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PERFORAMNCE ENHANCEMENT FOR AUTOMATED ANALYSIS IN HUMAN BRAIN SIGNAL PROCESSING TO FINDING ALZHEIMER'S SYNDROME USING INTELLIGENT TECHNIQUES

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ABSTRACT

Today efficient brain signal recognition is limited to find different brain diseases; using hardware like Electroencephalogram (EEG), Magnetoencephalograms (MEG), and Functional MRI (fMRI). Alternatively, abnormal brain waves have shown to be associated with particular brain disorders (e.g., Alzheimer's disease and epilepsy). But the problem with this approach is that there are not many algorithms that could efficiently extract signals from a brain to find Alzheimer's disease. In this research paper, we suggest the design of new algorithm which could do this job of translating brain signals to digital text data for Alzheimer's disease. We propose a new approach using which the problem of recognizing brain signals for Alzheimer's disease can be solved. We also provide the implementation details of this software. For the implementation of our idea, we propose a new intelligent technique Architecture. The technique adopted by the EEG signals used in brain for Alzheimer's disease, guided and stimulated us to design this research work. Details regarding the automatic preprocessing and decoding interpretation that would be essential and the shortcomings are also included in the research work. Received on: 10th-March-2015 Revised on: 18th-May-2015 Accepted on: 26th-May-2015 Published on: 8th -Aug-2015

KEY WORDS

Electroencephalograph (EEG); Alzheimer; Back Propagation Network (BPN); Independent Component analysis (ICA; Non-Linear Energy Operator (NLEO); Discrete Wavelet Transform (DWT).

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INTRODUCTION

In this paper we propose a novel method for the classification of memory disorders and Alzheimer. Memory disorders now a days gain much more attention in the research area because it is the basic symptoms of some major diseases such as cancer and psychiatric problems [1]. After pain, memory disorder is the second most indicator of illness. Memory loss is the basic symptoms of some major diseases such as cancer and Psychiatry. So memory disorder should be detected earlier and thereby give better treatments for the patients. Alzheimer is the abnormal activity of the brain. It is noticed that one in hundreds of the populations are the victims of this diseases. Sometimes Convolutions and unconscious are the symptoms of Alzheimer. All the above two diseases are diagnosed by the encephalograph (EEG).

The electrical fauna of the human nervous classification has been predictable for more than a period. It remains well recognized that the difference of the external potential circulation on the scalp replicates functional happenings emerging from the essential brain. This external potential difference can be verified by sticking a group of electrodes toward the scalp, and computing the electrical energy among couple of these electrodes, which remain before clarified, amplified, and verified. The resultant information is titled the EEG [13]. The EEG needs the lesser signal generosity in the range of microvolts (μ V). EEG frequency band are normally classified into five categories. The meaning of these different frequencies is not completely known. They are alpha, beta, theta, delta and gamma. Alpha waves are rhythmic waves occurring at a frequency between 8 and 13 hertz. These waves are found in the normal persons when they are awake in a quiet, resting state [1]. When the subject is in memory loss, the alpha waves disappear completely. Beta waves and beta 2 waves. Beta 1 is elicited by the mental activity and the other is inhibited by it. Theta waves have frequencies between 4 and 7 hertz. These waves occur during emotional stress, particularly during periods of disappointment and frustration. Delta waves occurs only once every 2 or 3 seconds.

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They occur in deep Alzheimer, in infants and in serious organic brain diseases. Gamma waves consist of lowamplitude, high-frequency waves resulting from attention or sensory stimulation. Architecture for implicated processes is shown in **Figure-1**.

All these waves have their own particular shapes in the signals and if any kind of diseases occur then the normal wave's shapes have changed. Theta and delta waves are normally used to diagnosis the memory disorders. Sometimes the signal shape of Alzheimer and one kind of memory loss disorder say narcolepsy may overlap. Visual inspection of EEG signals is very time consuming and very laborious work. So the EEG signal parameters extracted and analyzed using computers, are highly useful in diagnostics [11]. The information can be as several for example 128 channels then usually 20 channels remain used and copies characteristically last used for 30 to 60 minutes of time domain data, through a bandwidth among 0.1 to 150Hz, which remains demonstrated digitally arranged on a computer screen [15].

