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STATIONARY WAVELET TRANSFORM USING EEG SIGNAL ON CROSS-VALIDATION METHOD CLASSIFIER

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Abstract

The diagnosis system presents to classify the EEG brain signal of patient to distinguish between normal and abnormal which are tumor and epilepsy with better classification accuracy. To design cross-validation method classifier based EEG classifier which distinguishes between the EEG signal of a normal patient and that of an abnormal patient (tumor or epileptic cases). Here, the system uses the back propagation with feed forward for classification which follows the cross-validation method classification with data set training. For training, the statistical principal features will be extracted with facilitate of data base samples. The test sample is going to be classified using cross-validation method classifier parameters and its features. The system gives better performance accuracy for different test samples.

Key words: Stationary wavelet transforms, cross validation classifier, MATLAB, EEG Signal, Entropy, Mean variance. Standard Deviation.

Introduction

Automated classification and finding of Tumors indifferent medical signals is activated by the requirement of high accuracy ones addressing some one's life. Also, the computer help is demanded in medical establishments owing to the actual fact that it may improve the results of humans in such a domain where the false negative cases should be at an awfully low rate. It's been proven that double reading of medical images could lead to better Tumor detection. But the cost involvedin double reading is very high.That's why sensible software system to assist humans in medical institutions is of nice interest nowadays.

Conventional strategies of observance and diagnosing the diseases rely on finding the presence of particular features by a human observer. Owing to the sizable amount of patients in medical care units and the want for continuous Observation of such conditions, many techniques for automatic diagnostic systems are developed in recent years to try to unravel this this downside. Such techniques work by reworking the largely qualitative diagnostic criteria into afurther objective quantitative feature classification drawback. Automated classification of Brainsignals by victimization some previous information like intensity and some anatomical features are proposed. At present there are no methods widely accepted therefore automatic and trustable methods for Tumor detection are of great interest. The application of BPN with in the classification of knowledge for graphical record signals issues aren't absolutely utilized however. These enclosed the feature extraction and classification techniques particularly for CT pictures issues with immense scale of knowledge and intense times and energy if done manually.

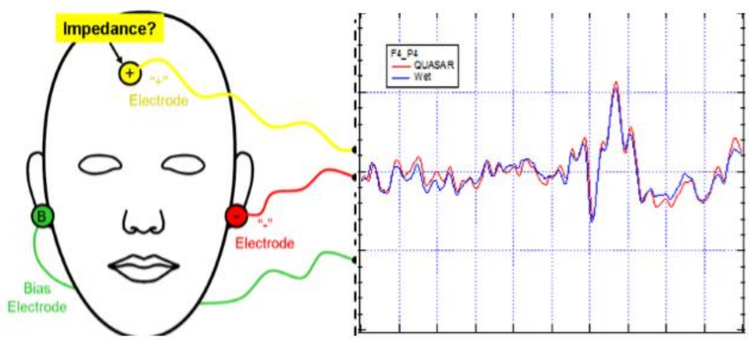

Fig1: Extraction of EEG signal from Human Brain.

Brain–Computer Interfaces (BCI) is the best possible way of providing the communication between the human and the system by means of brain signals. By using this BCI the patients can put across their views or needs by means of their brain signals just by thinking process. The signal classification module consists of the obtained EEG signal features extraction and therefore the transformation of those signals into device instructions. The EEG classification tactic depends on the inducement and, thereby, the reaction to detect motor imagery, event related potentials, slow cortical potentials, or steady-state evoked potentials. The predicted EEG drives the categorization to few accurate feature extraction methods.

Objective

The diagnosis system presents to classify the EEG brain signal of patient to distinguish between normal and abnormal which are tumor and epilepsy with better classification accuracy. Here, the system uses the back propagation with feed forward for classification which follows the supervised training and non-knowledge based classification. For cross validation training, the statistical principal features will be extracted with help of data base samples. The test sample will be classified using network parameters and its features. The system gives better performance accuracy for different test samples.

Proposed Method Analysis

Electroencephalography, a medical imaging technique that examine the scalp electrical activity generated by brain structures

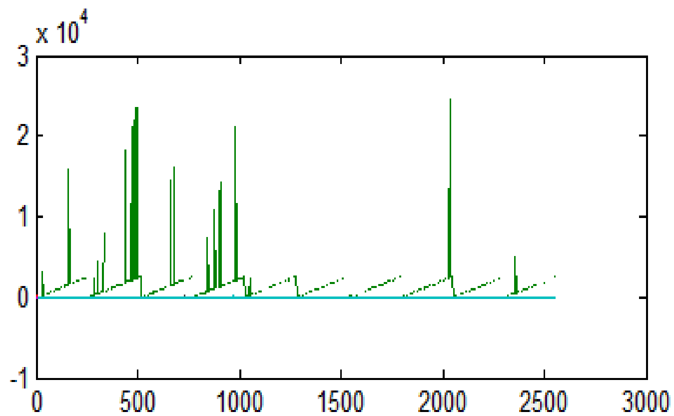

Fig 2: Input EEG Signal.

