormal EMG , the true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) are defined appropriately as shown below:
FP: classifies normal as abnormal.
TP: classifies abnormal as abnormal.
FN: classifies abnormal as normal.
TN: classifies normal as normal.
In our study, the unique neuron of the output layer corresponds to the normal and abnormal EMG. In practice, the number of neurons in the hidden layer varies according to the specific recognition task and is determined by the complexity and amount of training data available. If too many neurons are used in the hidden layer, the network will tend to memorize the data instead of discovering the features. This will result in failing to classify new input data. Fig.8 displays the error of the training of the network versus epoch's number. The resulted accuracy and sensitivity for BPNN-Db4, BPNN-Haar are shown in Table 1.

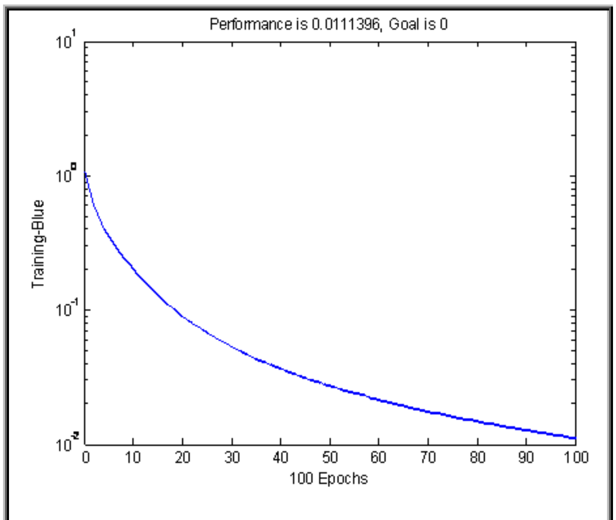

Figure (8). Error of the training versus epochs

6. Conclusions

EMG signals of the human generated by the muscle non-stationary signals. A method based on signal processing techniques is used for data acquisition of the EMG cases.
In the present work, classification of EMG patterns was achieved by means of DWT combined with Back Propagation neural

networks. In its current form, BP algorithm uses the gradient descent to train the network. The objective is to minimize the BP error to reach the desired response. WD process is used to remove different types of noise corrupted to the EMG samples. The EMG signal can be used as a reliable indicator of muscular diseases. In the present work, DWT and the neural network classifier are presented as diagnostic tools to aid the physician in the analysis of muscular diseases. A wavelet based neural network classifier has been proposed for EMG classification. The feature set has been carefully chosen to have enough information for good accuracy. The average accuracy of recognition for "Haar" wavelets was (88%) whereas the obtained accuracy for the "Db4" wavelets is fund to be (91%). The result showed that Db4 wavelets is a good and promoting for non stationary signals classificationThis feature set is a subset of DWT coefficients based on 'Haar' and 'Db4' wavelets.

7. References

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الذكاء الاصطناعي لتصنيف اشارة العضلة

علي حسين علي التميمي ،نبراس حسين غائب وطه ياسين خلف

قسم هندسة الطب الحياتي-كلية هندسة الخوارزمي- جامعة بغداد

الخلاصة

ان تصنيف اشارة العضلة الكهربائية هو مجال مهم في معالجة الاشارة الطبية الرقمية. تم تطوير خوارزميات متعددة لتصنيف اشارة العضلة الكهربائية.يقدم البحث طريقة لتصنيف اشارات العضلات بأستعمال تحويل المويجة والشبكات العصبية الاصطناعية.تم الحصول على عدد من العوامل بأستعمال تحويل المويجة.استعملت هذه الفحوصات كمدخلات للشبكة العصبية الاصطناعية.تم أختبار كفاءة الخوارزمية، تم حساب الدقة للشبكة ووجد انها ٩١% ومن هذا البحث نستنتج ان النظام المقترح يعطي تصنيف جيد ودقيق لامراض العضلات.