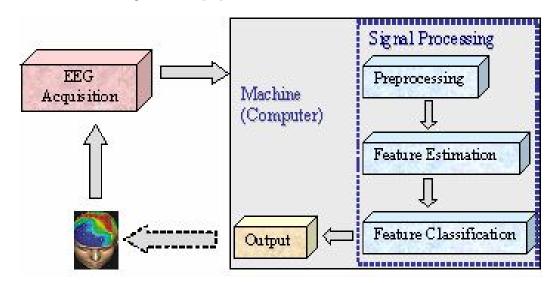


Fig: 1. Architecture for implicated processes

TECHNIQUES AND RESOURCES

The brain analysis and classification follows a specific method custom designed for the identification of brain diseases. Figure –2 shows the block diagram of the proposed neural network [2] based automated brain signal analysis system.

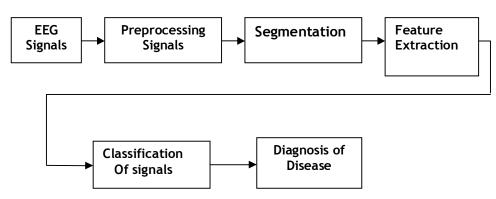


Fig: 2. Automated System design of the proposed system.

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Signal attainment and EEG database

EEG acquisition collects these underlying electrical patterns from the scalp, and digitalizes them for computer storage. In our experiments, we have used the10-20 Classification of Electrode Location, which is constructed on the association among the position of an electrode besides the original part of cerebral cortex ["10" and "20" mention to the 10% or 20% interelectrode distance]. These signals include normal and abnormal signals of EEG. Divide them and name them as set A and set B. Set A contain normal signals. B contains abnormal signals such as memory disorders and Alzheimer signals. In the present study we classify them as two datasets.

Preprocessing

This Once the signals are acquired, it is necessary to clean them. Usually EEG signals are contaminated [5]. These contaminations may leads to misdiagnosis of diseases. So before analyzing the signals, it should be artifact free [6]. To remove the artifacts there are various methods. However, environments with large, low-frequency electromagnetic fields can cause a significant interference to EEG recordings. The second limitation is the activity of muscles in the head region (e.g. chewing, speaking, etc). The electrical activities of these muscles have, usually, much large amplitude then the EEG. With some effort in quality control and artifact processing the disadvantages can be compensated [14]. The best method for EEG signal preprocessing is Independent Component Analysis (ICA) [10]. ICA is a method for finding underlying factors or components from multivariate statistical data. Figure-3 shows the ICA is a method for finding underlying factors or components from multivariate statistical data.

ICA outperforms the traditional principal component analysis (PCA) in numerous applications; in specific, it has been suitable in the place of removal of optical artifacts after the EEG, wherever principal PCA could not distinct eye artifacts from brain signals, specifically when they must comparable amplitudes [13]. Principal component analysis (PCA) is alternative technique that remains accessible, when associated with ICA for the selected application went short of effectiveness and efficiency [16].

Let s (t) is the signals generated. These signals are linearly combined through a memory less channel, mathematically described by the mixing matrix A. A has M rows, N columns, and xi (t) (I = 1 ...M) are the signals observed at the channel output.

The mixing model is described by the following equation

X (t) = A.S (t)....(1)

Where s (t) and x (t) are the source and mixture signal vectors, respectively.

After mixing, the preprocessing of ICA involves the following steps. Centering, whitening and rotation. Centering make the signals centered in zero.

The main purpose of centering is to make the zero mean. Centering is achieved by simply subtracting the mean of signal from each reading of that signal.

