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Research Article

Spatiotemporal Image Encoding for Cross-Subject Zero Calibration Driver's Drowsiness Detection through EEG Signals

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Abstract
In this digital signal processing procedure, which analyses Electroencephalogram (EEG) data within a specified framework, the signal's frequency sub-bands were broken down using DWT, and a collection of features representing the distribution of wavelet coefficients was retrieved from the sub-bands. With the use of feature extraction techniques like mean, standard deviation, and variance, the size of the data is decreased. Following that, the classifier utilised these attributes as input to determine if the input data was normal or drowsy, and it classified the data accordingly. To demonstrate the superiority of the classification process, the performance of classification is evaluated. The system's main goal is to increase the precision of patient monitoring systems, remove variations in EEG signals, and enhance process accuracy.

1. Introduction

Systems engineering as well as applied mathematics all deal with the manipulations or analysis of analogue and digital signals that reflect time-changing or spatially variable physical values. This field is known as signal processing. Sound, electromagnetic radiation, pictures, and sensor readings for instance electrocardiograms, control system signals, telecommunication transmission signals, and many more, can all be considered signals of interest.

The following categories can be used to generally group signal processing objectives.

- Signal acquisition and reconstruction, which entails capturing and maybe subsequently reconstructing the original signal or an approximation of it. This often comprises quantization and sampling for digital systems.
- The enhancement of quality, such as echo cancellation, picture enhancement, and noise reduction.
- Signal compression (Source coding), which includes audio, picture, and video compression.
- Feature extraction, which includes speech and visual comprehension.

In older radio, telephone, radar, and television systems, analogue signal processing is used to handle signals that have not been converted to digital form. This applies to both linear and non-linear electrical circuits. Examples of the former include delay lines, integrators, additive mixers, passive and active filters, and passive filters. Compandors, multiplicators, voltage-controlled amplifiers and frequency mixers, voltage-controlled filters, and phase-locked loops are examples of non-linear circuits.

Discrete-time signal processing has been utilised for sampled signals that are exclusively described at discrete moments in time. As result, the signals are quantized in time but not in amplitude. Electronic components including sample and hold circuits, analogue time-division multiplexers, analogue delay lines, and analogue feedback shift registers are the foundation of the technology known as analogue discrete-time signal processing. The sophisticated processing of gigahertz transmissions still uses this technique, which was a forerunner to digital signal processing.

The processing of discrete-time sampled signals by digital means. General-purpose computers or digital circuits like ASICs, field-programmable gate arrays, or specialised digital signal processors are used for processing (DSP chips). Fixed-point and floating-point, real-valued and complex-valued, multiplication and addition are common mathematical operations. Circular buffers and look-up tables are two more typical hardware activities.

Audio signal processing is the deliberate alteration of acoustic perception, or sound, and it is commonly carried out using an audio effect or effects unit. Since audio signals may be electrically described in both digital and analogue ways, signal processing can be done in any of these domains. Overmodulation in audio transmission must be avoided and minimised by the audio processor. Additionally, you should rectify audio level mistakes and compensate for non-linear transmitters, which are more prevalent with medium wave and shortwave transmission. The overall loudness should be adjusted to the required level.

Electrical engineering and computer science both utilise video processing, a specific type of signal processing that frequently includes video filters but instead employs video files or video streams as both the input and output signals. Televisions, VCRs, DVD players, video codecs, video players, video scalers, as well as other gadgets all employ video processing methods. For instance, most TV sets from different manufacturers only differ in terms of visual processing and aesthetics.

Sleep apnea is the term used to describe someone who has breathing pauses or very low breathing while they are asleep. The analysis of short-duration electrocardiogram (ECG) data epochs is the main objective of an automated classification approach utilised in this operation. Sleep apnea recording datasets have been used to train and test support vector machines (SVM), which have been used to categorise apnea features. In this process, it is discussed how different sleep disorders impact the electrical activity of the human brain. Using time-frequency analysis of an electrocardiogram (ECG) signal and data on internal changes in brain state, the study aims to pinpoint distinct types of sleep disorders in humans. The method illustrates the identification of sleep issues relying on a few significant ECG signal features. Thus the major goal of this research is to predict the severity of sleep apnea using a reliable classification system, increase classification accuracy, and decrease miss class.

