DOI: https://doi.org/10.17762/turcomat.v10i1.13560

Research Article

Application of SVM Algorithm for Fetal ECG Extraction from a Single Maternal Abdominal Record

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Abstract

The electrical activity of the foetal cardiac muscles is known as foetal ECG (FECG), and it can provide crucial details on the health of the fetus's heart. A pregnant woman's belly can be used to non-invasively capture this signal during pregnancy. However, since additional sources of noise, including the maternal ECG generally overpower the FECG recording, it would be ineffective. However, a clean FECG may be retrieved from the abdominal recording if it is correctly processed, and FECG can be used to evaluate the functioning of the foetal heart. In order to extract foetal electrocardiogram (ECG) from a single abdomen record, a unique two-tier approach is presented in this work. The abdominal signal is processed through a smoothing filter in the first layer of the proposed approach in order to determine the maternal ECG's estimated value. Findings on synthetic and actual abdominal ECG data demonstrate that the intended technique can extract foetal ECG with signal quality equivalent or superior to that retrieved by multichannel based mechanisms. The anticipated maternal ECG is then nonlinearly matched with the abdominal signal through polynomial networks.

Keywords: Foetal Cardiac Muscles, FECG Recording, electrical Activity, Polynomial Network, Abdominal Signal.

1. Introduction

The underlying theory, applications, methods, and implementations of processing or conveying information stored in a variety of physical, symbolic, or abstract representations that are collectively referred to as signals are all included in the key enabler known as signal processing. It employs formalisations and methods for representation, modelling, analysis, synthesis, finding, recovery, sensing, acquisition, extraction, learning, security, or forensics that are mathematical, statistical, computational, heuristic, and linguistic in nature. Analog to digital converters, which sample signals in the time domain and transform them to digital form, must be used before analogue acoustic signals may be used in DSP. The signal may then be sent to an integrated DSP processor or a PC running DSP software when this is complete. The DSP programme must then separate the intended signal from background noise and produce the right output for the input signal.

The electrophysiological monitoring technique of electroencephalography (EEG) is a tool used to capture brain electrical activity. It is non-invasive since the electrodes are often implanted along the scalp, while invasive electrodes may occasionally be employed in certain situations. Ionic current in the brain's neurons causes voltage changes, which are measured by EEG. The term "EEG" is used in therapeutic contexts to refer to the technique of utilising several electrodes that are positioned on the scalp to record the time-varying spontaneous electrical activity of the brain. The majority of diagnostic applications concentrate on the spectrum content of the EEG, or the kinds of neural oscillations (the term "brain waves" is frequently used) that may be seen in EEG data. Epilepsy creates abnormal EEG readings, which may be used to identify the condition most frequently. Furthermore, it is used to detect brain death, encephalopathy, comas, and sleep problems. The use of EEG has decreased for the detection of tumours, strokes, and other localised brain diseases as high-resolution anatomical imaging methods like magnetic resonance imaging as well as computed tomography have developed. The EEG is nevertheless a useful tool for study and diagnosis even with its poor spatial resolution, especially when millisecond-range temporal resolution is required (which is impossible with CT or MRI).

A scalp-based electroencephalogram records the electrical activity of the brain. Epileptiform and non-epileptiform activity are the two main categories of abnormal activity. Focal activity is characterised by rapid, synchronous potentials in a significant number of neurons in a relatively defined brain region. These reflect a region of cortical irritability that may be susceptible to produce epileptic seizures and can appear as interictal activity, between episodes. As potential indicators for Alzheimer's disease, more sophisticated measurements of aberrant EEG signals have also drawn interest.

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The electroencephalogram is a recording made from the scalp of the brain's electrical activity. The frequency of alpha is 7.5 to 13 Hz. is on both sides of the head are frequently affected at the rear, with the dominant side having a higher amplitude. It might be viewed as a symptom of localised subcortical lesions, but it can also be observed in diffuse illnesses such metabolic encephalopathy or in some cases of hydrocephalus with a broad distribution. Beta: Beta activity is considered to have a typical rhythm and is "rapid."

