A Complete Model for EMG Signal Filtration, Feature Extraction and Classification using ICA Wavelet and SVM

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Abstract: A precise and computationally efﬁcient method for classification of electromyography (EMG) signal has been the subject of extensive research in recent history. Because of its importance in prognosis of neuromuscular diseases and applicability in development of man machine interfaces. In this study, we presented a complete model of EMS signal classification which covers the filtration, feature extraction and classification. In the presented model the independent component analysis (ICA) with some filters is used for filtration of raw EMG signals then after the features of the signals are extracted using discrete wavelet transform (DWT) after that these coefficients are used as training vectors for the support vector machine (SVM) which finally trained to perform the classification. The performance of the presented technique is evaluated by extensively testing the algorithm for various conditions like number of training samples, duration of samples, level of decompositions and type of kernel function, similarly the different performance measures like TPR, FPR, Accuracy, F-measure etc. are calculated. The results obtained by simulation shows that the presented algorithm provides excellent accuracy.

Keywords: EMG, ICA, DWT, SVM.

1. Introduction

Presently a number of neuromuscular diseases that inﬂuence the spinal cord, nerves or muscles are identified. Early ﬁnding and analysis of these diseases by clinical examination and pathological tests is required for their better treatmentsand also for preventing the upcoming generation through pre-birth conclusion and hereditary advising. These information can also provide significant helps in examination, which may prompt the understanding of the nature and possible treatment of these diseases. The EMG signal is a biomedical signal that measures electrical signals produced in muscles when it performs any kind of physical activity. In clinical EMG motor unit potentials (MUPs) are recorded by placing electrodes at location of interest. The MUP reﬂects the electrical activity of a single anatomical motor unit. It is the compound activity potential of all muscle filaments inside the recording electrode. The MUPs is a time domain potential measurement and its characteristics are represented as, amplitude, frequency and phases which can be exceptionally useful in detecting the muscle and nerve diseases especially the frequency measure which is being utilized as the key parameter of clinical practice. Since the MUPs contains the composite signals from all the muscles covered by the electrodes it is difficult to identify the specific motor behavior the difficulties further increases with muscle force which causes higher rate of pulse firing, making it very difﬁcult for the neurophysiologist to identify the individual MUP signals.

2. Literature Review

This section presents the brief review of the related literatures found useful during writing of this paper. A feed-forward error back-propagation artiﬁcial neural networks (FEBANN) and wavelet neural networks (WNN) based classiﬁers for classiﬁcation of EMG signals were developed and compared in [4],[13],[10] which shows that The WNN-based classiﬁer outperformed the FEBANN counterpart. AngkoonPhinyomark et al [1],[8] presented two novel mean and median frequencies (MMNF and MMDF) for robust feature extraction that tolerate with white Gaussian noise (WGN). As a result, noise removal algorithm is not needed. FarzanehAkhavanMahdavi et al [2] presented Wavelet Transform (WT) based technique to extract Surface EMG (SEMG) features, considering it’s consistent with the nature of EMG as a non-stationary signal. They show an improvement in class separability of hand movements in feature space. Furthermore it has been shown features extracted from first and second level of WT decomposition by second order of Daubechies family (db2) yielded the best class separability. A. Phinyomark et al [3],[9],[11] investigated usefulness of extraction of the EMG features from multiple-level wavelet decomposition of the EMG signal using different levels of various mother wavelets for obtaining the useful resolution components from the EMG signal. They also analyzed the component selection criteria for Optimal EMG resolution component (sub-signal) and Noise and unwanted EMG components. M. B. I. Reaz et al [5],[7] illustrate the various methodologies and algorithms for EMG signal analysis to provide efficient and effective ways of understanding the signal and its nature. they further point up some of the hardware implementations using EMG focusing on applications related to prosthetic hand control, grasp recognition, and human computer interaction. A comparison study is also given to show performance of various EMG signal analysis methods. Optimization of the response of an EMG with surface electrodes, used in patients with foot drop through data processing techniques and pattern recognition methods ((i.e. Principal Component Analysis (PCA) and Neural networks (NN) for classification of measures is presented by Cristhian Manuel Durán Acevedo et al [6],[12].

