Classification of brain signals based on proposed method

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Abstract

Electroencephalography (EEG) signals are used to uncover brain processes, and researchers can use them to explore psychological factors that underpin behavior and perception. Because EEG signals are aperiodic and non-stationary in nature, selecting features that are appropriate for a certain application is complicated. Furthermore, EEG signals have a large number of dimensions, which decreases the speed and efficiency of the classifier. The suggested approach for the categorization of brain signals aims to address such issues, and it varies from current approaches in that it skips the feature extraction .

To process the nature of non-stationary, aperiodic, or unstable EEG signals, a segmentation approach has been used. Each one of the EEG channels is divided into N-segments, while each segment is divided into M-sub-segments. The covariance matrix was utilized to minimize EEG's dimensions while maintaining the signal data's core features. This is what allows the suggested approach to quickly become familiarized with all datasets. A recognized classifier was employed to classify EEG data: Least Square Support Vector Machine (LS-SVM).

The suggested system was put to test with the use of 4 datasets: a non-focal and focal epileptic dataset from the University of Bern-Barcelona, a motor imagery dataset (IVa) from brain-computer interface (BCI) competition III, a mental imagery tasks dataset (V) from BCI competition III, and epileptic dataset from Bonn University. For each one of the datasets, LS-SVM classification results for sensitivity, accuracy, FPR and specificity are 100%, 100%, 0%, and 100%, respectively

Keywords: Electroencephalography (EEG), Magnetoencephalography(MEG), Covariance- System., event-related brain potentials (ERPs), functional magnetic resonance imaging (fMRI).

.١ Introduction

The brain is considered as one of the major complicated organs in human body, allowing us to remember events from the past and comprehend all of our current sensory impressions. It is in charge of memories, ideas, and predictions for future .[١]

Also, the human brain is in charge of all bodily functions. Many brain cells are engaged in moving and doing various activities. To perform the correct response, the brain sends electrical impulses to the targeted muscle .[٢]

Magnetoencephalography(MEG),electroencephalography (EEG), functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and optical imaging are some of the techniques used to identify brain responses .[٣]

EEG is one of the non-invasive technologies which uses electrodes on the scalp for providing a direct measure related to brain electrical activities. EEG instantly measures the electrical activities with high accuracy. EEG allows researchers to explore psychological factors underpinning behavior and perception by analyzing event-related brain potentials (ERPs) and frequencies .[٤]

.٢ Datasets and its description

Four datasets have been used to demonstrate the unique characteristics of the proposed system, its quality in performance and to clarify the difference between the first and second system, as the second system is as simulations of the common systems used to classify the brain signals due to similarities between it and those systems. The four datasets are as follow:

- The first dataset [5] is the mental imagery tasks dataset (V) from competition III of the Brain-Computer Interface (BCI).
- The second dataset [6] is a Bonn University epileptic dataset.
- The third dataset [7] is an EEG dataset from the University of Bern-Barcelona that includes both focal and non-focal epilepsy.
- The forth dataset [5] is the motor imaging dataset (IVa) from competition III of the Brain-Computer Interface (BCI).

.٣ Suggested System

In this work two systems were developed to characterize EEG signals , one of which is the suggested system known as (covariance-system) and the other known as (features-system). The main structure regarding the two systems is depicted in Fig.1 .

In the two systems, the general structure is similar, yet there are differences in the third block, the data reduction part, in which the covariance matrix was utilized for reducing the signals' dimensions in the covariance-system, yet features extraction was utilized as an approach for data reduction in the features-system.

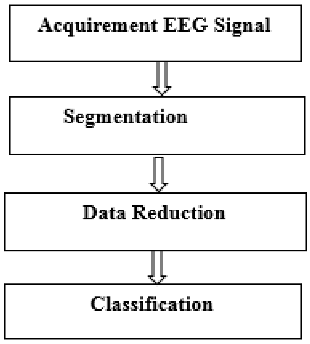

Fig.1 Block Diagram of the Two Systems.

The suggested system (covariance-system) to classify EEG signals is distinguished by its capacity for distinguishing distinct brain signal types, as well as high classification accuracy and suitability for real-time applications. There are 4 stages to the system design. Fig.2 depicts the components of the suggested system in further details.

Although the features-system has a high level of classification accuracy and is suitable for real-time use, it isn't suitable for the majority of EEG applications and is more efficient in Medical Diagnosis applications. The parts of the features-system are depicted in Fig.3.