The EEG measured directly from the cortical surface of human brain is known as electrocortio-gram while when using depth probes it is known as electro-gram.

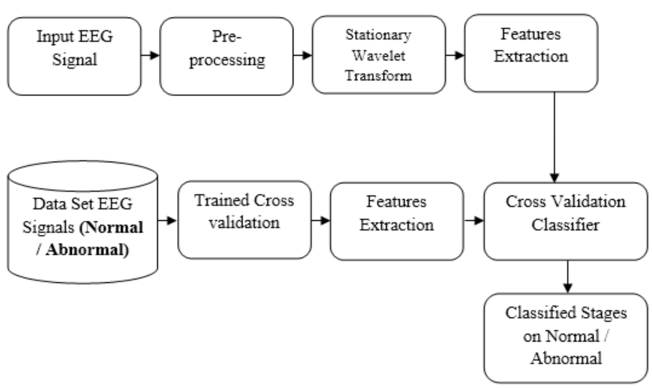

Fig 3: Overall Block Diagram.

Pre-processing signals commonly involves removing low-frequency background noise, normalizing the intensity of the individual particles signals, removing echo structure, and masking portions of signals.Signal pre-processing is the technique of enhancing data signals prior to computational processing.

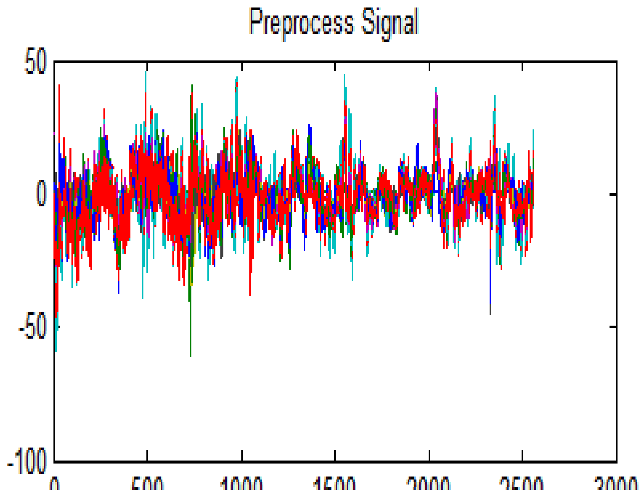

Fig 4: Pre-processing Signal.

Stationary wavelet transform (SWT)is wavelet transform algorithm designed to overcome the lack of translation-invariance of discrete wavelet transform. Translation-invariance is gained by eradicating the down samplers and up samplers in the DWT and up sampling the filter coefficients.

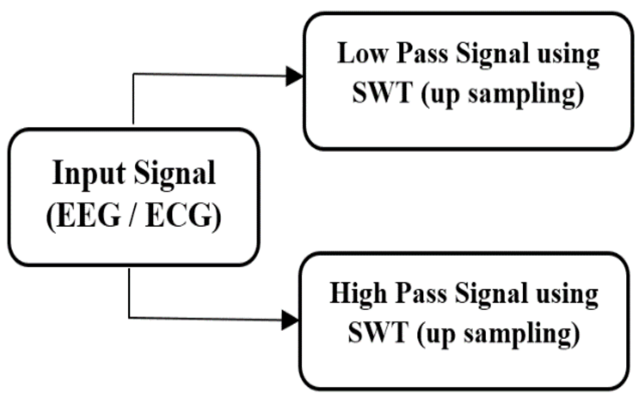

Fig 5: Feature extraction in stationary Wavelet Transform.

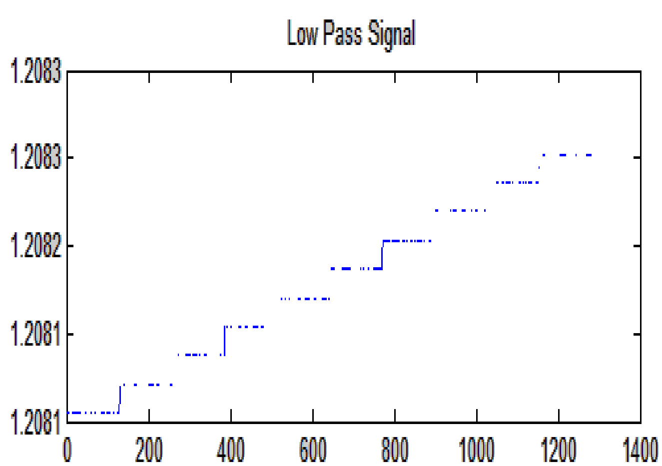

Fig 6: Low pass Signal.