3. EMG Signals

EMG remains for electromyography. It is the investigation of muscle electrical signals. EMG is frequently referred to as myoelectric action. Muscle tissue conducts electrical signals like the way nerves do and the name given to these electrical signals is the muscle activity potential. Surface EMG or sEMG is a strategy for recording the data exhibit in these muscle activities from the skin surface. At the point when distinguishing and recording the EMG signal, there are two primary issues of worry that impact the constancy of the signal. The primary is the signal to-Noiseratio (SNR). That is, the proportion of the energy of EMG signals to the energy of noise signals. As a rule, noise is characterized as electrical signals that are not piece of the expected EMG signal. The other issue is the improper frequency response which may cause different attenuations or gains for different frequencies. Two sorts of anodes have been utilized to get muscle signal: invasiveelectrodes and non-invasive electrodes. At the point when EMG is obtained from electrodes mounted specifically on the skin, the signal is a composite of all the muscle fiber activity potential happening in the muscles inside the skin. These activities happens at arbitrary interims. So at any moment, the EMG signal may be either positive or negative voltage. To reduce these random fluctuations Individual muscle fiber activity potentials are frequently acquired utilizing wire or needle electrodes put straightforwardly in the muscle. The combinations of the muscle fiber activity potentials from all the muscle fibers of a singlemotor unit is called the motor unit activity potential (MUAP) which can be caught by a skin surface cathode (non-obtrusive) found close to this field, or by a needle terminal (intrusive) embedded in the muscle (3). Equation(3.1) demonstrates a basic model of the EMG signal:

Where represents the final EMG signal measured at the surface of the skin at the processing electrode, overall transfer function of MUAP, zero mean white Gaussian noise.

The signalsdetected at the electrodes are firstly amplifiedusing different types of amplifiers generally operational amplifiers are preferred. After amplifying the signal the next important task is to remove the high and low frequency noises which are simply classified by the understanding the expected frequency spectrum of EMG signals.

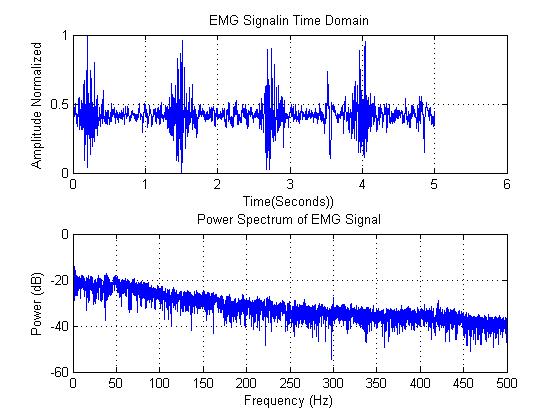
The nervous system of the human body performs both the controlling and communication between different organs of the body. This system comprises of an extensive number of sensitive associated cells called neurons that speak with diverse parts of the body by using electrical signals, which are quick and particular. The nervous system comprises of three fundamental parts: the mind, the spinal cord and the peripheral nerves. The neurons are the fundamental structural unit of the nervous system and differ significantly depending upon its current applicability. Neurons are special cells that direct and operates on messages and used as driving channel for signals within entire body.