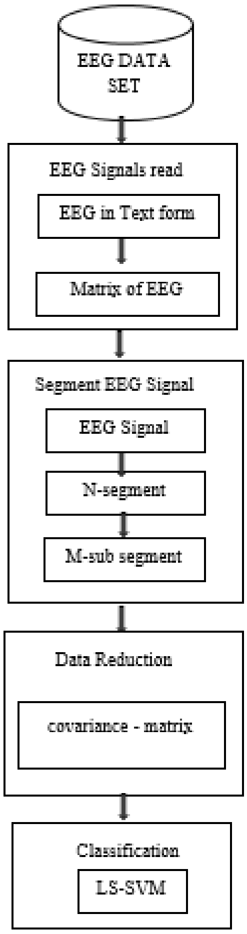

Fig.2 BlockDiagram of Proposed System (Covariance-System).

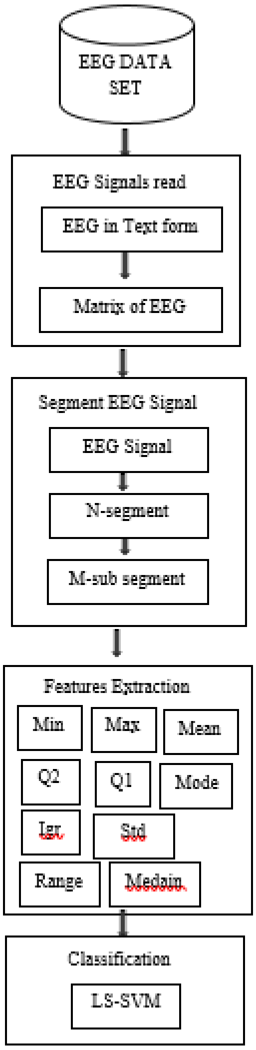

Fig.3 Block Diagram of Features-System.

The 4 phases of each of the 2 systems are:

Acquirement EEG Signal

Electrodes are placed in appropriate areas on the scalp to obtain EEG signals. EEG signals are either utilized immediately or saved in a specific format, like text files. EEG signals utilized in this investigation were located in text files saved on a computer. Also, all text files from the same class are grouped together in a single folder. To begin analyzing the EEG signal, all of the text files were compiled into a matrix (M file), with each class assigned to its own matrix.

Segmentation

Because each one of the brain signals comprises a significant number of data points, the brain signals regarding each one of the channels are separated into N segments, and each segment is divided further into M sub-segments in the second stage (EEG signals segmentation). The segmentation approach makes it easier for processing non-stationary and aperiodic brain signals because no signal part is ignored, increasing the accuracy of classification..For clarifying the method of segmentation, each matrix in the epileptic dataset of size 4096 * 100, in which each one f the columns in the matrix signifies channel signal, was divided into 4 segments, each of which has a size of 1024. Each of the 4 segments was after that divided into 4 sub-segments, resulting in a size of 256 for each sub-segment.

In this work propose storing all the sub-segments of each segment in single matrix called the sub-segments matrix so the number of sub-segments matrices equal to number of segments. Consider epileptic dataset, where each channel was divided into four segments and divided each segment into 4 sub-segments, the size of the sub-segments matrix for one segment is 4 * 256 because each sub-segment put in a separate column and the number of rows depend on length of sub-segments (256), the number of sub-segments matrices for one channel (one column in the main matrix of signals) is four matrices and the number of sub-segments matrices of the main matrix of signals 400 matrices of sub-segments.

Data Reduction

In the third stage (data reduction), the covariance-system reduces the dimensionality of EEG signals by using a covariance matrix. The features-system reduces the dimensionality of EEG signals by feature extraction, in which the purpose of extracting features is to decrease the amount of data while keeping enough discriminatory information for classification. This is a necessary and crucial aspect of all classification systems. The classifier's performance improves when the extracted features contain a substantial amount of discriminatory information. Each one of the sub-segments in the sub-segments matrix was represented by 10 statistical features.

Classification

Lastly, the third stage outputs were forwarded to the classifier (classification). EEG signals were classified using a classifier (LS-SVM).

4. Results

With 4 datasets, the LS-SVM classifier is utilized for comparing the 2 systems and determine which system produces the best results.

