AN EFFICIENT COMPRESSION ALGORITHM FOR EEG SIGNAL USING CONTINUOUS WAVELET TRANSFORM WITH COMPLEX VALUED MORLET WAVELET

A PROJECT REPORT

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BONAFIDE CERTIFICATE

Certified that this project report "**AN EFFICIENT COMPRESSION ALGORITHM FOR EEG SIGNAL USING CONTINUOUS WAVELET TRANSFORM WITH COMPLEX VALUED MORLET WAVELET"** is the bonafide work of "**GANESH RAAJU M (922319106005), MANOJ KUMAR S (922319106012), SABARI R (922319106026) and SUNDAR NAVEEN M (922319106029**)" who carried out the project work under my supervision.

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ABSTRACT

This project describes the EEG signal compression using continuous wavelet transform with complex values more wavelet transform, Electroencephalogram (EEG) signals are widely used in neuroscience research, clinical diagnosis, and brain-computer interface systems. However, the high dimensionality and large size of EEG data make it challenging to store, transmit, and process these signals efficiently.

Therefore, compression of EEG signals has become a crucial research area. Wavelet transform-based compression methods have been widely used in EEG signal compression due to their ability to capture both temporal and frequency information of the signals. In this method, the EEG signals are decomposed into multiple sub-bands using wavelet transform, and the coefficients of these sub-bands are quantized and encoded using entropy coding techniques. The quantization and encoding parameters are optimized to achieve a trade-off between compression ratio and signal quality.

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CHAPTER 1

INTRODUCTION

1.1 EEG SIGNAL COMPRESSION

Electroencephalography is the bio-signal which deals with recording the electrical activity of the human brain. It can produce the signals of up to 256 channels of up to 32 bps each, and it is sampled at the frequency of 1000Hz [5]. The EEG is used in the evaluation of brain disorders and it is used to find the brain damage. It has a high temporal resolution but poor spatial resolution. It can be efficiently stored and also transmit the huge amount of EEG signal by using the compression techniques. EEG compression has two types. They are lossy compression and lossless compression

In the medical applications, transmitting the large amount of data through the compressed form. An excellent way to determine the performance by lossless EEG compression techniques.

One of the most important organs of human body is brain. Brain is the vertebrate central nervous system that is enclosed within the cranium, spinal cord and also composed of gray and white matter. Brain is the prime centre for regulation and controls the functioning of the human body including heart bit and respiration. It is an extremely complex system in the entire body and exhibits rich spatiotemporal dynamics.[1] And it is often affected by some disorder and malfunction. One of the most common brain disorders is Epilepsy. Today about 60 million people are affected by this disorder

The Electroencephalogram which is abbreviated as (EEG) that is clinically used to investigate brain disorders or to diagnosis various brain functionalities.[2] The first attempt at measuring this brain disorder activity was done by British Physician Richard Caton in the year 1875. Electroencephalographic record is one of the most important tools for the study of the brain electrical activity and for the diagnosis of neurological diseases. It is also the electrical interpretation of the heart activity. Epileptic seizures are basically the manifestations of epilepsy. Electroencephalograph (EEG) records can provide valuable insight and improved understanding of the mechanisms causing epileptic disorders by careful analysis. Epileptic seizure is due to the temporary electrical disturbance of the brain. Epileptic seizure sometimes, goes unnoticed and sometimes bit confused with other events prevailing depending on their presentations such as strokes, cause falls and migraines. Out of every 100 persons, one is experiencing a seizure at some time in their whole life. Unfortunately, the occurrence of epileptic seizure seems somehow unpredictable and very little understood.[5] In the diagnosis of epilepsy, the detection of epileptiform discharges in the EEG is an important component. EEG signals are non-stationary.[3] The most important, useful and cost-effective modality for the study of epilepsy is EEG. Also, EEG is a graphical representation of cardiac activity which uses primary measure for the identification of various heart diseases and heart abnormalities. EEG signal is basically a one-dimensional biological signal. Analyzing of EEG signal is based on its frequency content. Hence, we can say that interpretation of EEG signal is based on the power of the frequencies it contains

Wavelet analysis has been used in recent years to analyze time-domain signals. Wavelet analysis is a type of time-frequency analysis, providing information about both frequency and time within signals. Since brain activity is highly time-dependent, the use of the wavelet transforms to generate characteristics, or features, of Electroencephalography (EEG) signals has provided researchers a new tool for investigating the time-frequency characteristics of the signal. Wavelet analysis generally reveals characteristics in the data that are missed by traditional frequency analysis. However, current methods of generating wavelet-based features do not take full advantage of the wavelet's unique ability to provide time resolution. Most methods involve generating features from wavelet transforms of the data in such a way as to average out the temporal information, for the purpose of producing higher classification rates. While helpful in classifying data, these kinds of features have an ambiguous physical interpretation. To create brain models using data from EEG studies, it is important to be able to interpret the data in a meaningful way, not just to be able to classify it

The first goal of this thesis is to examine the considerations involved in generating wavelet features and show their applicability in analyzing EEG signals in contrast to conventional frequency analysis. The second goal is to formulate a new method of generating wavelet features through time which makes better use of the wavelet's time-resolution than current methods but also retains its physically interpretable meaning. The third goal is to write a software tool in Matlab which can accomplish these first two goals; to generate features of EEG data by a few different methods including conventional, wavelet-based, and the time-segmented wavelet method described in this thesis. The fourth goal is to use the software tool to test the strength of each method using data from an EEG study on the attentional networks of individuals with autism spectrum disorder those who are considered neuro-typical.

While the Fourier transform reveals the frequency content of the time domain signal, it gives no information about where in the signal the frequencies were located. In this case of the signal above, none of the frequencies were localized in time, so the Fourier transform succeeds at revealing all the information that is contained in the signal. If, however, the signal's three frequencies were localized at different points in the signal, as in Figure 1.2, the Fourier transform would not reveal this information. It looks almost exactly like it did when they were not localized.

1.2 ELECTROENCEPHALOGRAPHY (EEG)

Electroencephalography (EEG) is the study of the electrical activity of the brain. The first attempt at measuring this activity was made in 1875 by a British physician named Richard Caton. Afterward, advancements in neurophysiology were made throughout all of Europe, but slowed to a crawl during both World Wars. After the second World War, the United States took the lead in Electroencephalography (EEG) research, and the American EEG Society was founded in 1947. In the decades that followed, EEG research in both Europe and America flourished, and every major university hospital had an EEG machine by the 1950s [1]. Although today there are other methods to measure brain activity such as functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), positron emission tomography (PET), and Diffusion Tensor Imaging (DTI), EEG remains one of the most widely used, primarily due to its relatively low cost and wide availability

The human brain contains around 100 billion nerve cells These nerve cells, or neurons, carry out the functions of the brain and make thought possible. They operate by sending electrical signals to one another. This exchange involves the passing of anions and cations through the membranes of the neurons, causing a change in electric potential that can be measured [1]. Although the electrical activity of a single neuron can be measured with a microelectrode, it is currently impossible to do so without the use of invasive procedures that involve insertion of electrodes into the brain. Alternatively, the measurement of EEG signals can be done using electrodes on the scalp, making a noninvasive measurement of large groups of neurons. The signals which are produced and picked up by the electrodes represent the behavior of large numbers of neurons located just beneath the skull where the electrode was placed. This does not take into account the activity located deeper inside the brain. The information gained from electrodes has led to the development of connectivity theory. Connectivity in the human brain refers to patterns of connections between groups of neurons or regions of the brain. The functions of the brain rely on the synchronization of these neurons, meaning that they perform similar operations within a period. Research in connectivity shows that the brain's normal function depends on the synchronization of activity inside distributed networks

The collapse of this synchronicity has been shown to result in schizophrenic behavior, attention and memory deficits, and speech disorders Increased synchronization has also been found during neuro-feedback training in subjects with autism The use of EEG to measure connectivity has advantages over other techniques because of its high temporal resolution, frequency specification, multiple source measuring, and the ease of elimination of correlated sources using statistic EEG signals are primarily analyzed by their frequency content. That is, the interpretation of the EEG signal is based on the power of the frequencies that it contains. The primary range of interest for EEGs is from one to 100 Hz.