A muscle is made out of groups of particular cells equipped for compression and extraction. The essential necessity of these particular cells is to produce movements, for example, speaking running or finger movements for writing. One more special properties of muscle tissue is its electrically controlled extensibility and elasticity. Henceit can be extracted or contracted byelectrical signals. Muscle tissue has four key functions: delivering movement, moving substance inside the body, giving stabilization, and maintaining temperature. Three sorts of muscle tissue can be distinguished on the premise of structure, contractile properties, and control components: (i) skeletal muscle, (ii) smooth muscle, and (iii) cardiovascular muscle. The EMG is connected to the investigation of skeletal muscle. The skeletal muscle tissue is joined to the quick and its compression is in charge of supporting and moving the skeleton. The constriction of skeletal muscle is started by impulses generated by the neurons to willful control of muscles. Skeletal muscle fibers are decently supplied with neurons for its constriction. This specific kind of neuron is known as "motor neuron" and it remains near to muscle tissue, however is not really associated with it. One motor neuron normally supplies incitement to numerous muscle fibers.

4. EMG Signal Characteristics

The unprocessed signal showing the aggregate MUAPs is called a raw EMG Signal. Raw sEMG it's well established that the amplitude of the EMG signal is random (random) in nature and might be fairly delineate by a normal distribution perform. The amplitude of the signal will vary from zero to ten mV (peak-to-peak) or zero to one.5 mV (RMS). The usable energy of the signal is proscribed to the 0 to 500 Hz frequencies vary; with the dominant energy being within the 50-150 Hz varies. Usable signals are those with energy higher than the electrical background level.

During the relaxation of muscle, a reasonably abundant uproarious free EMG Baseline will be seen. The raw EMG baseline noise depends on upon varied elements, significantly the character of the EMG process electronic equipment circuit, the environmental noise and also the nature of the given recognition system. Considering a correct low noise flat band response amplifier with legitimate skin preparation, the captured noise will be decreased to as low as three to five small volts, though it's desirable to cut back it up to 1-2 small volts.



**Figure 1. Time Domain and Frequency Domain Representation of EMG Signal for Normal Person taken from electrode mounted on teardrop musclein relation with the knee movements while theperson is marching.**

5. Noise in EMG Signals

The EMG signals are affected by noise from various sources such as:

Semiconductor Devices Noise: All electronics equipment generates electrical noise and it is an Inherent characteristic of semiconductors used in electronics components. This noise has frequency components that range from 0 Hz to several thousand Hz. This noise cannot be completely eliminated; but can be reduced to acceptable level by using high precision components, intelligent circuit design.

Ambient Noise: This is caused by the sources of electromagnetic radiation, such as cellular phones, RF broadcasts, electrical switching, fluorescent lamps, etc. In general almost any kind of electronic or electrical device may generate the noise. In present scenarios it is virtually impossible to avoid this kind of noise because of unavoidable requirements and adaption of these systems everywhere. However the most of the ambient noise radiation comes from power sources hence limited to 50 or 60Hz, with the amplitude one to three times greater than the EMG signals.

Motion artifacts:it is generally caused either by the interface between the detection surface of the electrode and the skin or the movement of the cable connecting the electrode to the amplifier. This kind of noise affect the signals in the band of 0 to 20Hz and can be avoided by proper fitting outline of the electronic hardware.

Inherent instability of the signal: The amplitude of the EMG signals is inherently quasi-random in nature, especially the frequencies somewhere around 0 and 20 Hz because of the fact that they are influenced by the quasi-random nature of the firing rate of the motor units which, in many cases, fire in this frequency band. Due to the chaotic nature in this frequency bandthey are consider as undesirable noise and filtered from the EMG signals.

5. Circuit Considerations for Noise Reduction in EMG Signals

It is required to get an EMG signal that contains the most accurate measure of data from the raw EMG signal and the minimum influence from electrical noise. Along with these, the amplification of the signal while maintaining signal-to-noise ratio as high as possible is preferable. Following design consideration should be consider for EMG system designing.