2. Literature Survey

For more than a century, scientists have studied brain signals to learn more about conditions including epilepsy, spinal cord injuries, Alzheimer's, Parkinson's, schizophrenia, and stroke. Moreover, they utilized in assistive, therapeutic, also entertaining brain computer and brain-computer interface technologies. The use of brain signals as a biometric feature for use in automatic person identification systems has just lately been examined by the scientific community, despite the widespread interest in therapeutic applications. More feature stability is achieved by Delta, Theta, Alpha, Beta, and Gamma. However, the cumbersome user acquisition setup, which involves several electrodes put on the scalp [2].

It was recently suggested to use electrodes inserted in the ear to measure the electroencephalogram (EEG) as a tool for monitoring the brain. This study's goal is to thoroughly compare the ear-EEG to traditional on-scalp EEG while further characterising the ear-EEG. This is accomplished throughout a population of people, spanning steady-state and transient paradigms, and for both auditory and visual evoked responses. Validation of ear-EEG and its distinct benefits (noninvasive, unobtrusive, user friendly, and discrete). However, the system's main drawback is that it requires more iterations, which takes more time [3].

This article describes the development of E-BIAS, a pervasive EEG-based security system that includes both identity and authentication features. Accuracy, timeliness, energy efficiency, usability, and robustness are the five key obstacles. The suggested system features a reduced training time (2 minutes) than prior studies, a high authentication/identification rate utilising commercially accessible devices, and implementation for widespread usages. However, the approach solely use binary categorization [4].

A common sleep problem called obstructive sleep apnea (OSA) affects 24% of adult males and 9% of adult women. Despite the fact that CPAP has become a common treatment for OSA, the majority of patients are not tolerant of it, mostly due to the uncomfortable nasal air supply while they sleep. For the purpose of forecasting and keeping track of chronic non-communicable illnesses, large data warehouses and cutting-edge information technology are used. Large data processing lengthens the process's duration, which is a serious drawback [5].

According to a technology called brain computer interface, it is possible to communicate with the outside world by utilising one's thoughts. The choice of techniques to process the brain data in each phase will determine if this methodology is successful. The purpose of this research was to discuss the numerous approaches that have to be modified for each stage of the processing of brain signals. Prior to conducting this survey, numerous approaches and some experimental findings from earlier surveys were identified and compared. This research provides an exhaustive illustration of the various signal processing approaches applied at each level of BCI signal processing. The survey's findings provide guidance for choosing the necessary signal processing technologies. Given the intricacy of the issue, BCI research is currently being done at a pretty rudimentary level. When it comes to categorising brain activity, BCIs are still only somewhat accurate [6].

This research compares several of the widely utilised algorithms on the same base dataset in an effort to identify the optimal feature extraction and classification approach. Cross-correlation and discrete wavelet transform (DWT) are two feature extraction methods that have been researched and contrasted. Logistic regression (LR),

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kernalized logistic regression (KLR), multilayer perceptron neural network (MLP), probabilistic neural network (PNN), and least-square support vector machine are the five classification techniques that have been applied (LS-SVM). The methods have been tested using Dataset IVa from the third BCI competition. Improved classification outcomes for EEG signal classification are being achieved via DWT, a feature extraction approach, and LSSVM, a classification algorithm. Cross correlation is producing positive findings, however it may not be recommended because it might make the temporal information in the EEG signal disappear [7].

3. Proposed System

In the current method, the short time Fourier transform (STFT) is employed to segment the ECG signals. The ECG signals are used to extract features using the Wigner-Ville distribution (WVD). The intrinsic mode functions (IMFs), which are decomposed into a limited and frequently small number by the EMD approach, were used to segment the ECG signals. Artificial Neural Networks were used for the categorization of the ECG signals, while EMD and HHT were integrated and used for the segmentation of the ECG data. The new technique was compared to the current methods using the benchmarked dataset that has been utilised in the previous publications.
But there were several drawbacks to this technique: Due to the inevitable trade-off between time and frequency firmness, methods like STFT frequently fail. The wavelet theory is constrained by the crucial uncertainty principle, the fundamental challenge of the WVD is the severe cross terms as demonstrated by the occurrence of negative power for specific frequency ranges. The first is to directly take into account all data in a single optimization formulation, and the second is to divide a multi-class issue into a number of binary problems. Unclassifiable areas are a drawback of pair-wise and on-against-all fuzzy neural networks.