Five main frequency ranges are normally included in all EEG studies, Delta (0.5-4 Hz), Alpha (4-8 Hz), Beta (8-12 Hz), Theta (12-30 Hz), Gamma (30-100 Hz). There are several conditions under which EEG may be acquired two common ones are resting state and task oriented. Resting EEG signals are recorded while a person is sitting still and not engaged in any concentrated mental activity. This type of signal is used for the detection of seizures, abnormal brain states, diseases, and cognitive disabilities. Often, resting state EEG is acquired under an “eyes-closed” condition. Task oriented EEG signals are recorded while a person is performing a mental task such as reasoning through a math problem or counting the number of objects on a screen. These signals are used to better our understanding of cognitive states and brain responses to cognitive or perceptual stimuli. Both types of signals make use of frequency analysis, but the nature of task-oriented EEG signals is such that the signal may contain temporal characteristics that may be lost or averaged out. The task-oriented EEG signals often contain abrupt changes in frequency due to the changing mental activity during a task. In order to gain information about these frequencies, the time-structure of the signal must be preserved. One method used in recent decades to accomplish this is wavelet analysis. One of the first instances of its use with EEG signals was for the detection of EEG spikes and seizures in 1993 [32]. Electroencephalographic spikes in EEG signals are points of sudden brain activity which contain certain frequencies. Whereas their presence alone within the EEG signal might be detected by a Fourier transform, they are revealed by a wavelet transform to be at a specific place in that signal. Due to the highly temporal nature of brain activity, wavelets are proposed as an ideal avenue for EEG analysis,

1.3 WAVELET ANALYSIS

A wavelet is a mathematical function that is used in the analysis and processing of signals and data. It is a type of mathematical tool that can be used to decompose signals into various frequency components, allowing for more efficient analysis and processing. Wavelets are different from traditional Fourier analysis methods, which rely on a fixed set of frequency components. Wavelets, on the other hand, are more flexible and adaptable, as they can be scaled and shifted to match the properties of the signal being analyzed. Wavelets have a number of practical applications in fields such as signal processing, image processing, and data compression. They can be used to remove noise from signals, compress large data sets, and extract important features from complex data.

1.3.1 Types Of Wavelets

There are several types of wavelets transforms that can be used for signal analysis and processing. Some of the most common types include:

1.Continuous Wavelet Transform (CWT):

The CWT is a type of wavelet transform that analyzes a signal at different scales and frequencies. It uses a family of wavelets with varying widths and centers to analyze a signal over a continuous range of frequencies. The CWT can be used to detect transient features in a signal that occur at different frequencies and time points.

2. Discrete Wavelet Transform (DWT):

The DWT is a type of wavelet transform that decomposes a signal into a set of wavelet coefficients at different scales and positions. Unlike the CWT, which analyzes a signal over a continuous range of frequencies, the DWT operates at discrete scales and positions. The DWT can be used for signal compression, denoising, and feature extraction.

3. Stationary Wavelet Transform (SWT):

The SWT is a type of wavelet transform that uses a set of filters to decompose a signal into wavelet coefficients at different scales and positions. The SWT is like the DWT, but it has the added property of being stationary, meaning that the wavelet coefficients have constant variance across different scales. The SWT can be used for signal analysis, denoising, and feature extraction.

4.Undecimated Wavelet Transform (UWT):

The UWT is a type of wavelet transform that is like the DWT, but it does not down sample the signal at each scale. This allows for a more accurate representation of the signal at each scale and position, but it also results in a larger number of wavelet coefficients. The UWT can be used for signal compression, denoising, and feature extraction.

Wavelet transforms are powerful tools for signal analysis and processing, and there are many different types of wavelets transforms available to suit different applications and signal types**.**

The complex Morlet wavelet is a type of wavelet used in the Continuous Wavelet Transform (CWT) to analyze signals in both the time and frequency domains.

1.3.2 Properties

The complex Morlet wavelet has several useful properties that make it an effective tool for signal analysis. Some of these properties include:

1. **Localization in time and frequency**

   The complex Morlet wavelet has a Gaussian shape in the time domain, which means that it is well-localized in time. It also has a broad spectrum in the frequency domain, which makes it effective at detecting features across a wide range of frequencies.

2. **Admissibility**

   The complex Morlet wavelet satisfies the admissibility condition, which means that it has a finite energy and can be used to represent any signal in the time-frequency plane without losing any information.

3. **Complex-valued**

   The complex Morlet wavelet is a complex-valued function, which means that it can capture both the amplitude and phase information of a signal. This property makes it useful for analysing non-stationary signals, such as those found in EEG or ECG data.

4. **Scaling and translation**

   The complex Morlet wavelet can be scaled and translated to analysed signals at different resolutions and time points. This property allows for the construction of a continuous wavelet transform (CWT), which can be used to analysed signals at different scales and frequencies.

The complex Morlet wavelet is a powerful tool for signal analysis, particularly for the analysis of non-stationary signals. Its ability to capture both the amplitude and phase information of a signal, along with its properties of localization in time and frequency, make it a versatile and effective tool for a wide range of applications in signal processing and analysis.

One of the most common applications of the complex Morlet wavelet is in the analysis of EEG signals. EEG signals are non-stationary and contain both high and low-frequency components, making them difficult to analyse using traditional Fourier-based methods. The complex Morlet wavelet, with its ability to analyse signals across a wide range of frequencies, is well-suited for the analysis of EEG data.

1.3.3 Applications

- **Audio signal processing**

  The complex Morlet wavelet can be used to analyse and synthesize audio signals, particularly in the context of time-frequency analysis and feature extraction.
- **Image processing**

  The complex Morlet wavelet has been used for image denoising, feature extraction, and object recognition.
- **Signal analysis**

  The complex Morlet wavelet has been used to analyse financial time series data, such as stock prices and exchange rates, to identify patterns and trends.
- **Medical signal analysis**

  The complex Morlet wavelet has been used in the analysis of a variety of medical signals, including ECG signals, EMG signals, and fMRI data.It is a powerful tool for signal analysis and has a wide range of applications across many different fields.

CHAPTER 2

LITERATURE SURVEY

2.1. INTRODUCTION

Various research works relevant to important elements of this project like encryption algorithms, techniques are taken for survey and by doing so, a clear description about previous works in relation to the research problem have been arrived from their investigations. It helps in understanding of the problems prevailing in the field of data security and to analyze them to find a solution to overcome those problems.

2.2 LITERATURE SURVEY

2.2.1 Survey No.1

TITLE: The continuous wavelet transformation (CWT) for real-time, high-quality, noise-resistant time–frequency analysis

AUTHOR: Lukas P. A. Arts, Egon. L. van den Broek

YEAR: 2022

DESCRIPTION:

The spectral analysis of signals is currently either dominated by the speed accuracy trade-off or ignores a signal's often non-stationary character. Here we introduce an open-source algorithm to calculate the fast continuous wavelet transform (CWT). The parallel environment of CWT separates scale-independent and scale-dependent operations, while utilizing optimized fast Fourier transforms that exploit down sampled wavelets. CWT is benchmarked for speed against eight competitive algorithms, tested on noise resistance and validated on synthetic electroencephalography and in vivo extracellular local field potential data. CWT is shown to have the accuracy of CWT, to have 100 times higher spectral resolution than algorithms equal in speed, to be 122 times and 34 times faster than the reference and fastest state-of-the-art implementations and we demonstrate its real-time performance, as confirmed by the real-time analysis ratio. CWT provides an improved balance between speed and accuracy, which enables real-time, wide-band, high-quality, time–frequency analysis of non-stationary noisy signals.