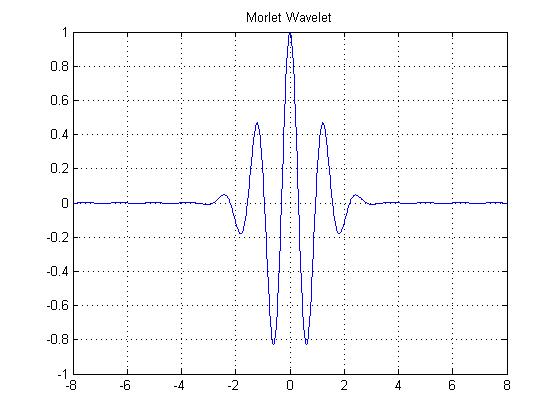
1. Application of Differential Amplifier: since the noise from the power line could be falsely taken as input signal. The differential amplifier can play an important role is such cases because of its high Common mode rejection ratio (CMRR) it can attenuate (reject) the power line noise.
2. Proper impedance matching: the impedance of the measurement circuit when seen from electrode must be very high to avoid loading effect because the skin impedance can reach up to mega ohms, which is easily achievable by operational amplifiers.
3. Measurement Cable Length: a Large cable can easily catch the environmental noises hence it is required to reduce the cable length or place the amplifier with low output impedance at the electrode to avoid such occurrences.
4. Filtering: as we have discussed in previous section a number of noises has their specific spectrum ranges hence a properly designed filter must be used to filter these noises.

6. Wavelet Transform

A ripple could be a signal that contains wave like oscillation with associate amplitude that begins at zero, increases, then decreases back to zero and also the ripple rework could be a reworking methodology that utilizes the properties of those signals. The ripple rework is just like the Fourier rework (or considerably a lot of to the windowed Fourier rework or short term Fourier transform) with a very distinctive basis operate. The principle variations between these two are: Fourier rework disintegrates the signal into sines and cosines, i.e. the reworks confined in frequency domain only; in opposite the ripple rework uses basis functions such the transform shows each the time and frequency domain. Generally, the ripple rework is bestowed by following mathematical expression:

Where represents the complex conjugate of. Here represents the basis wavelet or mother wavelet function, while is called scaling and is called time or translation. From the two useful property of wavelet function can be explained on it has a possible time shifting by using variable while the frequency variation can be performed by hence we can get the frequency information at any specific time also which is not possible with Fourier transform.

There are many basic wavelet function are available such as Haar, Daubechies, Morlet, etc.



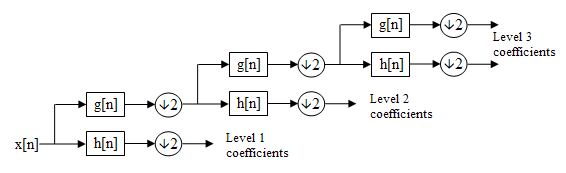
**Figure 2: The Morlet wavelet plot (approximated by 10 iteration)**

6.1 Discrete Wavelet Transform

The discrete wavelet transform (DWT) is a specialized kind of wavelet transform utilizing a discrete set of the wavelet scales and translations complying with some characterized principles. As it were, this transform decomposes the signal into orthogonal set of wavelets, which is the principle contrast from the consistent wavelet transform (CWT), or its execution for the discrete time arrangement at times called discrete-time continuous wavelet transform (DT-CWT).The wavelet can be developed from a scaling function which depicts its scaling properties. The limitation that the scaling function must be orthogonal to its discrete interpretations and fulfill some numerical conditions.

Discrete wavelet transform (DWT), which transforms a discrete time signal to a discrete wavelet representation.It converts an input series, into one high-pass wavelet coefficient series and one low-pass wavelet coefficient series (of length each) given by:

Where and are called wavelet filters (low pass and high pass respectively). This decomposition has halved the time resolution since only half of each filter output characterizes the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled.In practice, such transformation will be applied recursively on the low-pass series until the desired number of iterations is reached.



**Figure 3: DWT cascaded decomposition procedure.**

7. Independent Component Analysis (ICA)

The “standard” ICA algorithm is described in this section. Idea behind the ICA can be simply explained using an example of two separate signalsources and which were mixed by an unknown linearprocess. Let the resultant measure be a mixture of both signals and denoted as, and,then relations amongst the signals can be given as follows:

Where and are unknown coefficients of linear mixing process. Now the problem is to recover the signal and from resultant signals and without anyprior information about the original signals and andthe mixing coefficientsand, although the signals mustbe statistically independent which is fundamental requirement of the ICA concept.