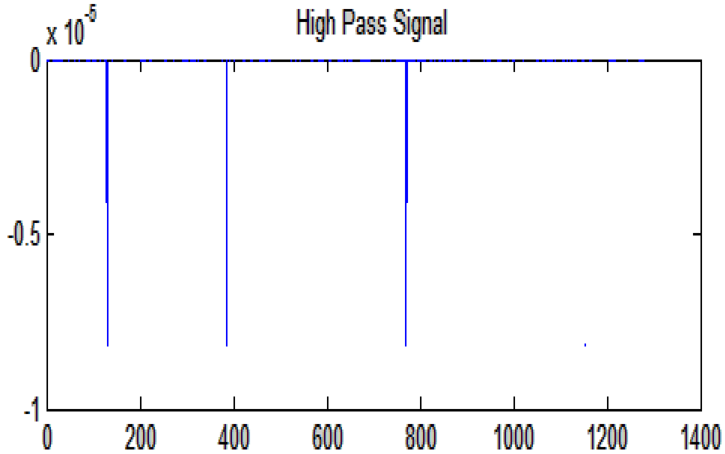

Fig 7: High pass Signal.

Features Extraction

1. Mean (Average) Value Detection:

Minimum Stem on Input Voice Signal (Low Pass Signal) using "min" command process on

Feature Average=mean (low_pass_signal)

2. Entropy:

E = entropy(I) returns E, a scalar worth representing the entropy of low pass signal I. Entropy is a statistical measure of randomness that can be used to characterize low pass signal . Entropy is defined as

Feature Average=-sum (p.*log 2(p))

3. Variance: Variance is a measurement to disperse widely between numbers in a data set. The variance measures how far each number in the set is from the mean.

Feat variance=sum (sum(X-X)^2)/ ((m-1)*(n-1))

4. Standard Deviation: The Standard Deviation is a measure of how opened up out numbers are. Its symbol is σ (the Greek letter sigma) the formula is easy: it is the square root of the Variance.

Feat Standard Deviation =sqrt(sum(sum(X-X)^2)/((m-1)*(n-1)))

Cross Validation Classifier

Cross-validation typically known as rotation estimation, is a model validation technique for assessing however the results of a statistical analysis will generalize to a freelance data set. It is mainly used in settings where the goal is prediction, and one wants to estimate how accurately a predictive model will perform in practice. During a prediction drawback, a model is often given a data set of acknowledged knowledge set of known data on which training is run (training knowledge set), and a knowledge set of unknown data (or first seen data) against that model is tested (testing dataset).

The goal of cross validation is to stipulate a dataset to "test" the model within the training phase (i.e., the validation dataset), in order to limit issues like overfitting, provide associate insight on however the model will generalize to an freelance dataset (i.e., an unknown dataset, as an example for a true problem), etc.

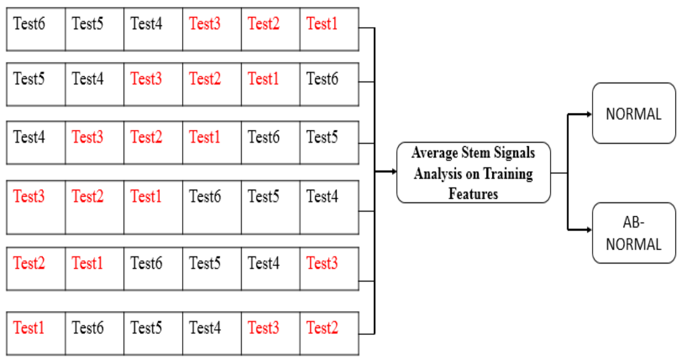

Fig 8: Cross Validation Method Classifier.