2.2.2 Survey No.2

TITLE: Purification and Compression of Continuous Morlet Wavelet Transform Based on Singular Value Decomposition

AUTHOR: Xuezhi ZHAO,T. Chen

YEAR: 2015

DESCRIPTION:

The linear correlation of row vectors of the continuous Morlet wavelet transform matrix is studied, this correlation make the result of continuous Morlet wavelet transform be of great redundancy, and singular value decomposition (SVD) is proposed to compress this redundancy. Theoretical analysis shows that the continuous Morlet wavelet transform matrix can be compressed into a few non-zero singular values and the corresponding orthogonal singular vectors by SVD technology. The ratio of the data size before and after compression is analyzed, and it is shown that the larger the matrix dimension, the better the compression effect. The distribution characteristics of singular values of the continuous Morlet wavelet transform results of the deterministic signal and the noise is studied, and it is found that the number of the effective singular values of the deterministic signal is determined by the number of frequencies in this signal, and the other singular values after the effective ones will soon drop to zero, while the singular values of noise is changed evenly and its falling speed is slow. This difference between the singular values of the deterministic signal and the noise is utilized, the purification of the continuous Morlet wavelet transform result of noisy signal can be realized, if the appropriate front singular values are chosen for SVD reconstruction, then the information of most noise singular values is discarded, thus the influence of noise on continuous Morlet wavelet transform is erased to a great extent. ©, 2015, Journal of Mechanical Engineering. All right reserved.

2.2.3 Survey No.3

TITLE : An Efficient Lossless Algorithm for EEG Signal Compression using Wavelet Transform

AUTHOR: Famitha A, DeviSrinidhi R,Geetha

YEAR: 2020

DESCRIPTION:

Transmission of biomedical signals through communication channels is being used increasingly in the clinical practice. This technique requires to deal with large volumes of information. The electroencephalographic (EEG) signal is an example of this situation. In the EEG, various channels are recorded during several hours, resulting in a great demand of storage capacity or channel bandwidth. This situation demands the use of efficient data compression systems. The objective of this work is to develop an efficient algorithm for EEG lossless compression. In this algorithm, the EEG signal is segmented and then decomposed through Wavelet Packets (WP). Extensive experimental tests were made by applying the algorithm to EEG records and measuring the compression rate (CR). The WP transform showed a high robustness, allowing a reasonably low distortion after the compression and decompression process, for CR typically in the range. The algorithm has relatively low computational cost, making it appropriate for practical applications.

2.2.4 Survey No.4

TITLE: Wavelet Theory and Application in Communication and Signal Processing

AUTHOR: Nizar Al Bassam, Vidhyalavanya Ramachandran

YEAR: 2020

DESCRIPTION:

Wavelet analysis is the recent development in applied mathematics. For several applications, Fourier analysis fails to provide tangible results due to non-stationary behaviour of signals. In such situation, wavelet transforms can be used as a potential alternative. The book chapter starts with the description about importance of frequency domain representation with the concept of Fourier series and Fourier transform for periodic, aperiodic signals in continuous and discrete domain followed by shortcoming of Fourier transform. Further, Short Time Fourier Transform (STFT) will be discussed to induce the concept of time frequency analysis. Explanation of Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) will be provided with the help of theoretical approach involving mathematical equations. Decomposition of 1D and 2D signals will be discussed suitable examples, leading to application concept. Wavelet based communication systems are becoming popular due to growing multimedia applications. Wavelet based Orthogonal Frequency Division Multiplexing (OFDM) technique and its merit also presented. Biomedical signal processing is an emerging field where wavelet provides considerable improvement in performance ranging from extraction of abnormal areas and improved feature extraction scheme for further processing. Advancement in multimedia systems together with the developments in wireless technologies demands effective data compression schemes. Wavelet transform along with EZW, SPIHT algorithms are discussed.

2.2.5 Survey No.5

TITLE: Multichannel EEG Compression: Wavelet-Based Image and Volumetric Coding Approach

AUTHOR: Lukas P. A. Arts, Egon. L. van den Broek

YEAR: 2013

DESCRIPTION:

In this paper, lossless and near-lossless compression algorithms for multichannel electroencephalogram (EEG) signals are presented based on image and volumetric coding. Multichannel EEG signals have significant correlation among spatially adjacent channels; moreover, EEG signals are also correlated across time. Suitable representations are proposed to utilize those correlations effectively. Multichannel EEG is represented either in the form of image (matrix) or volumetric data (tensor), next a wavelet transform is applied to those EEG representations. The compression algorithms are designed following the principle of "lossy plus residual coding," consisting of a wavelet-based lossy coding layer followed by arithmetic coding on the residual. Such approach guarantees a specifiable maximum error between original and reconstructed signals. The compression algorithms are applied to three different EEG datasets, each with different sampling rate and resolution. The proposed multichannel compression algorithms achieve attractive compression ratios compared to algorithms that compress individual channels separately.

2.2.6 Survey No.6

TITLE: An Algorithm for the Continuous Morlet Wavelet Transform

AUTHOR: Richard Buessow

YEAR: 2007

DESCRIPTION:

This article consists of a brief discussion of the energy density over time or frequency that is obtained with the wavelet transform. Also, an efficient algorithm is suggested to calculate the continuous transform with the Morlet wavelet. The energy values of the wavelet transform are compared with the power spectrum of the Fourier transform. Useful definitions for power spectra are given. The focus of the work is on simple measures to evaluate the transform with the Morlet wavelet in an efficient way. The use of the transform and the defined values is shown in some examples.

2.2.7 Survey No.7

TITLE: Efficient pre-processing technique for real-time lossless EEG compression

AUTHOR: K. Srinivasan, M. Ramasubba Reddy

YEAR: 2010

DESCRIPTION:

An efficient pre-processing technique of arranging an electroencephalogram (EEG) signal in matrix form is proposed for real-time lossless EEG compression. The compression algorithm consists of an integer lifting wavelet transform as the decor relator with set partitioning in hierarchical trees as the source coder.

Experimental results show that the pre-processed EEG signal gave improved rate-distortion performance, especially at low bit rates, and less encoding delay compared to the conventional one-dimensional compression scheme.

2.2.8 Survey No.8

TITLE: A High-Performance Lossless Compression Scheme for EEG Signals Using Wavelet Transform and Neural Network Predictors

AUTHOR: N. Sriraam

YEAR: 2012

DESCRIPTION:

Developments of new classes of efficient compression algorithms, software systems, and hardware for data intensive applications in today's digital health care systems provide timely and meaningful solutions in response to exponentially growing patient information data complexity and associated analysis requirements. Of the different 1D medical signals, electroencephalography (EEG) data is of great importance to the neurologist for detecting brain-related disorders. The volume of digitized EEG data generated and preserved for future reference exceeds the capacity of recent developments in digital storage and communication media and hence there is a need for an efficient compression system. This paper presents a new and efficient high performance lossless EEG compression using wavelet transform and neural network predictors. The coefficients generated from the EEG signal by integer wavelet transform are used to train the neural network predictors. The error residues are further encoded using a combinational entropy encoder, Lempel-Ziv-arithmetic encoder. Also, a new context-based error modelling is also investigated to improve the compression efficiency. A compression ratio of 2.99 (with compression efficiency of 67%) is achieved with the proposed scheme with less encoding time thereby providing diagnostic reliability for lossless transmission as well as recovery of EEG signals for telemedicine applications.