Although we have taken only two sources for the simplicity the presentation can be generalized for number of sources as follows:

Where is called signal source, is the corresponding mixture signal,is the mixing process coefficient between and, and isthe total number of sources and mixture signals. The same thing can be expressed in matrix form as follows:

Where is the matrix of resultant mixture signals, with each row presenting one mixture signal; is the matrix of original signals,in which each rowrepresents one original signal; and is the transformation matrix of mixing coefficients.

As it is already stated that the feasibility of solving the ICA problem tightly bounded with the condition that the sources are statistically independent of eachother.

Since the signals are considered statistically independent then according to the Central Limit Theorem, the sum of independent random variables results a variable with Gaussian distribution. Hence the solution of ICAcan be achieved if the distribution diverges from Gaussian, and this deviation can be determined using negentropy (negative entropy).

Negentropy is one of the many measures of testing of non-Gaussian distribution on the basis of entropy, which is the basic representation of information. The Entropy for a discreterandom variable can be define as follows:

Where is the possible values of of and presents theprobability to being. Similarly for a continuous is defined as:

Where is the PDF (probability distribution function), Now the negentropy, is defined as:

Where is a Gaussian random variable with covariance matrix similar to.However it is already known that for the same variance the Gaussian random variable gives the maximum entropythe value of negentropy is always positive, and it can only be zero in casethe test variable also follows the Gaussian distribution.

The exact estimation from equation (7.7) is computationally complex hence an approximation based approach based on the maximum entropyprinciple is preferred. As presented in equation (7.8)

Where and are constants and can be set to zero, while is a zero mean and unit variance Gaussian random variable. Putting these values the equation (7.8) can be rewritten as:

Where functions and the following formulations for are have been proved veryuseful in practical applications:

Before applying the fundamental transforming operations of the ICA, it is frequently important to perform some preprocessing. Generally, the two separate operations are directed: centering (or forcing to zero mean) and whitening. Centering obliges that the random variable is a zero-mean random variable, and it is performed by subtracting its mean vector. Whitening will make the random variable uncorrelated and set their variances equivalent to zero by utilizing the eigenvalue decomposition of their covariance matrix:

Where presents the eigenvectors and presents the eigenvalues. Now, the new random variable after whitening, can be given as:

After whitening the problem changes from estimating mixing matrix to as follows:

The essential principle of ICA is to discover a direction to maximize non-Gaussianity of , which can be calculated by negentropy as given in equation (7.8) and (7.9).

The basic procedure of thealgorithm.

1. Initialize a weight vector.

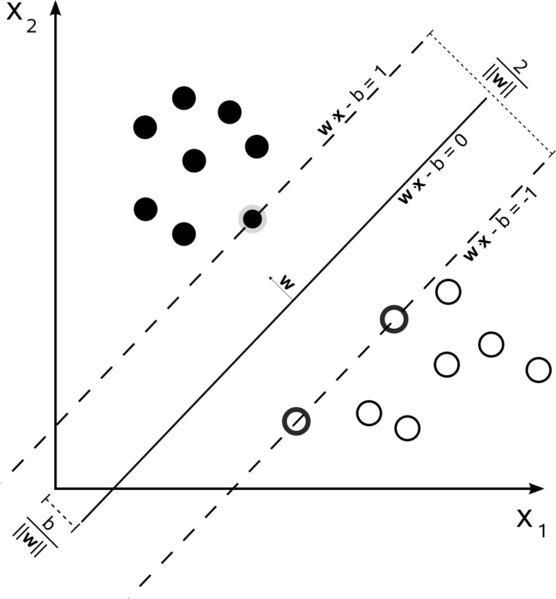
2.Modify the according to the following equation:

Normalize the weight vector as

3. If the weights does not converges (successively calculated weight vectorshaving the same direction), repeat the step 2.