When a patient is aware, worried, or has their eyes open, this rhythm predominates. The electrophysiological monitoring technique of electroencephalography is generally employed to record the electrical activity of the brain. EEG is the term used to describe the method of continuously monitoring the electrical activity of the brain using many electrodes positioned on the scalp. The EEG monitors voltage changes brought on by ionic current in the brain. It is most frequently used to identify epilepsy, which affects the EEG and results in aberrant findings. The development of MRI and CT has led to a decline in the use of EEG, which was formerly the go-to diagnostic technique for tumours, strokes, and other localised brain illnesses. EEG is a concept that utilized in clinical circumstances to illustrate the long-term recording of the brain's impulsive electrical activity from multiple electrodes positioned on the scalp. The key objective of the suggested strategy is to use the Blind source separation technique, which will produce results that are more accurate than those of the current method and require less effort.

2. Literature Survey

Alzheimer's illness The Neuroimaging Initiative (ADNI) is a multicenter, continuing, longitudinal research that aims to create biomarkers for Alzheimer's disease that may be used for early identification and monitoring (AD). The Neuroimaging Initiative (ADNI) is a multicenter, continuing, longitudinal research that aims to create biomarkers for early identification and monitoring of AD that are related to clinical, imaging, genetic, and metabolic factors. The creation of standardised techniques for clinical examinations, magnetic resonance imaging, positron emission tomography, and cerebrospinal fluid biomarkers are among ADNI's most notable achievements. While brain shrinkage and hypometabolism levels reflect anticipated patterns but demonstrate varying CSF biomarkers are compatible with disease trajectories anticipated by the tau-mediated neurodegeneration and the -amyloid cascade hypotheses for Alzheimer's disease, with rates of change dependent on region and disease severity [1].

The use of brain imaging and pattern recognition tools in the efficient and precise diagnosis of AD has lately attracted more interest. However, the majority of current research is on using single-modality or single-level biomarkers for AD diagnosis. In this article, we provide a theoretical foundation termed multi-modal imaging and multi-level features with multi-classifier (M3) to separate AD sufferers compared to healthy controls. In order to quantify three different levels of functional features, such as the amplitude of low-frequency fluctuations, regional homogeneity, also regional functional connection strength, this method analyses data from two imaging modalities: structural MRI, that was utilized to assess the regional grey matter volume, as well as resting-state functional MRI. In order to calculate the values for each measure, the author used 90 areas of interest taken from a previous atlas. These values were then used to train a multi-classifier that was built on four basic classifiers for maximum uncertainty linear discriminant analysis. Utilizing leave-one-out cross-validation, the effectiveness of this strategy was assessed. Using the M3 technique, classification accuracy was 89.47%, sensitivity was 87.50%, and specificity was 90.91% for the dataset of 16 AD patients with 22 healthy controls [2].

In contrast to age-matched healthy participants, EEGs from people with Alzheimer's disease are "slower" (i.e., have greater low-frequency power) and simpler, according to medical research. These two occurrences' relationship has not yet been investigated, and it is frequently tacitly believed that they are independent of one another. This research demonstrates the close connection between the two phenomena. Two distinct EEG datasets, one with moderate cognitive impairment (MCI) patients and controls and the other with mild Alzheimer's disease patients as well as controls, both show a strong association among sluggish and loss of complexity. The two data sets came from several hospitals, various patients, and various recording methods. The article also looks at the possibility that EEG slowdown and loss of complexity might be early signs of AD. To differentiate MCI and MiAD patients from age-matched control participants, comparative strength and complexity scores are utilised as characteristics. Classification rates of 83% (MCI) and 98% (MiAD) are obtained when two synchrony metrics (Granger causality and stochastic event synchrony) are combined. The classification rates are somewhat higher when the compression ratios are included as features compared to just using relative power and synchronisation measurements [3].