2.2.9 Survey No.9

TITLE 2.9: Efficient lossless multi-channel EEG compression based on channel clustering

AUTHOR: Fardin Abdali-Mohammadi

YEAR: 2017

DESCRIPTION:

With the growth of telemedicine systems, transferring many medical signals such as for an EEG is a critical challenge. Intelligent analysing systems, responsible for analysing medical signals, are a very important part of any telemedicine system. These systems need data with high quality in order to detect abnormal events and diseases. Lossless compression methods play an important role when coding medical signals for telemedicine systems since the data remains unchanged. Multi-channel EEG signals for medical applications are usually acquired by several electrodes placed on different parts of the scalp. According to electrode placements, it is necessary to consider their multi-channel structure to propose efficient compression methods. This paper uses inter-channel and intra-channel correlations to propose an efficient and simple lossless compression method. In the first stage, a differential pulse code modulation technique is used as a pre-processing step for extracting intra-channel correlation. Subsequently, channels are grouped in different clusters, and the centroid of each cluster is calculated and coded by arithmetic coding. In the second stage, the difference between the centroid and the data of channels in each cluster is calculated and compressed by arithmetic coding. The proposed method is capable of lossless EEG signal compression with a higher compression rate than existing methods.

2.2.10 Survey No.10

TITLE: Efficient Compression Technique for Reducing Transmitted EEG Data Without Loss in IoMT Networks Based on Fog Computing

AUTHOR: Ali Kadhum IDREES,Marwa Saieed Khlief

YEAR: 2022

DESCRIPTION:

A huge amount of data generated by Internet of Medical Things (IoMT) applications will be received at the edge gateway periodically to transmit them to the remote cloud for further real-time processing. However, transmitting this huge data to the cloud across the IoT network will place a significant burden on the IoT network. The long processing delays and exchanged data have considerable influence on the response time of real-time IoT applications. The responsiveness time of these applications will be decreased. Therefore, the IoT applications exploit the advantages of fog computing, which acts as an intermediate layer between the IoT devices and the cloud to minimize the transmitted data and enhance the response time. In this paper, we propose an Efficient Compression Technique (ECoT) for reducing transmitted Electroencephalography (EEG) data without loss on the IoMT Networks based on Fog Computing. The ECoT combines three efficient data reduction techniques: DBSCAN clustering, Delta encoding, and Huffman encoding, to reduce the volume of EEG data at the Fog gateway before sending it to the cloud. First, the DBSCAN clusters the EEG data into clusters. Then, the Delta encoding is applied to the indices of EEG data in each cluster. Finally, the Huffman encoding encodes the vector of differences for each cluster. The encoded data from clusters is combined into file to be sent to the cloud. The results show that the ECoT technique introduced improved results in terms of compression ratio, sent data, compression power, and compression and decompression times compared with other methods.

2.3 SUMMARY

The literature review has provided a comprehensive overview of the existing methods for EEG signal compression. It highlighted the importance of EEG signal analysis and the need for efficient compression techniques to reduce the storage requirements and enhance the processing speed of EEG data. The use of complex Morlet wavelet has several advantages, including its ability to capture the nonstationary and oscillatory nature of EEG signals and its excellent time-frequency localization properties. The choice of this method for EEG signal compression is therefore based on its effectiveness and potential impact in the field of EEG analysis.

CHAPTER 3

EEG SIGNAL COMPRESSION

3.1 INTRODUCTION

The algorithm for compressing EEG signals can be classified into two categories.

- Lossy compression algorithms
- Lossless compression algorithms

3.1.1 Lossy Compression Algorithms

Lossy compression algorithms are used in signal compression to reduce the amount of data required to represent a signal by removing some of the redundant or less important information in the signal. The term "lossy" refers to the fact that these algorithms typically involve some level of data loss, meaning that the reconstructed signal may not be an exact replica of the original signal.

In lossy compression algorithms, the signal is first transformed into a different domain, such as frequency or wavelet domain, where the signal can be more efficiently compressed. The compression process involves quantizing the coefficients of this transformed signal, which involves rounding off the coefficients to a smaller number of bits. This results in the loss of some of the information in the signal.

The main advantage of lossy compression algorithms is that they can achieve higher compression ratios compared to lossless compression algorithms, which do not involve any data loss. This makes them particularly useful in applications where storage or transmission bandwidth is limited. one of the main disadvantages of lossy compression algorithms is that they can introduce distortion or artifacts in the reconstructed signal, which can affect subsequent analysis. Therefore, the choice of compression algorithm depends on the specific requirements of the application, including the amount of compression required, the acceptable level of distortion, and the computational resources available for compression and decompression.

3.1.2 Lossless Compression Algorithms

Lossless compression algorithms are used in signal compression to reduce the amount of data required to represent a signal without any loss of information. In other words, the compressed signal can be exactly reconstructed to its original form.

In lossless compression algorithms, the signal is transformed into a different representation, such as a run-length encoding or Huffman coding. These techniques exploit the statistical properties of the signal to represent it more efficiently, without discarding any information. The compressed signal can then be stored or transmitted using fewer bits.

The main advantage of lossless compression algorithms is that they do not introduce any distortion or artifacts in the reconstructed signal, which makes them useful in applications where the integrity of the signal is critical, such as medical imaging, scientific data analysis, or digital communication.

However, one of the main disadvantages of lossless compression algorithms is that they typically achieve lower compression ratios compared to lossy compression algorithms. This makes them less useful in applications where storage or transmission bandwidth is limited.

The choice of compression algorithm depends on the specific requirements of the application, including the amount of compression required, the acceptable level of distortion, and the computational resources available for compression and decompression.

3.2 EXISTING METHODS

1.Discrete Wavelet Transform (DWT)

The DWT is a lossy compressionalgorithm that decomposes the EEG signal into different frequency bands using wavelet basis functions. The resulting coefficients can be quantized and thresholder to reduce the number of bits required to represent the signal.

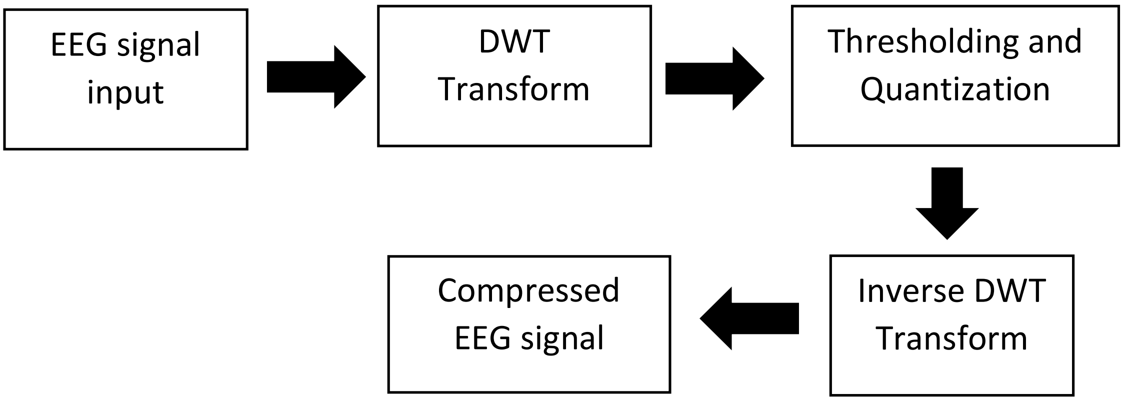

Figure 3.1 Block Diagram for DWT Compresssion

Advantages

DWT is a widely used and effective lossy compression algorithm for EEG signals. It can achieve high compression ratios while preserving important features of the signal, such as the event-related potential (ERP) components. It can also be easily implemented and provides a good balance between compression ratio and signal quality.