8. SVM classification

Let be a feature vector or a set of input variables and let be a corresponding class label, where is the dimension of the feature vector. In linearly separable cases a separating hyper-plane satisfies [8].



**Figure 4: Maximum-margin hyper-plane and margins for an SVM trained with samples from two classes. Samples on the margin are called the support vectors.**

Where the hyper-plane is denoted by a vector of weights and a bias term. The optimal separating hyper-plane, when classes have equal loss-functions, maximizes the margin between the hyper-plane and the closest samples of classes. The margin is given by

The optimal separating hyper-plane can now be solved by maximizing (8.2) subject to (8.1). The solution can be found using the method of Lagrange multipliers. The objective is now to minimize the Lagrangian

and requires that the partial derivatives of and be zero. In (8.3), are non negative Lagrange multiplier. Partial derivatives propagate to constraints. Substituting ***w***into (8.3) gives the dual form

Which is not anymore an explicit function of or. The optimal hyper-plane can be found by maximizing (8.4) subject to and all Lagrange multipliers are nonnegative. However, in most real world situations classes are not linearly separable and it is not possible to find a linear hyper plane that would satisfy (8.1) for all. In these cases a classification problem can be made linearly separable by using a nonlinear mapping into the feature space where classes are linearly separable. The condition for perfect classification can now be written as

Where is the mapping into the feature space. Note that the feature mapping may change the dimension of the feature vector. The problem now is how to find a suitable mapping to the space where classes are linearly separable. It turns out that it is not required to know the mapping explicitly as can be seen by writing (8.5) in the dual form

and replacing the inner product in (8.6) with a suitable kernel function. This form arises from the same procedure as was done in the linearly separable case that is, writing the Lagrangian of (8.6), solving partial derivatives, and substituting them back into the Lagrangian. Using a kernel trick, we can remove the explicit calculation of the mapping and need to only solve the Lagrangian (8.5) in dual form, where the SVM product has been transposed with the kernel function in nonlinearly separable cases. In the solution of the Lagrangian, all data points with nonzero (and nonnegative) Lagrange multipliers are called support vectors (SV).

Often the hyper plane that separates the training data perfectly would be very complex and would not generalize well to external data since data generally includes some noise and outliers. Therefore, we should allow some violation in (8.1) and (8.6). This is done with the nonnegative slack variable

The slack variable is adjusted by the regularization constant, which determines the tradeoff between complexity and the generalization properties of the classifier. This limits the Lagrange multipliers in the dual objective function (8.5) to the range *0 ≤ αi ≤ C*. Any function that is derived from mappings to the feature space satisfies the conditions for the kernel function.

The choice of a Kernel depends on the problem at hand because it depends on what we are trying to model.

The SVM gives the following advantages over neural networks or other AI methods (link for more details http://www.svms.org).

SVM training always finds a global minimum, and their simple geometric interpretation provides fertile ground for further investigation.

Most often Gaussian kernels are used, when the resulted SVM corresponds to an RBF network with Gaussian radial basis functions. As the SVM approach “automatically” solves the network complexity problem, the size of the hidden layer is obtained as the result of the QP procedure. Hidden neurons and support vectors correspond to each other, so the center problems of the RBF network is also solved, as the support vectors serve as the basis function centers.

Classical learning systems like neural networks suffer from their theoretical weakness, e.g. back-propagation usually converges only to locally optimal solutions. Here SVMs can provide a significant improvement.

The absence of local minima from the above algorithms marks a major departure from traditional systems such as neural networks.

SVMs have been developed in the reverse order to the development of neural networks (SVMs). SVMs evolved from the sound theory to the implementation and experiments, while the SVMs followed more heuristic path, from applications and extensive experimentation to the theory.