This study examines current developments in the electroencephalogram (EEG)-based diagnosis of AD. There have been three main changes in the EEG associated with AD: a slowing of the EEG, a reduction in the complexity of the EEG signals, and disturbances in EEG synchronisation. To find these small changes in AD patients' EEGs, a range of advanced computational methods have been presented recently. The study first discusses techniques for identifying EEG slowness. The paper then discusses several EEG complexity measurements and describes how these measures have been applied to research EEG complexity variations in AD patients. The context of diagnosing AD is therefore taken into account while looking at various EEG synchrony metrics. Additionally, a brief discussion of EEG pre-processing is included. It is required to eliminate artefacts caused by things like head and eye motion or interference from electronic equipment before one may study EEG. Pre-processing of EEG has drawn a lot of interest recently. This study describes a number of cutting-edge pre-processing methods, such as blind source separation and various non-linear filtering paradigms. The research also discusses the advantages and disadvantages of computational methods for AD diagnosis based on EEG. Finally, current issues and upcoming difficulties are examined [4].

AD is a neuro-degenerative condition that includes the most prevalent kind of dementia [6] [8]. It is the most costly illness in contemporary society and is defined by cognitive, intellectual, and behavioural disorder. As a result, early illness detection is crucial since it enables patients and their families to take preventative actions. EEG is a commonly used as a screening procedure for AD patients. The EEG signals of AD patients exhibit a number of anomalies. Therefore, it is necessary to create a method for detecting dementia in its early stages, with mild cognitive impairment as its first stage (MCI). In recent decades, the function of EEG in the diagnosis and clinical study of Alzheimer's disease has grown in importance [7]. The diagnosis of AD and its early identification in the preclinical stage are now the most crucial tasks. The EEG signal's diagnostic accuracy has to be increased. The concepts for improving the signal's accuracy by utilising various techniques are presented in the study. Generally, signal sluggishness, shift of power spectrum to low frequencies, etc. are characteristics of anomalies in the EEG signals. EEG can be used in this way to aid in the AD illness is best diagnosed early [5].

3. Proposed System

The diagnosis of Alzheimer disease involves the use of several clinical approaches, including genetic testing, physiological indicators, and neuroimaging procedures. One of the recognised techniques for making a certain diagnosis of dementia is neuroimaging. Alzheimer disease is diagnosed using a variety of neuroimaging techniques. The early detection of AD has been made possible by a number of measures, such as magnetic resonance imaging, positron emission tomography, and single-photon emission computerised tomography. Furthermore, the biggest issue with PET and SPECT is the radiation hazards they provide. Other drawbacks include their high expenditures, which are often time-consuming and inconvenient. So, in addition to all of these neuroimaging techniques, EEG is a widely utilised technique for Alzheimer disease diagnosis. One method for systematically screening the group of people at threat for Alzheimer's is the use of electroencephalography. As a specialised medical tool, EEG is non-invasive, repeatable, and simple to use at home via wireless body area networks. EEG is another clinical tool used to track brain activity that is a direct indicator of brain function. In order to identify neurological conditions like Parkinson's, epilepsy, and Alzheimer's, non-linear analysis of the collected EEG data has demonstrated the special properties.

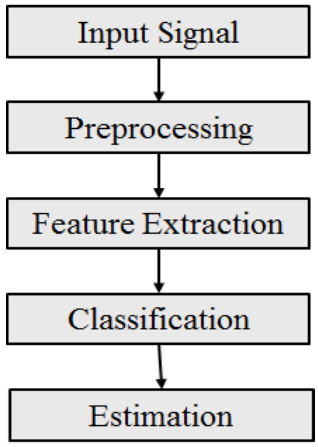

Fig 1: System Architecture

One technique for determining AD diagnosis is EEG. The fact that AD is affordable, practical, and affordable is one of their benefits. In addition, people with Alzheimer disease or those throughout the initial stages of the condition known as Mild Cognitive Impairment have some anomalies in their EEG (MCI). EEG is one of the techniques used to diagnose AD. One of the most significant phenomena seen in AD patients' EEGs is this one. We are initially extracting the EEG signal from the dataset. The signal is subsequently pre-processed. This comprises amplification and the first elimination of artefacts from the EEG signal. Various techniques, like Blind Source Separation along with Independent Component Analysis, are also employed to get EEG data that are more improved. The EEG signal is post processed utilising the time frequency domain after the aforementioned approach. The signals' features were then extracted. The classifier receives its input from the characteristics that were retrieved in the previous step. For classification, we can employ the support vector machine (SVM) or the linear discriminative analysis (LDA). Using the Classifier's output, we may determine if a person has Alzheimer's disease or is experiencing mild cognitive impairment, which is an early stage of the disease (MCI). The following are some of the proposed approach's benefits:

- This approach lessens complexity.
- High precision
- It is affordable and practical.

