EEG Signal Processing and Classification of Sensorimoter rhythm-based BCI

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Abstract: **Brain Computer Interface (BCI) on mu sensorimoter rhythms uses 2D-movement imagery tasks. The signal processing of electroencephalogram (EEG) consists of filtration, spike detection, feature extraction and signal classification. Filtration method removes various artifacts and noise signal from the row EEG signal and extract the sensorimoter mu-rhythms(8 to 12Hz) from the data signal. Application BCI require spike sorting in order to (1) obtain single unit activity and (2) perform data reduction for wireless transmission. Feature extraction algorithm described briefly with non-linear energy operator (NEO) which is chosen as optimal spike detection. Algorithm, being most robust over noise. Classification is done using statistical k-means named as mahalanobis distance.**

Keywords–**Brain Computer Interface(BCI), Non Linear Energy Operator (NEO), K-means algorithm.**

1. INTRODUCTION:

Communication and the ability to interact with the environment are basic human needs. Millions of people worldwide suffer from such severe physical disabilities that they cannot even meet these basic needs. Even though they may have no motor mobility, however, the sensory and cognitive functions of the physically disabled are usually intact. This makes them good candidates for Brain Computer Interface (BCI) technology, which provides a direct electronic interface and can convey messages and commands directly from the human brain to a computer. BCI technology involves monitoring conscious brain electrical activity via electroencephalogram (EEG) signals and detecting characteristics of EEG patterns via digital signal processing algorithms that the user generates to communicate. It has the potential to enable the physically disabled to perform many activities, thus improving their quality of life and productivity, allowing them more independence and reducing social costs. The challenge with BCI, however, is to extract the relevant patterns from the EEG signals produced by the brain each second.[3][6]

Human-Computer interfaces can use different signals from the body in order to control external devices. Beside muscle activity (EMG-Electromyogram), eye movements (EOG-Electrooculogram) and respiration also brain activity (EEG-Electroencephalogram) can be used as input signal. EEG-based brain-computer interface (BCI) systems are realized with motor imagery. For BCI experiments the subject or the patient is connected via electrodes or sensors to a biosignal amplifier and a data acquisition unit (DAQ board) containing the analog-to-digital conversion (as shown in Figure 1). Then the data are passed to the real-time system to perform the feature extraction and classification.

EEG-based communication systems measure specific components of EEG activity and use the results as a control signal. In some systems, these components are potentials evoked by stereotyped sensory stimuli. Other systems, including the one employed in the present study, use EEG components that are spontaneous in the sense that they are not dependent on specific sensory events. Our system uses the mu rhythm, an 8-12 Hz rhythm recorded from the scalp over somatosensory cortex, and/or closely related higher frequency components recorded from the same region.

The objective of this work is to set up and use such a software platform to support research for exploration of robotics BCI applications whose performance could be evaluated in a general way. This software platform work on EEG signals. It includes their filtration, spike detection, feature extraction and finally their classification on the basis of command given/imagined for the motor imagery application[1]. Fig 1. shows the basic working of this paper.

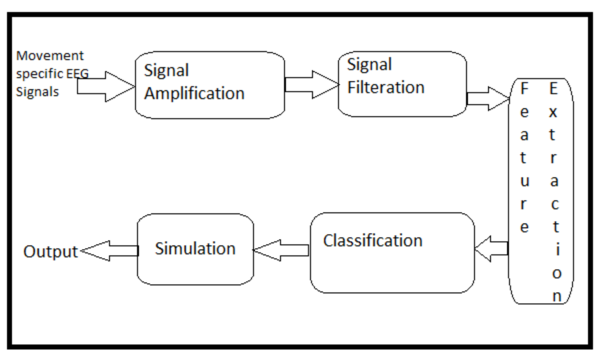

Fig. 1. Block diagram for the development of software platform

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2. METHODOLOGY

2.1 EEG data acquisition and Filteration

The implementation process is carried out using the database available in the physonet website. The database was in MAT format. The tests described were carried out 21 year old male healthy subjects, the signals capturd is for 2 dimensional movement, out of which for every direction movement there are some actual movement data and some imagined movement data. In order to facilitate the mental concentration on the proposed activities, the experimentswere carried on in a room with low level of noise and under controlled environmental conditions, all electronic equipments external to the experiment around the subject were switched off to avoid electromagnetic artifacts. For complete processing MATLAB platform is choosen, as it is user friendly, having more compatibility, give easiness to the user and most importantly can work on real time applications. The data is then directly loaded in MATLAB 7.9 and onwards versions compatibility. The obtained data has used 19 channel electrodes system for capturing EEG from the subject.