9. Proposed Algorithm

As itcan be seen in Figure 1, the third step of the proposed methodis an independent component analyzer, designed to find sub-signals decompositions ofthe EMG, asdescribed in section 7. The proposed method utilizes ICA to remove the noisy components. Considering the noisy nature of the typical raw EMGsignal, in this study, noisy signals due to electrodes capacitance variation at very low frequencies (below 20 Hz), power line interference in fixed frequency (50 or 60 Hz)while other interference at relatively high frequencies (above 60 Hz) of the EMGare filtered usinglow pass filter, high pass filter and notch filter respectively, a separate gain control is adapted for each filters because the EMG signals contains some information at these frequency also after that these filtered signals from each filters are combined for the input of ICAalgorithm. Moreover, with regard to the inputs fed to the ICAalgorithm, in this study, only a single-channel EMG signal is studied. Therefore, knowing that ICA requires multichannelsignals to process as its input, in order to use ICA to remove noise, one needs to build multichannel signalsfrom the single-channel EMG. After that the filtered signal is pass through the normalizer which rescales the amplitude of the signals between zero and one this removes amplitude ambiguity during measurement or filtration the normalized signal is then pass to DWT block which calculates the wavelet coefficients depending upon the mother wavelet and the decomposition levels provided by the user. Now only the coefficients of interest are selected from these coefficients to form the feature vectors these feature vectors are then grouped with their labels (normal or abnormal) and then sanded to SVM block which searches the appropriate support vectors for future classification.

The proposed algorithm can be described in following steps.

1. Firstly divide the signals into given time segments.
2. Now these segments of signals are passed through the filters.
3. The output of the filter is modified by the gains (dependsupon the importance of each band).
4. Combine the band pass signals to form reconstructed signal.

**Figure 5: flow chart of the proposed algorithm.**

1. Perform ICA decomposition and remove the noisy components.

Component Selection

Feature Vector Formation

SVM

Kernel Type

Gain

Gain

Gain

LPF Filter

= 50Hz

HPF Filter

= 50Hz

NotchFilter

= 50Hz

Perform ICA Decomposition

Remove Noisy Components

Filtered Signal

Normalization

DWT

Decomposition Levels

Wavelet Type

1. After that the filtered signal is pass through the normalizer which rescales the amplitude of the signals between zero and one this removes amplitude ambiguity during measurement or filtration.
2. The normalized signal is then pass to DWT block which calculates the wavelet coefficients depending upon the mother wavelet and the decomposition levels provided by the user.
3. Now only the coefficients of interest are selected from these coefficients.
4. To form the feature vectors these feature vectors are then grouped with their labels (normal or abnormal).
5. Then the grouped feature vectors are sanded to SVM block which searches the appropriate support vectors for future classification.
6. For detection purpose the input signals vectors are calculated in same way as during training and then it is applied on the classifier.

**7. Simulation Results**

We used the superficial electromyography Database (EMG), (for analysis in lower limb, available at UCI machine learning database repositories) for testing of our algorithm. This database contains 2 different groups normal and abnormal each group has 11 different subjects with 3different samples of each subject. The accuracy of the algorithm is tested for different number of samples, wavelet decomposition levels and kernel functions.

Table 1: Results for different training samples using LinearSVM Kernel: Measurement Duration = 0.5 Seconds, Number of Electrodes = 4, Number of Movements = 3, Levels of Wavelet Decomposition = 4, wavelet Type = Haar.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Training Samples | TPR | TNR | FPR | FNR | Accuracy | Precision | Recall | F-Measure |
| 4 | 0.6364 | 0.8182 | 0.1818 | 0.3636 | 0.7273 | 0.7778 | 0.6364 | 0.7 |
| 6 | 0.7273 | 0.7727 | 0.2273 | 0.2727 | 0.75 | 0.7619 | 0.7273 | 0.7442 |
| 8 | 0.9091 | 0.9091 | 0.0909 | 0.0909 | 0.9091 | 0.9091 | 0.9091 | 0.9091 |