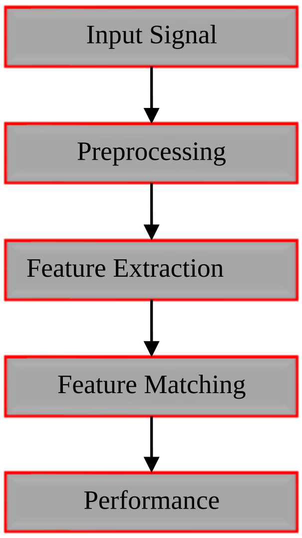

Fig 1: System Architecture

EEGs are pictures or recordings of the electrical potentials that the brain generates. Since Hans Berger began recording rhythmic electrical activity from the human scalp, analysis of EEG activity has mostly been done in clinical settings to pinpoint diseases and epilepsies. In this paper, we provided a flexible framework for electroencephalogram (EEG) data processing and analysis (EEG). One way to think about epileptic seizure detection in EEG is as a kind of pattern recognition idea. It comprises of seizure detection, feature extraction, feature reduction, signal processing, and data collecting. It is suggested to use SVM classification, dimension reduction (based on ICA, PCA, and LDA), and DWT to create a unique EEG signal classification approach.
Using DWT, the signals were separated into frequency sub-bands in this structure, and a collection of statistical characteristics representing the distribution of wavelet coefficients was recovered from the sub-bands. The dimension of the data is reduced using principal components analysis, independent components analysis, and DWT. Then, a support vector machine with two discrete outputs—epileptic seizure or not—was utilised using

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these attributes as its input. The following are a few benefits of the recommended method for identifying drowsiness in drivers:

- Peak signal that can be accurately recovered from an EEG signal, even one that is extremely noisy.
- Our EEG simulator's key benefits include time savings and the elimination of risks while recording the EEG using non-invasive techniques.

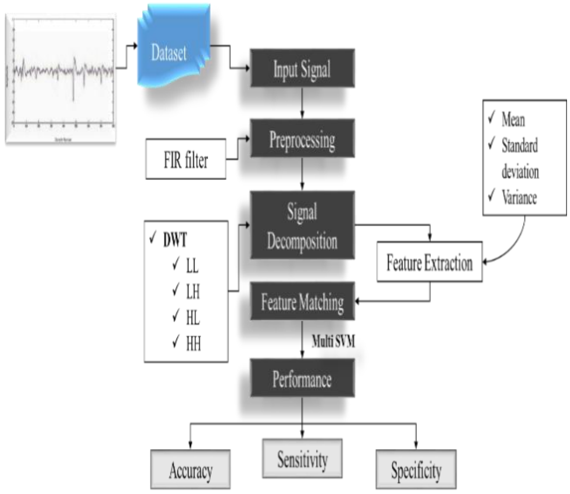

Fig 2: System Flow Diagram

Various phases that are implemented has been explained under following section:

1. Input Signal

An EEG is a test that checks for anomalies in the electrical activity or brain waves of your brain. During the procedure, electrodes—tiny metal discs with frail wires—will be applied to your scalp. The electrodes are able to detect the tiny electrical charges that your brain activity produces. There will be 16 to 25 electrodes connected to various locations on your scalp by the technician after being coated with a sticky gel glue. The electrodes transmit electrical impulse data from your brain to the recording device as soon as the test is underway. The electrical impulses are transformed by this device on a screen, it's possible to perceive patterns. A computer has preserved these patterns. While the test is being conducted, the technician may give you instructions. They could instruct you to remain quiet, close your eyes, take deep breaths, or focus on stimuli (such as a flashing light or a picture). The technician will take the electrodes out of your scalp after the test is over. You won't experience any discomfort since there isn't much electrical current flowing between the electrodes and your skin throughout the test.

2. Preprocessing

IIR and Bandpass filters are used for preprocessing. Networks called filters handle signals in a frequency-dependent way. Signal fading, reverberations, echo, multipath reflections, and missing samples are examples of alterations in a signal caused by the non-ideal features of the communication channel. The phrase "signal distortion" is frequently used to characterise a systematic undesired change in a signal. A bandpass filter is an electrical part or circuit that rejects signals at other frequencies whereas allowing signals between two predetermined frequencies to pass. One of the most common types of digital filters used in digital signal processing is the IIR filter. Because of the filter's feedback, the impulse response is "infinite."