X = x-E (x)......(2)

The next step is to whiten or sphere the data. This means that remove any correlations in the data [7]. Whitening is achieved by the eigen-value decomposition of the covariance matrix. Taking the covariance between every pair of signals can form a covariance matrix

This matrix will be square and symmetric.

COV(X) = E(XXT)

Perform eigen-value decomposition on the covariance matrix and then transform the data so the covariance matrix of the transformed data is equal to the identity.

This procedure is called sphereing or whitening.

 $V = ED^{-1/2}E^{T}$(3)

(Eigen value decomposition of covariance matrix E {XX^T} = EDE^T and D-1/2 = diag (d1-1/2, d2-1/2 ... dn-1/2)]

Now rotation can be done by the inverse of whitening operation on the mixing matrix A.

 $S = \tilde{A}^{-1}Z$(4)

Where Z = VX.

The disadvantages of EEG are that the signal to noise ratio is poor; and it is necessary to deal with large subject-specific, inter- and intra-trial variability; hence, sophisticated data analysis has to be completed.

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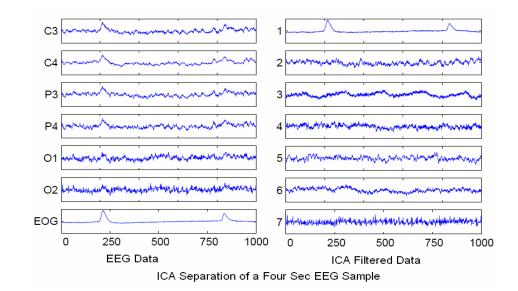


Fig: 3. ICA separation of a four sec EEG sample.

Segmentation

Novel way to examine non-stationary signals, it remains occasionally calmer to fragment signals hooked on pseudo-stationary sections. By means of adaptive segmentation algorithms [4], the non-stationary signals can be broken down into segments that are pseudo-stationary, and analyzed or processed separately. Signal segmentation is based on energy and frequency of signal and the signal has to be divided according to its characteristics. The main purpose segmentation is to find the edge and the energy of the signal. Among the various segmentation algorithm's NLEO is the best one.

A segmentation algorithm involving a non-linear energy operator (NLEO) is defined as follows.

Where x (n) is the input EEG signal at current time n and Ψ [(x (n)] = x (n -1) x (n-2) -x (n) - x (n-3) is the nonlinear energy operator. Using NLEO, we can calculate the localized energy, and segment boundary. To detect a sudden change in the NLEO, a variable used for segmentation criteria is defined as follows.

n+N Gnleo (n) = $\sum_{n=1}^{\infty} \Psi(m) - \sum_{n=1}^{\infty} \Psi(m)$ m = n - N + 1m = n+1

Where 2N is the window size. Gnleo (n) reaches a peak when the Ψ (m) is discontinuous. The boundaries can be detected by the peaks of Gnleo (n). According to the windowing and thresholding equation the significant level can be obtained. The threshold equation can be defined as

T(n) = max [Gnleo (n - L/2 : n+L/2)], L window length)]).....(7)

Where Gnleo (n) is the energy change in the window obtained by using a moving window with length 2N at center n, and T (n) is the threshold value obtained by using another moving window with length L. G (n) represents the significant energy change after thresholding.

Feature extraction

After segmentation features should be extracted. Different features are suited for different diseases. The proposed system uses discrete wavelet transform (DWT) for memory disorders and spectral entropy for Alzheimer [8]. Spectral entropy quantifies the spectral complexity of the time series. Power spectral density is defined as

 $P(\omega) = I / N(|X(\omega)|)....(8)$

Where X (ω) represents fast Fourier transform of the signal. The normalization of equation (8) gives the spectral entropy and is defined as

H (ω) = — $\sum pω \log pω$(9)

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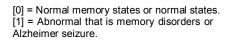


Discrete wavelet transform (DWT) is suited to non-stationary signals and performs a multiresolution analysis of a signal. It builds on the concept of scales. The following features were found to be suitable for Alzheimer detection [3]. Zero crossing Extrema.