Table 2: Results for different training samples using Quadratic SVM Kernel: Measurement Duration = 0.5 Seconds, Number of Electrodes = 4, Number of Movements = 3, Levels of Wavelet Decomposition = 4, wavelet Type = Haar.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Training Samples | TPR | TNR | FPR | FNR | Accuracy | Precision | Recall | F-Measure |
| 4 | 0.6545 | 0.4909 | 0.5091 | 0.3455 | 0.5727 | 0.5625 | 0.6545 | 0.605 |
| 6 | 0.7182 | 0.7455 | 0.2545 | 0.2818 | 0.7318 | 0.7383 | 0.7182 | 0.7281 |
| 8 | 0.8273 | 0.8455 | 0.1545 | 0.1727 | 0.8364 | 0.8426 | 0.8273 | 0.8349 |

Table 3: Results for different training samples using RBF SVM Kernel: Measurement Duration = 0.5 Seconds, Number of Electrodes = 4, Number of Movements = 3, Levels of Wavelet Decomposition = 4, wavelet Type = Haar.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Training Samples | TPR | TNR | FPR | FNR | Accuracy | Precision | Recall | F-Measure |
| 4 | 0.3636 | 1 | 0 | 0.6364 | 0.6818 | 1 | 0.3636 | 0.5333 |
| 6 | 0.5455 | 1 | 0 | 0.4545 | 0.7727 | 1 | 0.5455 | 0.7059 |
| 8 | 0.7273 | 1 | 0 | 0.2727 | 0.8636 | 1 | 0.7273 | 0.8421 |

Table 4: Results for different Wavelet Decomposition Levels: Measurement Duration = 0.5 Seconds, Number of Electrodes = 4, Number of Movements = 3, Training Samples = 6, wavelet Type = Haar, SVM Kernel= Linear.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Decomposition | TPR | TNR | FPR | FNR | Accuracy | Precision | Recall | F-Measure |
| 4 | 0.7273 | 0.7727 | 0.2273 | 0.2727 | 0.75 | 0.7619 | 0.7273 | 0.7442 |
| 6 | 0.7273 | 0.7636 | 0.2364 | 0.2727 | 0.7455 | 0.7547 | 0.7273 | 0.7407 |
| 8 | 0.7273 | 0.8091 | 0.1909 | 0.2727 | 0.7682 | 0.7921 | 0.7273 | 0.7583 |

Table 3: Results for different Wavelet Type: Measurement Duration = 0.5 Seconds, Number of Electrodes = 4, Number of Movements = 3, Training Samples = 6, Levels of Wavelet Decomposition = 4, SVM Kernel= Linear.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Wavelet Type | TPR | TNR | FPR | FNR | Accuracy | Precision | Recall | F-Measure |
| Haar | 0.7273 | 0.7727 | 0.2273 | 0.2727 | 0.75 | 0.7619 | 0.7273 | 0.7442 |
| Coiflets | 0.7273 | 0.7455 | 0.2545 | 0.2727 | 0.7364 | 0.7407 | 0.7273 | 0.7339 |
| Symlets | 0.7273 | 0.7455 | 0.2545 | 0.2727 | 0.7364 | 0.7407 | 0.7273 | 0.7339 |

8. Conclusion

This paper presents an ICA and Wavelet based approach for EMG signal filtration and feature extraction and, the Support Vector Machine (SVM) during the classification phase. The complete algorithm is for training samples, kernel functions, wavelet types and decomposition levels. The experimental results indicated that the linear kernel performs better than Quadratic and RBF for TPR, FNR, Accuracy, Recall and F-measure however when compared for TNR, FPR and Precision, RBF kernel out performs the leaner kernel. Looking on the wavelet side the change in decomposition level does not affects the performance greatly but it increases the performance of classifier. Also the haar wavelet gives the best results although it’s just in the rage of two percent hence making any decision about these parameter required much larger scale testing and could be performed in the future work.

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