The mu rhythm control signal is an 8-12 Hz component that is focused over sensorimoter cortex. Thus, spatial filter selection is best effected by determining which filter actually provides the highest signal- to-noise ratio, and therefore is likely to support the most accurate and rapid imagery movement(in real time). Spatial filtering method can increase the signal-to-noise ratio by enhancing the control signal and/or reducing noise. [10]

2.2 Feature Extraction:

Feature extraction (FE) emphasizes the difference between waveforms and reduces the dimensionality of these differences, which serve as input to clustering. Various methods for feature extraction are principal component analysis, the discrete wavelet transform, discrete derivatives, and the integral transform but in this paper principal component analysis is used. For applications such as neural prosthetics and neuroscience research, spike sorting is a critical step in neuronal signal processing for two reasons. The first reason is functional: Adjacent cells may encode completely different information. Neuroscientists often need to know which spikes come from which neurons in order to understand the neuronal circuitry, and brain-machine interfaces (BMIs) often depend on single unit activity as input. The second reason is practical: data reduction. Requirements on hardware for spike sorting are that it must be low-power in order to prevent heat-related tissue damage and low-area in order to be implantable. Spike detection algorithms involve two main steps: (1) pre-emphasis of the spike and (2) application of a threshold. This section describes three very different methods of pre-emphasis: absolute value, nonlinear energy operator, and stationary wavelet transform product. The method of automatically determining the threshold for each method is also stated. Spike detection using all of the methods was accomplished as follows: When a sample in the reemphasized signal crosses the threshold, a 3-ms window is applied to the signal and the result is saved as a spike. This window length was chosen because a spike duration is unlikely to be longer than this and because it assures that we do not capture more than one spike from the same neuron in the window. [7]

Nonlinear Energy Operator: The nonlinear energy operator (NEO), also called the Teager energy operator (TEO), has been proposed for use in spike detection. In discrete time, the NEO ψ is defined as

$$\psi\,[x(n)] = x2(n) - x(n + 1) \cdot x(n - 1). \qquad (1)$$

The NEO is large only when the signal is both high in power (i.e., x2(n) is large) and high in frequency (i.e., x(n) is large while x(n+1) and x(n−1) are small). Since a spike by definition is characterized by localized high frequencies and an increase in instantaneous energy [2], this method has an obvious advantage over methods that look only at an increase in signal energy or amplitude without regarding the frequency.

Similarly the threshold Thr was automatically set to a scaled version of the mean of the NEO:

$$Th=C\frac{1}{N}\sum_{n=1}^{N}\psi[x(n)] \qquad (2)$$

where N is the number of samples in the signal. The scale was initially chosen to be C = 8 (explained in [7]) and then used as a constant.

Fig.2 shows the plotting of 19 channels input signal along time axis. When NEO function is applied, the signal to noise ratio (SNR) of the signal is increased, and displayed in fig. 3. For checking out this output of individual channel (consider we want to check the output of 5th channel) fig.4 and fig.5 shows the output of single/selected channel.