Following are the social demands of the suggested approach:

- The AD may be diagnosed with ease.
- Due to the lack of a necessity for an external equipment, it can be detected early in the preclinical stage.
- Use of it is trustworthy.

The next section explains the several steps that make up the implementation of the suggested approach:

1. **Input Signal**

It is necessary to produce an ECG signal for processing and analysis. Read input signals using the format that is specified. The ECG waveform displayed it.

2. **Pre-processing**

Prior to processing the signal, the input signal required to be prepared. Mean subtraction, moving average filtering, high-pass filtering, as well as low-pass Butterworth filtering are only a few of the preprocessing procedures that are included here. Asystole, noise, and poor-quality signals will all be eliminated by using this technique.

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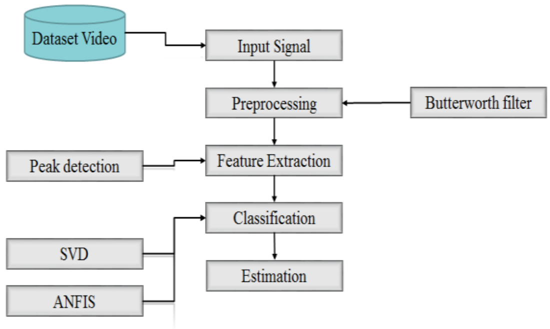

Fig 2: Flow Diagram

3. **Feature Extraction**

Use the peak detection method to extract features during the feature extraction process. The development of derived values (features) intended to be helpful and non-redundant commences with a collection of measured data. The learning and generalization processes are accelerated by this mechanism, which under some circumstances also enhances human interpretations. Low-level also high-level picture features have been considered in feature extraction. Extraction of low-level features focuses on the edges.

4. **Classification**

The ANFIS approach is used in this procedure for categorization. The ANFIS is put up against linear systems and neural networks for comparison. The primary function of the ANFIS is its ability to gather neural network and fuzzy logic data for non-linarites.

5. **Estimation**

Peak signal-to-noise ratio, which is sometimes shortened, is a technical term used to compare a greatest extent of signal's intensity to the power of corrupting noise that distorts the signal's representation of its integrity. Because many signals have a significant dynamic range, PSNR is frequently expressed using a logarithmic decibel scale. The most common method for evaluating the quality of reconstruction produced by lossy compression codecs is PSNR (e.g., for image compression). Here, the noise is caused by the error introduced by compression, whereas the signal represents the actual data. PSNR is a proxy for the impression of reconstruction quality by humans when comparing compression codecs. Even while a greater PSNR often denotes a higher-quality reconstruction, this may not always be the case.

4. Results

The electrical activity of a developing fetus's cardiac muscles is called a foetal ECG (FECG), which can provide important details on the cardiac condition of the foetus. During pregnancy, a pregnant woman's belly can be used to non-invasively capture this signal. The maternal ECG (MECG) and other noise sources completely overpower the FECG in such a recording, making it unusable. To evaluate the functioning of the foetal heart, a clean FECG may be recovered from the abdominal recording provided it is processed appropriately. A novel approach for utilising EEG signals to diagnose Alzheimer's disease is suggested in this study, which will improve the diagnostic efficacy of the EEG signals and diagnosis. EEG Spectro-temporal Modulation Energy Based Aspects, Spectral Features, Coherence Features, and other features of EEG Signals are examined in detail. It may be inferred from the properties of the EEG signal that were previously mentioned that it can be useful in the identification of dementia and AD. Finally, an SVM classifier is used to determine if a signal is normal or abnormal, and wavelet characteristics are also used to identify features during the process. The screenshots that follow show the results of the suggested method.