LS-SVM with Covariance-System

The classification results of covariance-system obtaining when using LS-SVM was excellent in every sense of the word, for sensitivity, accuracy, and specificity, the results were 100%, 100%, and 100%, respectively, as was the false positive rate (FPR) was 0% for each datasets used. Fig.4 illustrate the accuracy, sensitivity, specificity, FPR for each dataset.

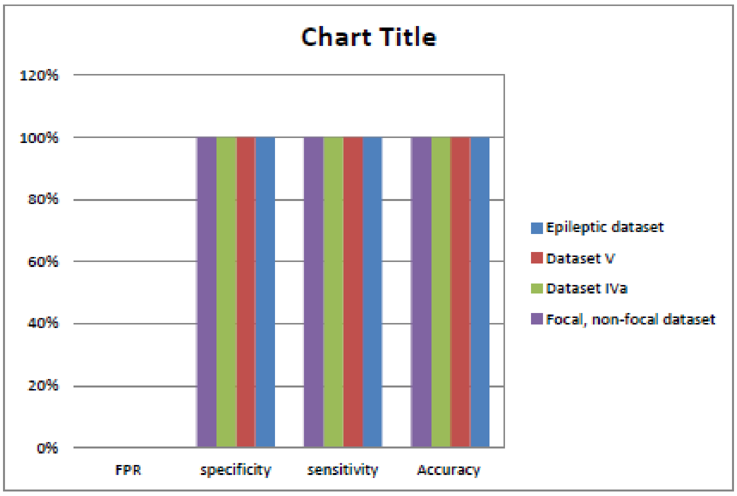

Fig.4 Classification Results of Covariance-System with LS-SVM for each Dataset.

LS-SVM with Features-System

After using the LS-SVM classifier to test the features-system, it is found that this system gives very good results with epileptic dataset and focal and non-focal dataset but results of dataset V not well and results of dataset IVa was bad. The results of all dataset using features-system and LS-SVM classifier are shown in table 1.

Table 1: Classification result for Features-System with LS-SVM

Dataset	Accuracy	Sensitivity	Specificity	FPR
Epileptic dataset	100%	100%	100%	0%
Focal, non-focal	94.25%	94.34%	94.24%	5.76%
Dataset V	81.67%	85.83%	82.15%	17.85%
Dataset IVa	62.50%	63.33%	61.90%	38.10%

From results of all datasets, it is noted that this system is effective in Medical Diagnosis applications not for other applications such BCIs applications. Fig.5 illustrates the accuracy, sensitivity, specificity, FPR for each dataset

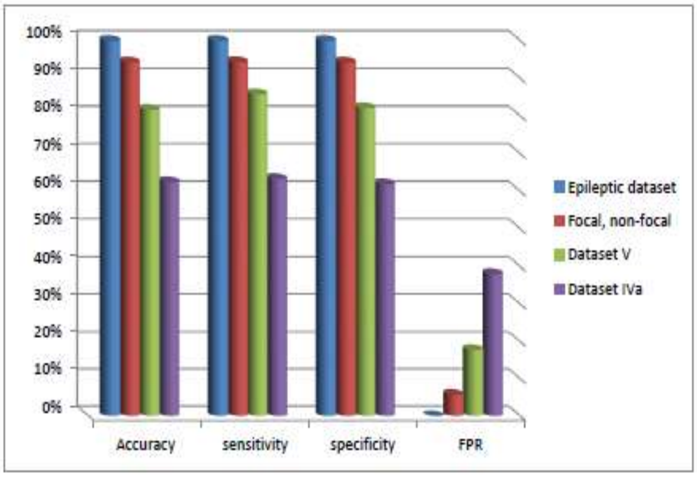

Fig.5 Shows the Accuracy, Sensitivity, Specificity, FPR for each Dataset Using Features-System and LS-SVM.

5. Conclusions

Working on this research and analyzing the results of the experiments has led us to a few conclusions, one of which is that acquiring brain signals is a complex process which needs a great deal of precision for placing the electrodes in the correct locations and, in the majority of cases, needs the assistance of a professional in the field.

Brain signals are periodic and unstable. This should be considered in the case when processing such signals so that no part of the signal is overlooked. There are 2 techniques to deal with the signal's instability. The first method is to interlace a window along the signal's length. This strategy is efficient, yet it considerably increases the data volume. The second approach, which is superior, is to break the signal into a number of parts, after that dividing each one of the pieces into a number of sub-components.

6. References

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