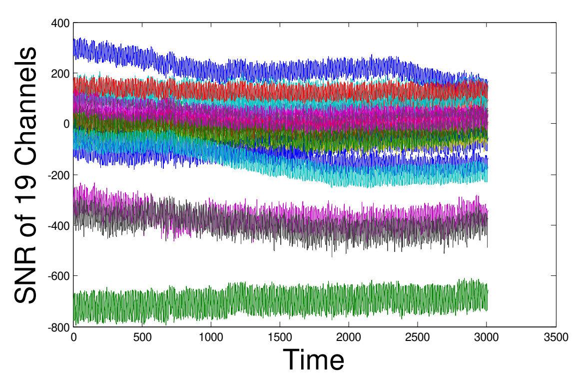

Fig. 2 Plotting (filtered) raw signal

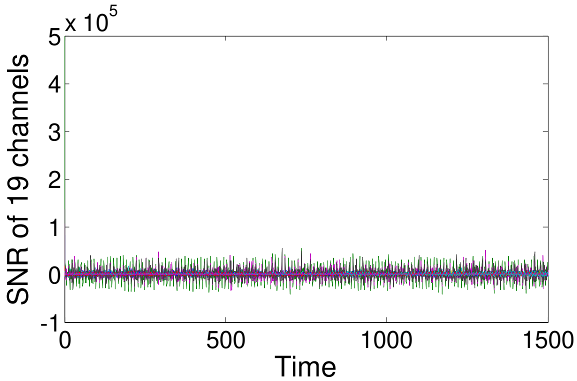

Fig. 3. Plotting signal of 19 channels using NEO

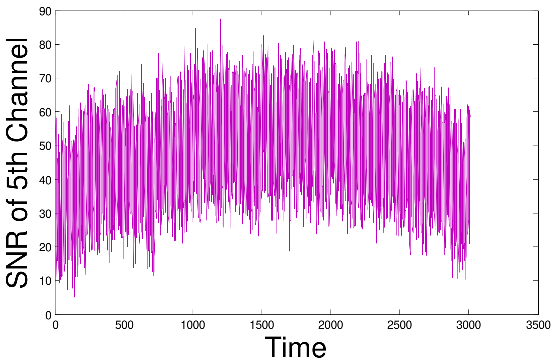

Fig. 4. Plotting (filtered) raw signal of 5th Channel

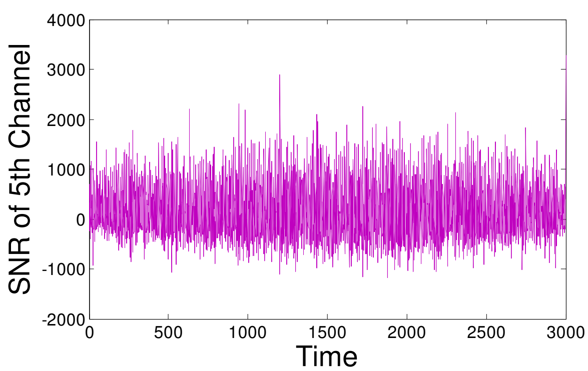

Fig. 5. Plotting 5yh Channel signal using NEO

The formula (2) used to get the Threshold value of each channel, which is plotted in fig. 7 where x axis indicates numbers of channels and y axis indicates their corresponding threshold.

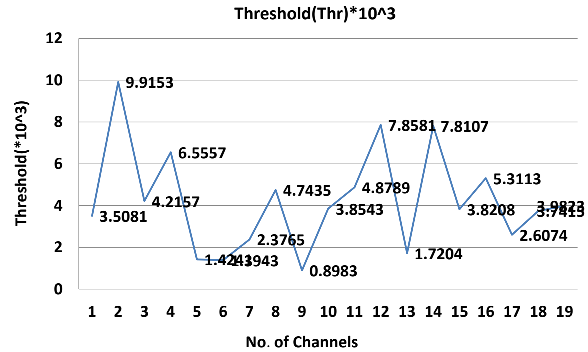

Fig. 6. Threshold of every channel of left direction

Principal Component Analysis (PCA): Since PCA has become a benchmark FE method in neural signal processing, we have included it in our analysis as a basis for comparison. In PCA, we find an orthogonal basis (i.e., the ―principal components‖ or PCs) for our data that captures the directions in the data with the largest variation, and we express each spike as a series of PC coefficients ci:

$$ci = \sum_{n=1}^{N} PCi(n).s(n) \qquad (3)$$

where s is a spike, N is the number of samples in a spike/PC, and PCi is the ith PC. The PCs are found by performing eigen value decomposition of the covariance matrix of the data; in fact, the PCs are the eigenvectors themselves. See [7] [8] for a more detailed description of the method. PCA results in the same number of coefficients as samples in the original spikes (N). However, as most of the energy is captured in the first few components, we kept only the 3 largest PC scores for our analysis.

2.3 K-means algorithm

K-means is one of the simplest unsupervised learning algorithm which is being used as a classifier int this work.In this algorithm Mahalnobis distance is used to detect the K-complex. Mahalanobis distance is a distance measure introduced by P. C. Mahalanobis in 1936. It is based on correlations between variables by which different patterns can be identified and analyzed. It gauges similarity of an unknown sample set to a known one. It differs from Euclidean distance in that it takes into account the correlations of the data set and is scale-invariant. In other words, it is a multivariate effect size.

The statistical distance or Mahalanobis distance between two points $x = (x1, \ldots, xp)^t$ and $y = (y1, \ldots, yp)^t$ in the p dimensional space Rp is defined as

$$d_S(x, y) = \mathrm{sqrt}\,((x - y)^t S^{-1}(x - y))$$

$$d_S(x, y) = 0 \qquad \text{if } x = y$$

The detection of K-complex using k-means algorithm is achieved by the following procedure:

- define the refernce waveform to be detected.
- isolate, in the signal, segments which are similar to the reference signal.
- decide if the isolated segments belongs or not to the category under consideration.

For detection of k-complex,the statistical features are extracted based on the the amplitude and duration measurement.The k-means algorithm considers the features of reference signal and isolated signalas a input.Mahalnobis distance of the two input is calculated in the form of distance matrix.If the features of both the signals are same then the digonal elements of the matrix is 0.

3. SENSITIVITY AND SPECIFICITY

The performance of the above mentioned classifiers is measured using sensitivity and specificity.Sensitivity is the probability that the test says a person has the disease when in fact they do have the disease. Sensitivity measures the proportion of actual positives which are correctly identified as such. Specificity measures the proportion of negatives which are correctly identified minimum error bound known as the Bayes error rate.

Sensitivity = TP/ (TP+FN)

Specificity = TN/ (TN+FP)

4 CONCLUSION

It has been concluded that this algorithm proved out the more efficient, accurate and ease method for processing of EEG signals used as the command for wheelchair movement. As it has been developed in MATLAB, hence become more user friendly and compatible for working in real time environment.Mahalnobis distance gives the accurate distance measure between the reference and targeted signal.Which helps to detect and classify the unknown signal by comparing it with the reference signal.The sensitivity the classifiers shows good result.These automatic computerized processes provide quantitative,objective,reproducible results for every subject.

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