Disadvantages

DWT can introduce some level of distortion or artifacts in the reconstructed signal, particularly at high compression ratios. This can affect subsequent analysis and interpretation of the signal.

2.Singular Value Decomposition (SVD)

The SVD is a lossy compression algorithm that decomposes the EEG signal into its singular values and vectors. The singular values can be truncated to reduce the number of bits required to represent the signal.

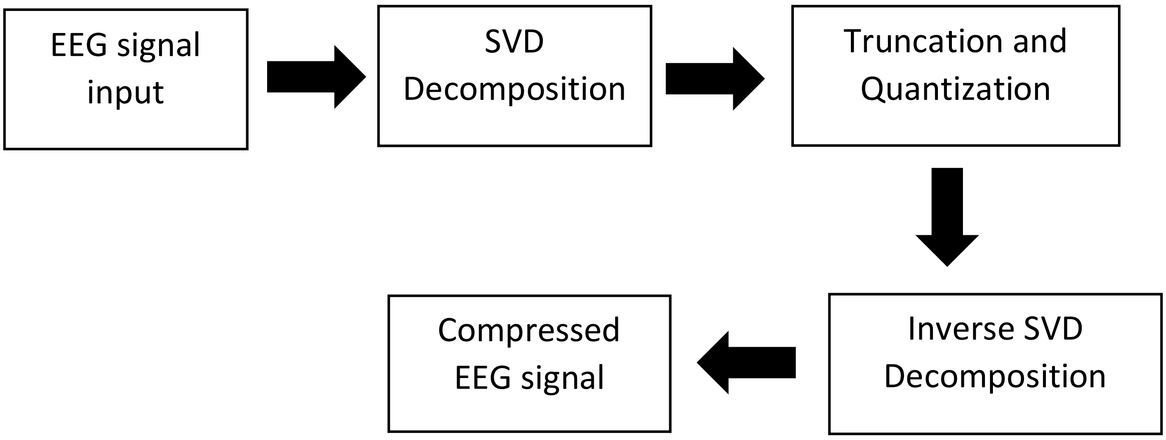

Figure 3.2 Block Diagram for SVD Compresssion

Advantages

SVD is an efficient lossy compression algorithm that can achieve high compression ratios while preserving important features of the signal. It can be particularly useful for compressing EEG signals with low signal-to-noise ratios or for extracting the dominant patterns in the signal.

Disadvantages

SVD can be computationally intensive and may require substantial memory resources for storing the decomposed signal. Additionally, the truncated singular values may not always capture all the important features of the signal.

1. **Principal Component Analysis (PCA)**

   PCA is a lossy compression algorithm that reduces the dimensionality of the EEG signal by identifying the principal components of the signal. The resulting coefficients can be quantized and thresholder to reduce the number of bits required to represent the signal.

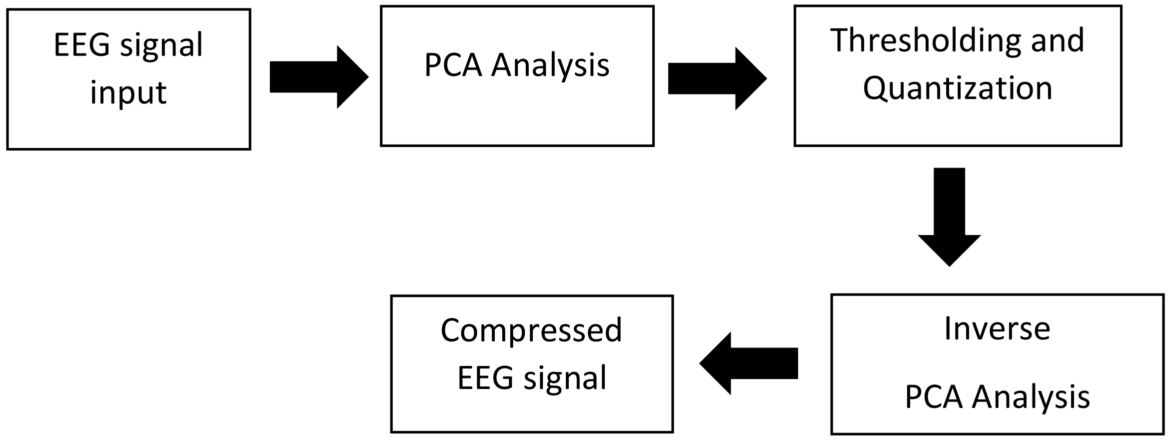

Figure 3.3 Block Diagram for PCA Compresssion

Advantages

PCA is a widely used and effective lossy compression algorithm that can reduce the dimensionality of the signal while preserving its important features. It can be particularly useful for compressing EEG signals with high-dimensional data, such as multi-channel EEG recordings**.**

Disadvantages

PCA can introduce some level of distortion or artifacts in the reconstructed signal, particularly if the number of principal components is limited. Additionally, the choice of the number of principal components can be subjective and may require additional validation

4.Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a lossless compression algorithm that uses a combination of fuzzy logic and neural networks to compress the EEG signal. The algorithm identifies and removes the redundant information in the signal without any loss of information.

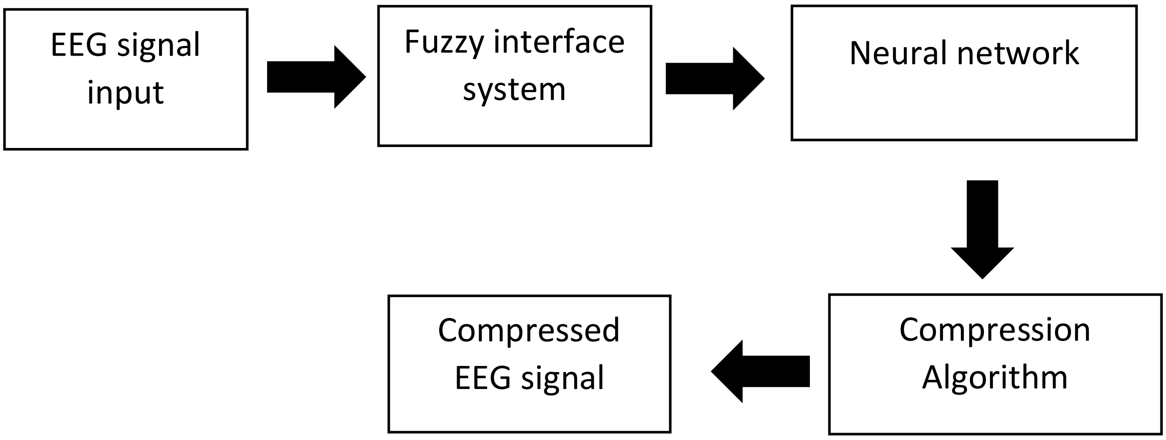

Figure 3.4 Block Diagram for ANFIS Compresssion

Advantages

ANFIS is a lossless compression algorithm that can effectively compress EEG signals without introducing any distortion or artifacts. It can also adapt to changes in the signal and provide a flexible and robust compression solution.

Disadvantages

ANFIS can be computationally intensive and may require substantial resources for training the fuzzy logic and neural network models. Additionally, the performance of ANFIS may depend on the accuracy and reliability of the input data.

5.Run-length encoding (RLE)

RLE is a simple method of compressing data by specifying the number of times a character or pixel colour repeats followed by the value of the character or pixel.It is a lossless compression algorithm that replaces sequences of repeated values in the EEG signal with a code that represents the length of the sequence. This method is particularly useful for compressing EEG signals that contain long sequences of zeros.