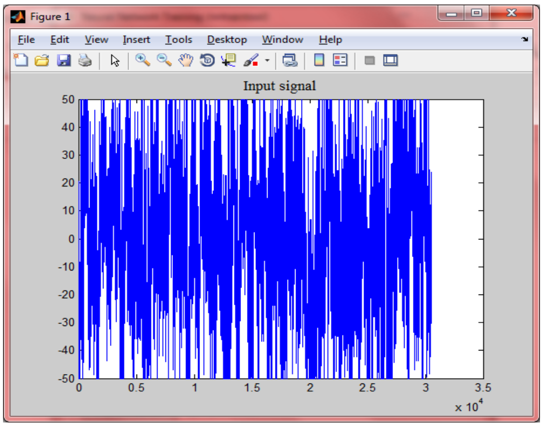

Fig 3: Input Signal

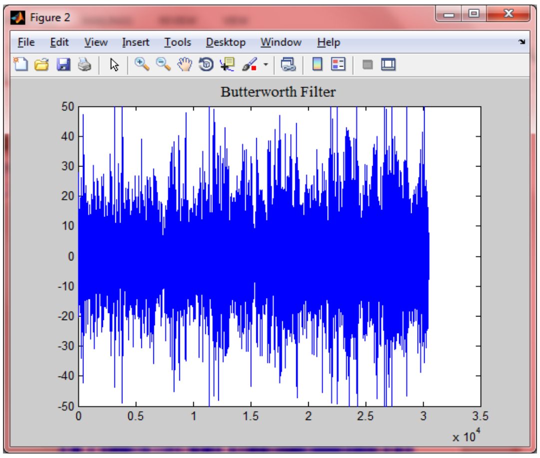

Fig 4: Butterworth Filter

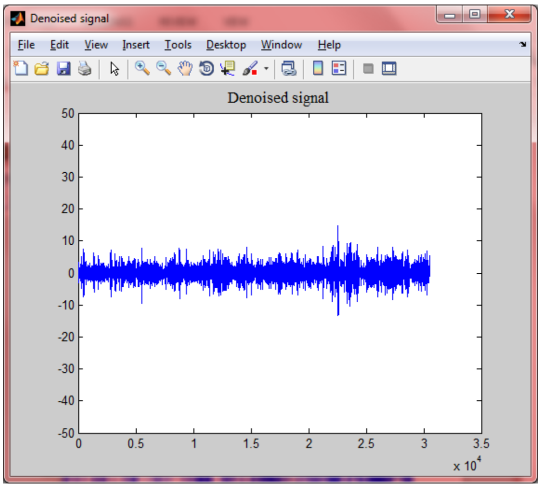

Fig 5: Denoised Signal

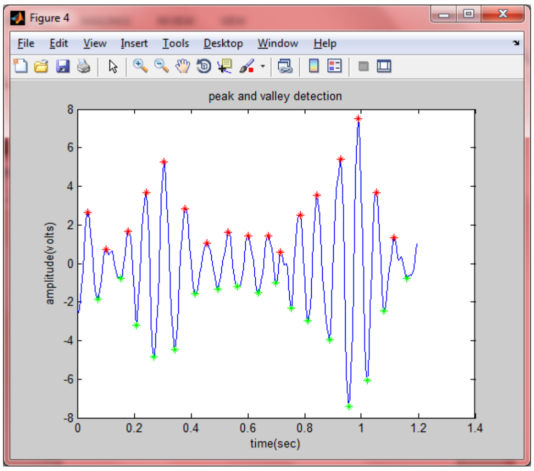

Fig 6: Peak and Valley Detection

5. Conclusion

A novel approach for utilising EEG signals to diagnose Alzheimer's disease is suggested in this study, which will improve the diagnostic efficacy of the EEG signals and diagnosis. EEG Spectro-temporal Modulation Energy Based Aspects, Spectral Features, Coherence Features, and other features of EEG Signals are examined in detail. It may be inferred from the properties of the EEG signal that were previously mentioned that it can be useful in the identification of dementia and Alzheimer's disease. Finally, an SVM classifier is used to determine if a signal is normal or abnormal, and wavelet characteristics are also used to identify features during the process.

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