3. Feature Extraction

A tried-and-true technique for feature extraction and dimensionality reduction is PCA. With the use of the feature extraction method referred to as independent component analysis (ICA), multivariate random signals are converted into signals with independently varying constituents. Filter banks are the most appropriate metaphor for DWT-based analysis.

4. Feature Matching

The characteristics that were retrieved in the preceding phase were fed into an SVM that had two distinct outputs: epileptic seizure or not.

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A Support Vector Machine, a discriminative classifier, is technically defined as a separating hyperplane. In two dimensions, this hyperplane splits a plane in half, with one class on either side of the line. Using conventional optimization tools, a distinct global optimum for its parameters may be discovered. It is possible to employ nonlinear boundaries with little additional computing work. Its performance is also fairly competitive with those of other approaches. One disadvantage is that the difficulty of the issue is inversely proportional to the number of samples rather than sample size.

4. Results

This study recommends combining deep learning methods with image encoding representations that make advantage of the time recurrences and correlations of EEG data in order to detect fatigue while driving. We tested our methods on a challenging dataset and outperformed earlier work in the field. Overall, the results emphasise the need for more research in this field to improve tiredness detection and offer a trustworthy safety mechanism for cutting-edge driving aid programmes. The performance of classification is assessed in order to show how great the classification process is. The system's major objectives are to improve process accuracy, eliminate fluctuations in EEG signals, and raise the precision of patient monitoring systems. The next screenshots demonstrate how successfully it is accomplished.

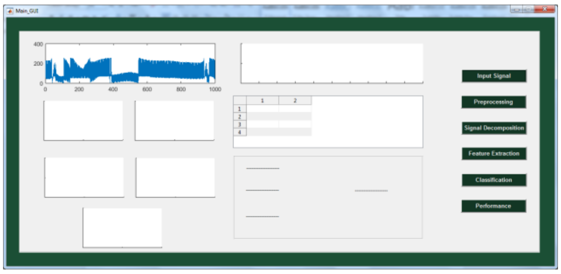

Fig 3: Input Signal

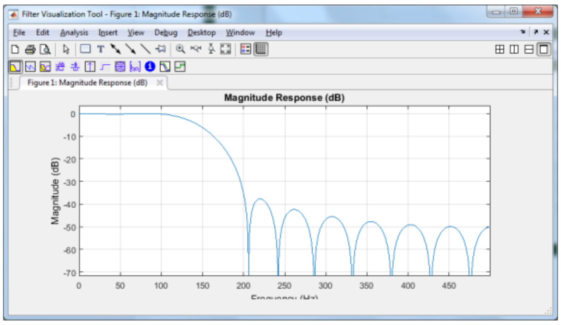

Fig 4: Magnitude Response

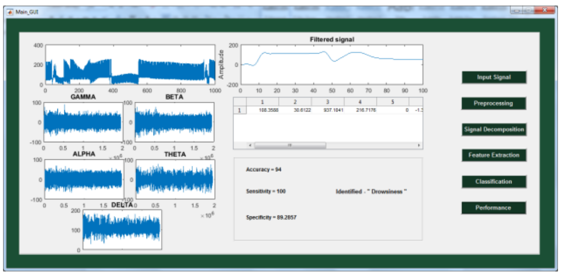

Fig 5: Performance Analysis

5. Conclusion

In order to identify tiredness while driving, this research suggests using deep learning techniques in conjunction with picture encoding representations that take use of the time recurrences and correlations of EEG data. With a

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difficult dataset, we verified our approaches and outperformed previous research in the field. Overall, the findings continue to point to the need for more study in this area to enhance sleepiness detection and provide a trustworthy safety system for advanced driver aid systems. Regarding the usefulness of the suggested technique in practise, a limitation of this study may be found. The utilisation of 32 channels is not a viable option for a real-world scenario; these systems are challenging to implement into a commercial product due to this physical restriction. The absence of online validation is especially notable because it is an essential step for the future.

6. Future Improvement

In order to fully use the representation and extract deeper characteristics outside of the spatiotemporal domain, we want to concentrate on the architecture design of the CNN in the future. We intend to investigate sequential analysis employing methods from the field of natural language processing, like recurrent neural networks with attention mechanisms, in light of the shown potential of time recurrences and correlations discovered in our study.

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