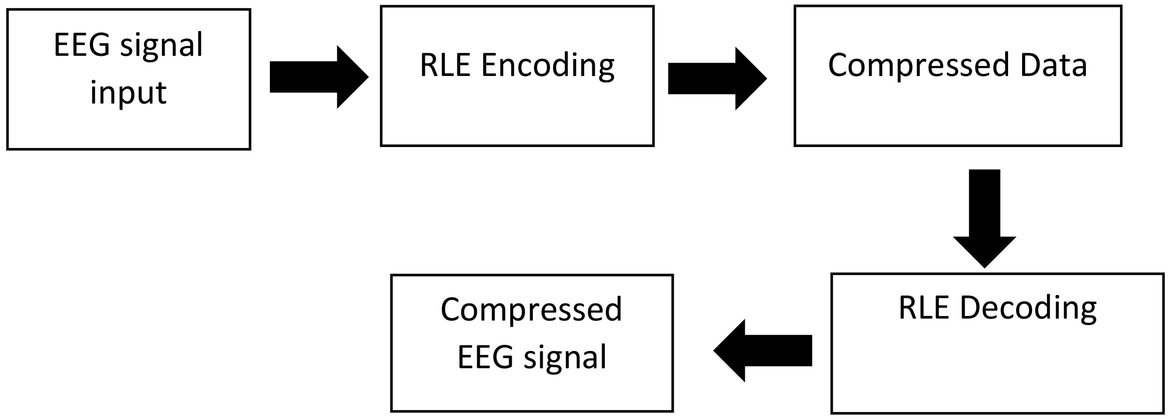

Figure 3.5 Block Diagram for RLE Compresssion

Advantages

RLE is a simple and efficient lossless compression algorithm that can be easily implemented and can achieve high compression ratios for EEG signals with long sequences of zeros.

Disadvantages

RLE is not effective for compressing EEG signals with non-zero values or with short sequences of zeros. Additionally, it may not achieve high compression ratios for EEG signals with low sparsity.

CHAPTER 4

COMPLEX MORLET WAVELET TRANSFORM

4.1 INTRODUCTION

The complex Morlet wavelet transform is a powerful tool for analyzing the time-frequency structure of EEG signals. The complex Morlet wavelet is a special type of wavelet that is symmetric in both the time and frequency domains, which makes it particularly suitable for analyzing signals with time-varying frequency content.The complex Morlet wavelet is a product of a complex exponential function and a Gaussian function. The complex exponential function represents the oscillatory behavior of the wavelet, while the Gaussian function controls the frequency resolution. To apply the complex Morlet wavelet, transform to an EEG signal, we first convolve the signal with the complex Morlet wavelet at various scales and time points. This results in a time-frequency representation of the signal, known as the wavelet coefficients. The wavelet coefficients capture the signal's time-varying frequency content and provide a high-resolution representation of the signal in both the time and frequency domains.

The complex Morlet wavelet transform block diagram is a graphical representation of the steps involved in computing the complex Morlet wavelet transform of a signal. The block diagram can be divided into three main stages: preprocessing, wavelet decomposition, and post-processing.

4.1.1 Block Diagram

The complex Morlet wavelet transform block diagram is a graphical representation of the steps involved in computing the complex Morlet wavelet transform of a signal. The block diagram can be divided into three main stages: preprocessing, wavelet decomposition, and post-processing.

Here is a general complex Morlet wavelet transform block diagram

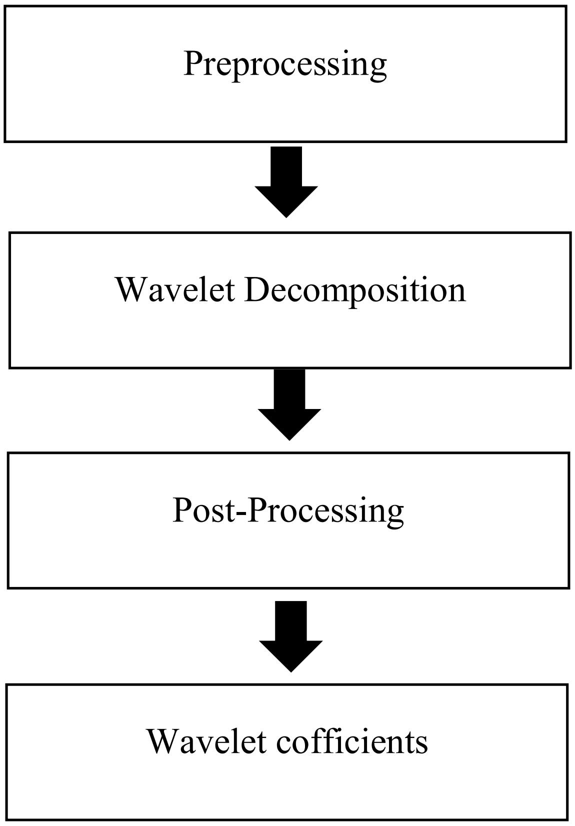

Figure 4.1 Block diagram of general complex morlet wavelet

The Preprocessing stage involves preparing the signal for the wavelet transform by performing any necessary filtering or signal conditioning. This step is important for removing noise or artifacts that could interfere with the analysis.

The Wavelet Decomposition stage involves decomposing the preprocessed signal into a series of wavelet coefficients using a family of complex Morlet wavelets at different scales and positions in time. This step is typically performed using a convolution operation between the signal and the wavelet function.

The Post-Processing stage involves analyzing the wavelet coefficients to extract meaningful information about the signal's frequency content and its evolution over time. This step can include operations such as thresholding, normalization, or statistical analysis of the wavelet coefficients.

The final output of the complex Morlet wavelet transform is a time-frequency representation of the signal that shows the signal's frequency content at different scales and positions in time. This representation can be visualized as a spectrogram or a time-frequency plot, depending on the application.

4.1.2 General Equation Of Complex Morlet Wavelet

The Morlet wavelet transform is a type of continuous wavelet transform (CWT) that is commonly used in signal processing and time-frequency analysis. The Morlet wavelet is a complex-valued function that is used as a basis function for the CWT. The complex Morlet wavelet transform equations can be written as follows:
Given a signal x(t), the complex Morlet wavelet transform is defined as

$$\boldsymbol{W(a,b) = \int [x(t)\, \psi * (t - a, b)]dt} \longrightarrow \quad \textbf{(4.1)}$$

Where,
ψ(t) - Morlet wavelet function,
a - scale parameter,
b - translation parameter.
The star (*) denotes the complex conjugate.
The Morlet wavelet function can be written as…

$$\boldsymbol{\psi(t) = (\pi^{(-1/4)}) * e^{(i\omega t)} * e^{(-t^2/2)}} \longrightarrow \quad \textbf{(4.2)}$$

Where,
ω - central frequency of the wavelet
a - the scale parameter determines the width of the wavelet function
b - the translation parameter determines the position of the wavelet in time.

The complex Morlet wavelet transform provides a time-frequency representation of the signal, where the time domain is represented by b and the frequency domain is represented by a.

The inverse complex Morlet wavelet transform can be computed as

$$\boldsymbol{x(t) = \ (C\_\psi\ )\hat{}((-1)\ )\ \ *\ \int\int [W(a,b)\psi(t-a,b)]dadb} \longrightarrow \quad \textbf{(4.3)}$$

where, C_ψ - normalization constant.