Cross-Validation is a statistical method of estimating and scrutiny learning algorithms by dividing information into two segments:one accustomed to learn or train a model and therefore the alternative accustomed to validate the model. In typical cross-validation, the coaching and validation sets ought to cross in serial rounds such every information of being valid against the essential kind of cross-validation is k-fold cross-validation.Different sorts of cross-validation square measure special cases of k-fold cross-validation or involve perennial rounds of k-fold cross-validation.Cross-validation is employed to gauge or compare learning algorithms as follows: in every iteration, one or a lot of learning algorithms

1.0000	1.1383	1.2063	0.9208	1.1616	1.6482	0.7841	0.8395	1.4251	0.9713
0.8785	1.0000	1.0597	0.8089	1.0204	1.4479	0.6888	0.7374	1.2519	0.8532
0.8290	0.9436	1.0000	0.7633	0.9629	1.3662	0.6500	0.6959	1.1814	0.8051
1.0860	1.2362	1.3101	1.0000	1.2614	1.7899	0.8515	0.9116	1.5477	1.0548
0.8609	0.9800	1.0386	0.7927	1.0000	1.4189	0.6750	0.7227	1.2269	0.8362
0.6067	0.6907	0.7319	0.5587	0.7048	1.0000	0.4757	0.5093	0.8647	0.5893
1.2754	1.4518	1.5385	1.1744	1.4814	2.1020	1.0000	1.0706	1.8176	1.2387
1.1913	1.3560	1.4371	1.0969	1.3837	1.9634	0.9340	1.0000	1.6977	1.1570
0.7017	0.7988	0.8465	0.6461	0.8150	1.1565	0.5502	0.5890	1.0000	0.6815
1.0296	1.1720	1.2420	0.9481	1.1959	1.6969	0.8073	0.8643	1.4673	1.0000

Fig 9: Dataset Values of samples.

Result Analysis

In this method we implement on cross validation based 10 data set trained values in these values we need to give input of our signal wavelet transform features after that we need to classifier on cross validation will give better performance than neural network and SVM classifier

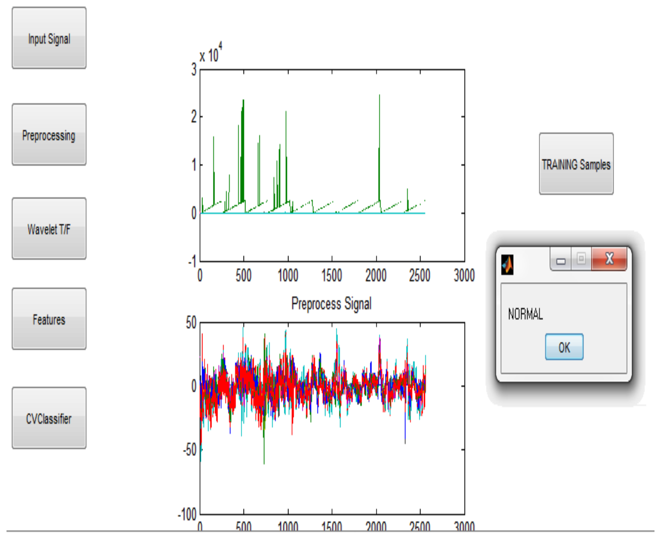

Fig 10: Signal Shows Normal EEG Signal.

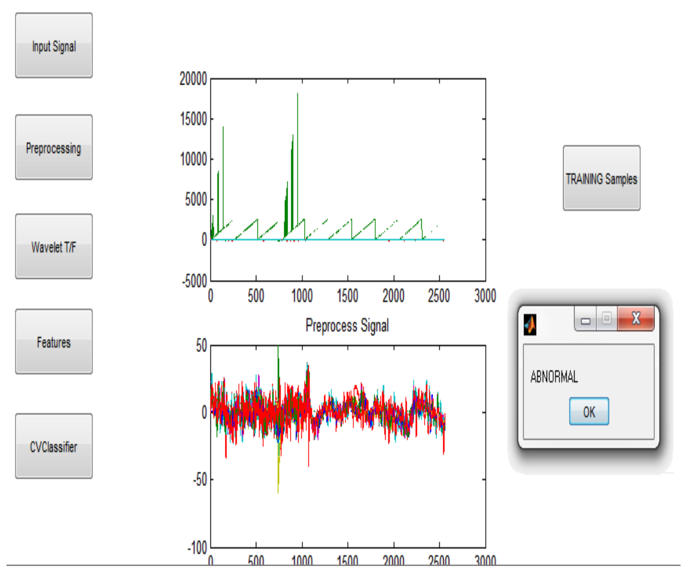

Fig 11: Signal Shows Abnormal EEG Signal.

Conclusion

We finally classified the EEG brain signal of patient by distinguish between normal and abnormal which are tumor and epilepsy with cross validation classification with the better accuracy of about 70% which is more when compared to other classifiers.

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