Neural network classifier

Artificial Neural Networks (ANN) is considered to be good classifier due to their inherent features such as adaptive learning, robustness, self-organization, and generalization capability [12]. ANN's are particularly useful for complex pattern recognition and classification tasks where enough data are available for training and where the simpler classification algorithms fail. In neural network [9], designing the architecture and network training are the main issues. If training is insufficient, then network will not learn properly. If excessive training of network is unable to generalize the training database. For each type of EEG signals, a corresponding output class is associated. In order to make neural network training [2] more efficient, the input features were normalized so that they fall in the range [0, 1]. Since the number of output class is 2, the ANN with one output is sufficient to produce a code for each class. Figure-4 shows the co-efficient analysis.

The output are represented by



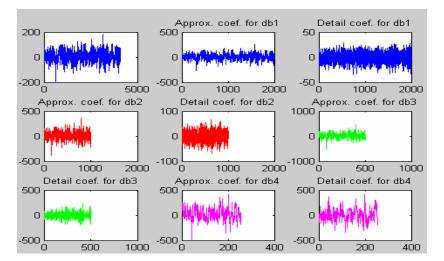


Fig: 4. Co-efficient analysis

The proposed system makes use of BPN. It is a multilayer, feed forward and supervised learning model. Back propagation remains the preeminent recognized training algorithm aimed at neural networks besides still one of the maximum suitable. It requires lesser memory necessities than utmost algorithms then frequently influences a suitable error level quite rapidly, even though it can be very slow to converge suitably on an error least possible. Figure-5 shows the BP network.

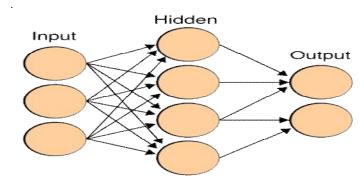


Fig: 5. Architecture of Back Propagation Network

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Validation

The performance of BPN are evaluated by using the two parameters namely sensitivity (SE) and specificity (SP) which are defined as follows.

SE = $TNcp/TNcp \times 100...$ (10)

Where TNCP signifies the entire quantity of properly identified positive patterns and TNAP signifies the entire amount of actual positive patterns.

A positive pattern specifies a perceived seizure.

 $SP = TN_{CN} / TN_{CN} \times 100.....(11)$

Where TN_{CN} signifies the entire quantity of properly identified negative patterns and TN_{AN} signifies the entire quantity of real negative patterns.

A negative pattern specifies an identified non seizure. Figure-6 shows the output screen shot of the final output.

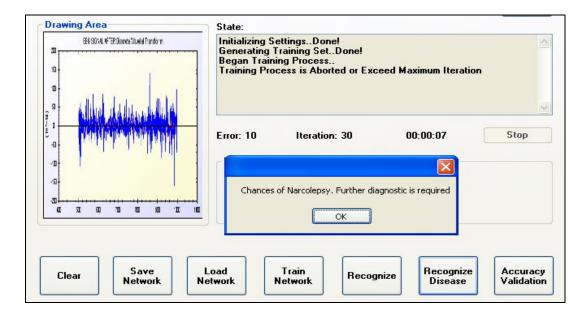


Fig: 6. Screen shot of the Final yield



CONCLUSION

The Work proposes an algorithm which will prove useful in biomedical signal processing where a specific underlying signal requires to be extracted from the possibly noisy multi-channel recordings. It is clear that the method is suitable for the extraction of independent components from the measured EEG. The algorithm worked efficiently in extracting memory spindle as well as Alzheimer seizures which were distributed throughout the measurement channels. We expect that this system will be valuable in the department of neurology and will help mankind. Current developments in computer hardware in addition to signal processing have made conceivable the consumption of EEG signals or "brain waves" for communication among humans and computers [13] and the same work can further be extended towards the domain also.

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CONFLICT OF INTEREST

No conflict of interest

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FINANCIAL DISCLOSURE

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