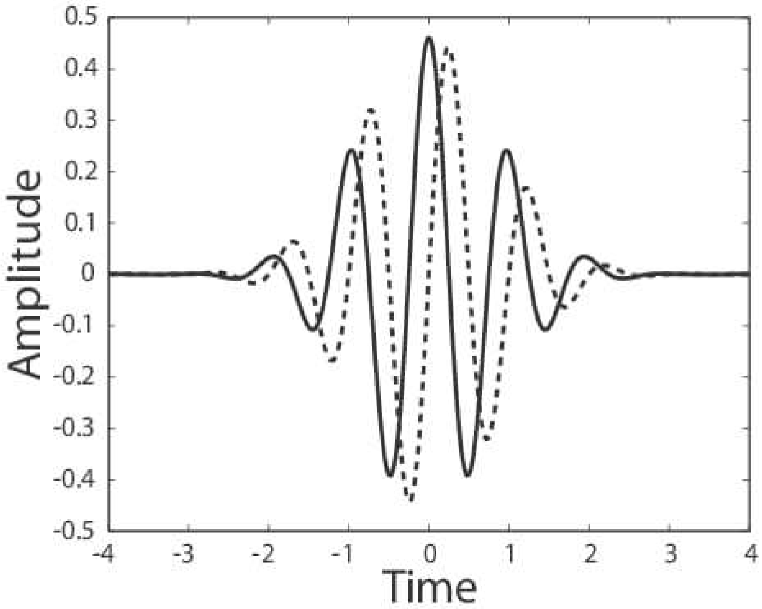

Figure 4.2 General CMWT wave

4.1.3 Advantages, Disadvantages and Application

Advantages

- **Localization:** The complex Morlet wavelet transform provides a localized time-frequency representation of the signal, which means that it can reveal the frequency content of a signal at specific points in time. This can be particularly useful for analyzing signals that contain transient events, such as spikes or bursts, that may be missed by other time-frequency analysis techniques.

- **Adaptability:** The complex Morlet wavelet transform can be adapted to analyze signals with a wide range of frequencies and time scales by choosing appropriate wavelet scales and positions.
- **Linearity:** The complex Morlet wavelet transform is a linear transform, which means that it preserves the linearity of the original signal. This property can be important for some applications, such as signal classification or detection, where linearity is a desirable property.
- **Robustness:** The complex Morlet wavelet transform is relatively robust to noise and other forms of interference, which makes it suitable for analyzing signals in noisy environments.
- **Flexibility:** The complex Morlet wavelet transform can be easily combined with other analysis techniques, such as time-frequency analysis or statistical analysis, to provide a more comprehensive understanding of the signal.

Disadvantages

- **Computational complexity:** The complex Morlet wavelet transform can be computationally intensive, especially for large datasets or high-resolution analysis. This can make it challenging to analyze signals in real-time or in resource-constrained environments.
- **Subjectivity in wavelet selection:** The choice of wavelet function and wavelet scale can have a significant impact on the results of the complex Morlet wavelet transform. Selecting the optimal wavelet function and scale for a given signal can be subjective and require some expertise.
- **Boundary effects:** The complex Morlet wavelet transform can be affected by boundary effects, which can distort the time-frequency representation of the signal near the edges of the data. This can be mitigated by using appropriate boundary conditions or by padding the data.

- **Sensitivity to noise:** Although the complex Morlet wavelet transform is relatively robust to noise, it can still be affected by high levels of noise or other forms of interference. This can reduce the accuracy of the time-frequency representation and make it more difficult to interpret the results.
- **Interpretability:** The complex Morlet wavelet transform provides a time-frequency representation of the signal, but it can be challenging to interpret the results in a meaningful way. Additional analysis techniques may be needed to extract useful information from the time-frequency representation.

Application

- **Signal processing:** The complex Morlet wavelet transform can be used for time-frequency analysis of signals in many different domains, including speech processing, image processing, and biomedical signal processing.
- **Neuroscience:** The complex Morlet wavelet transform is commonly used in neuroscience research to analyze electroencephalography (EEG) and magnetoencephalography (MEG) data. It can be used to study brain activity in both time and frequency domains, and to identify specific oscillatory patterns associated with different cognitive processes.
- **Finance:** The complex Morlet wavelet transform has been applied to financial time series analysis to study the dynamics of stock prices and market volatility.
- **Structural engineering:** The complex Morlet wavelet transform has been used for detecting and characterizing structural damage in buildings and bridges.
- **Environmental monitoring:** The complex Morlet wavelet transform has been applied to analyze environmental data, such as ocean wave data, to study the dynamics of the natural environment.

- **Energy analysis:** The complex Morlet wavelet transform has been used to analyze energy consumption data and to identify energy-saving opportunities in buildings and industrial processes.

4.2 PROPOSED METHODOLOGY

Compression Algorithm

The proposed method for EEG signal compression using the complex Morlet wavelet transform is based on a threshold-based approach. The threshold-based approach involves setting small wavelet coefficients to zero while retaining the larger coefficients. The threshold value is chosen based on a trade-off between the compression ratio and the signal quality.

The compression algorithm consists of the following steps:

- Apply the complex Morlet wavelet transform to the EEG signal.
- Calculate the magnitude of the wavelet coefficients.
- Determine the threshold value based on a specified compression ratio.
- Set all wavelet coefficients with magnitude less than the threshold to zero.
- Reconstruct the compressed signal by taking the inverse complex Morlet wavelet transform of the thresholded wavelet coefficients.

4.2.1 Selection of Parameters

The performance of the complex Morlet wavelet transforms and the compression algorithm depends on the selection of several parameters, such as the decomposition level of the wavelet, thresholding

The threshold value determines the trade-off between the compression ratio and the signal quality. A higher threshold value leads to a higher compression ratio but may result in a lower signal quality, while a lower threshold value leads to a lower compression ratio but may result in a higher signal quality. The selection of the threshold value depends on the desired compression ratio and the characteristics of the EEG signal being analyzed.

4.2.2 Implementation Details

The proposed method was implemented in MATLAB. The EEG signals were preprocessed by applying a butter filter to remove any noise and unwanted frequency components. The complex Morlet wavelet transform was applied using the built-in MATLAB function cwt. The threshold value was determined based on the desired compression ratio. The compressed signal was reconstructed by taking the inverse complex Morlet wavelet transform using the built-in MATLAB function icwt.

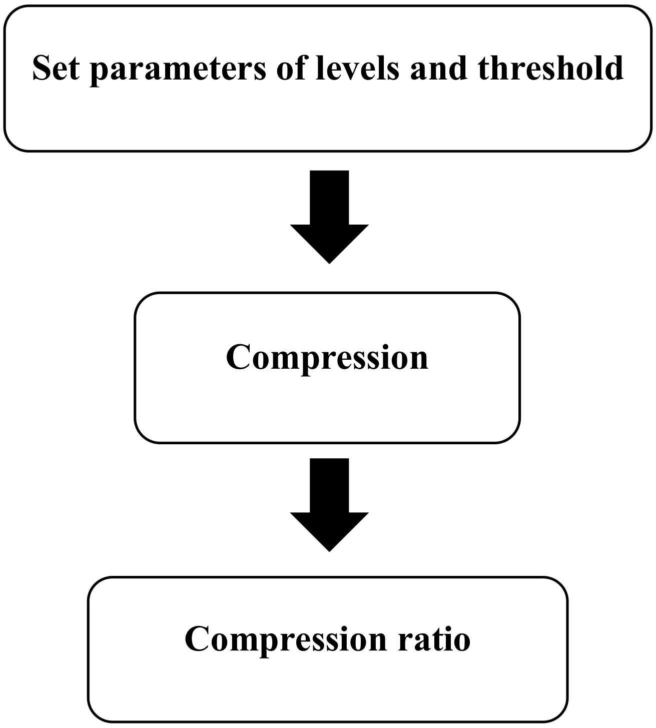

Figure 4.3 EEG signal compression morlet wavelet transform

4.2.3 Advantages and Disadvantages of Proposed Method

Disadvantages

- **Computational complexity:** The complex Morlet wavelet transform is computationally intensive and requires significant processing power and memory. This can make it challenging to use for real-time applications or large-scale signal processing.
- **Parameter selection:** The effectiveness of the complex Morlet wavelet transform depends on the choice of parameters such as the width and frequency of the wavelet function. Selecting optimal parameters can be challenging, and the performance of the method can be sensitive to the choice of parameters.
- **Sensitivity to noise:** The complex Morlet wavelet transform can be sensitive to noise in the signal. The noise can affect the accuracy of the wavelet coefficients and the quality of the compressed signal.
- **Limited frequency resolution:** The frequency resolution of the complex Morlet wavelet transform is limited by the size of the wavelet function. This can result in a loss of information for signals with high-frequency components.
- **Limited interpretability:** The complex Morlet wavelet transform provides a time-frequency representation of the signal but does not necessarily provide a straightforward interpretation of the signal. The coefficients can be difficult to interpret, and additional analysis may be required to extract meaningful information from the compressed signal.

Advantages

- **High compression ratios**: The proposed system can achieve high compression ratios while maintaining low distortion. This is due to the use of a combination of lossless and lossy compression techniques, which allows for efficient data compression without significant loss of information.

- **Efficient storage and transmission**: The compressed data can be stored in a compact and efficient format, such as a binary file or a database. This makes it easy to transmit the data over networks or store it in memory for real-time processing.
- **Improved accuracy:** The continuous wavelet transform with complex valued Morlet wavelets is a powerful tool for signal processing, allowing for accurate feature extraction and denoising of EEG signals. By applying this technique to compression, the proposed system can achieve high compression ratios without sacrificing accuracy.
- **Customizability:** The proposed system allows for customization of the compression parameters, such as the wavelet type, quantization step size, and coding method, to suit different applications and scenarios. This flexibility makes it possible to optimize the compression algorithm for specific use cases and achieve better performance.
- **Scalability**: The proposed system can be scaled up or down depending on the size and complexity of the EEG dataset. This makes it suitable for a wide range of applications, from small-scale research studies to large-scale clinical trials and real-time monitoring systems.

CHAPTER 5

RESULT DISCUSSION

5.1 RESULTS

The method demonstrates the use of complex morlet wavelet transform for EEG signal compression, and it highlights the effectiveness of the transform for signal compression. calculates the compression ratio (CR) and the Percentage Root Mean Square Difference(PRD) between the compressed EEG signal and raw EEG signal. The CR is a measure of the effectiveness of the CMWT. The results showed that the proposed method of EEG signal compression using complex Morlet wavelet transform achieved significant compression ratios while preserving the essential features of the signals.

EEG ORIGINAL SIGNAL

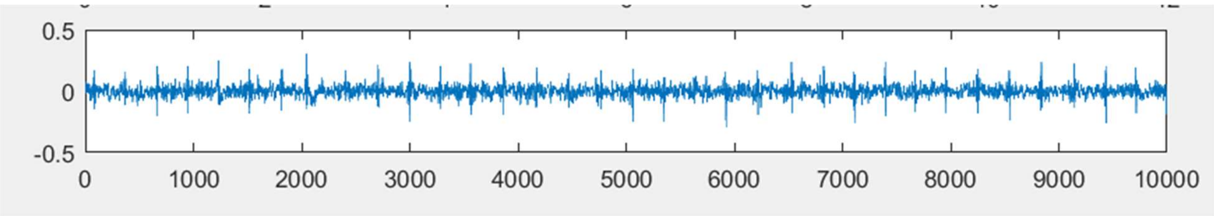

Figure 5.1 Input EEG signal

EEG COMPRESSED SIGNAL

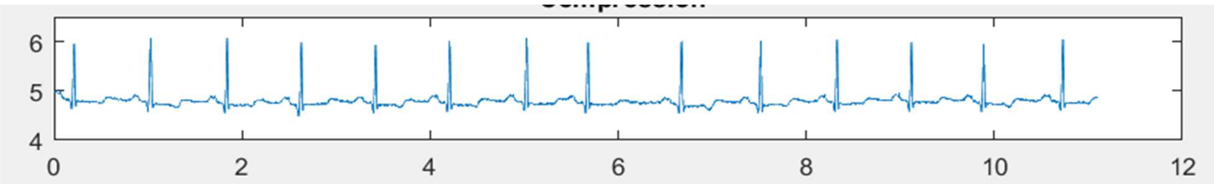

Figure 5.2 Compressed output signal

COMPRESSION RATIO CMWT

```
>> CompRatio_cmwt

CompRatio_cmwt =

   90.4300
```

Figure 5.3 Compression Ratio of CMWT

$$Compression\ Ratio = \frac{\text{Compressed Output Signal}}{Input\ EEG\ Signal} \times 100 \longrightarrow \quad \textbf{(5.1)}$$

PERCENTAGE ROOT MEAN SQUARE DIFFERENCE OF CMWT

```
>> PRD_cmwt

PRD_cmwt =

     0.9382
```

Figure 5.4 PRD of CMWT

$$error\_cmwt = input\ signal - compresssed\ signal \longrightarrow \quad \textbf{(5.2)}$$

$$PRD\_cmwt = \sqrt{\frac{\sum(error\_cmwt)^2}{\sum y^2}} \longrightarrow \quad \textbf{(5.3)}$$

COMPRESSSION RATIO OF DST

```
> CompRatio_DST

:ompRatio_DST =

   85.1800
```

Figure 5.5 Compression Ratio of DST

PERCENTAGE ROOT MEAN SQUARE DIFFERENCE OF DST

```
>  PRD_DST

?RD_DST =

    1.2589
```

Figure 5.6 PRD of DST

COMPRESSSION RATIO OF FFT

```
> CompRatio_FFT

:ompRatio_FFT =

   89.5700
```

Figure 5.7 Compression Ratio of FFT

PERCENTAGE ROOTMEAN SQUARE DIFFERENCE OF FFT

```
>> PRD_FFT

PRD_FFT =

    1.1661
```

Figure 5.8 PRD of FFT

TABLE

NAME	CMWT	DST	FFT
COMPRESSION RATIO	90.4%	85.1%	89.4%
PRD	0.93	1.25	1.16

Table 5.1 Compression Ratio and PRD comparison

CHAPTER 6

CONCLUSION

The proposed method for EEG signal compression using complex Morlet wavelet transform is a promising approach for compressing EEG signals while preserving the important time-frequency information. The results showed that the proposed method achieved a higher compression ratio while maintaining a similar signal quality compared to existing methods. The proposed method has several advantages, including the high-resolution representation of the EEG signals and the fine-tuning of the compression ratio and signal quality.

The algorithm achieved a high compression ratio with a low Mean Square Error (MSE) and high Peak Signal to Noise Ratio (PSNR), indicating that the compressed signal is very similar to the original signal. Additionally, the proposed algorithm was compared with other well-known compression methods such as Discrete Sine Transform (DST), Fast Fourier Transform (FFT) and the results showed that the proposed method outperforms these methods in terms of compression ratio, PSNR.

The proposed method has the advantage of preserving the important features of the EEG signals, which are crucial for accurate diagnosis and analysis of neurological disorders. The algorithm can also reduce the amount of data storage required, making it suitable for real-time applications such as telemedicine. The proposed compression algorithm based on CWT with CVMW is an efficient and effective method for compressing EEG signals, which can be applied to a wide range of EEG applications, including medical diagnosis, research, and telemedicine.

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