Multivariate Iterative Filtering Based Method for Automatic Imagined Speech Recognition using Multichannel EEG Signals

M.Tech. Thesis

By

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by

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **Multivariate Iterative Filtering Based Method for Automatic Imagined Speech Recognition using Multichannel EEG Signals** in the partial fulfillment of the requirements for the award of the degree of **Master of Technology** and submitted in the **Department of Electrical Engineering, Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from August 2025 to May 2026 under the supervision of Prof. Ram Bilas Pachori, Indian Institute of Technology Indore, India

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

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This is to certify that the above statement made by the candidate is correct to the best of my/our knowledge.

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Dedicated to My Parents

Abstract

Electroencephalogram (EEG) signals have a significant role in monitoring brain activities for biomedical and healthcare applications. However, accurate analysis of multichannel EEG recordings is still a challenging task due to the nonlinear, nonstationary and noisy nature of EEG signals. Traditional signal processing techniques are not always adequate for the analysis of such complex EEG signals. Therefore, adaptive signal decomposition techniques have gained much attention for the extraction of meaningful oscillatory information from EEG recordings. The thesis proposes a multivariate iterative filtering (MIF) based framework for automatic imagined speech recognition (AISR) using multichannel EEG signals. The proposed method is aimed at efficiently decomposing multichannel EEG recordings into multivariate intrinsic mode functions (MIMFs) while preserving the synchronized oscillatory behavior across the EEG channels. In the analysis of multichannel EEG, MIF uses an iterative moving average filtering method to improve mode alignment, reduce mode mixing, and ensure stable decomposition results. Significant features are extracted from the obtained MIMFs after decomposition to effectively represent the imagined speech EEG patterns. These features are further used for classification of different imagined speech categories using machine learning techniques. The proposed framework is tested on the multi-channel imagined speech EEG data and its performance is analyzed for different imagined speech classes. The experimental results show that the MIF-based decomposition method is effective in preserving the common frequency characteristics among EEG channels and enhancing the quality of extracted EEG features. The proposed framework offers better synchronized multichannel EEG analysis and enables efficient imagined speech recognition. Results on the overall performance show that MIF is a robust and effective approach for multichannel EEG decomposition and AISR applications.

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ACRONYMS

Acronym	Full Form
EEG	Electroencephalogram
AISR	Automatic Imagined Speech Recognition
BCI	Brain–Computer Interface
MEMD	Multivariate Empirical Mode Decomposition
MEWT	Multivariate Empirical Wavelet Transform
MVMD	Multivariate Variational Mode Decomposition
MIF	Multivariate Iterative Filtering
IMF	Intrinsic Mode Function
MIMF	Multivariate Intrinsic Mode Function
EMD	Empirical Mode Decomposition
EWT	Empirical Wavelet Transform
VMD	Variational Mode Decomposition
IF	Iterative Filtering
FT	Fourier Transform
STFT	Short-Time Fourier Transform
WT	Wavelet Transform
PSD	Power Spectral Density
CSP	Common Spatial Pattern
RVM	Relevance Vector Machine
ANN	Artificial Neural Network
RF	Random Forest
KNN	K-Nearest Neighbor
SVM	Support Vector Machine
CNN	Convolutional Neural Network
ELM	Extreme Learning Machine
HHT	Hilbert–Huang Transform
LDA	Linear Discriminant Analysis
SPML	Signal Processing and Machine Learning
HORC	Human-Oriented Robotics and Control

Chapter 1

Introduction

1.1 Background

Electroencephalogram (EEG) [1, 2, 4] is a non-invasive method to record electrical activity of the brain. Electrodes are placed on the scalp to record signals generated by neural activity [5]. EEG signals are useful for providing information about brain function and mental processes. EEG is widely used in biomedical engineering, neuroscience, and brain-computer interface (BCI) [7, 8] applications due to its high time resolution, low cost, portability, and ease of recording. The EEG based systems are widely used for medical diagnosis, analysis of neurological disorders, monitoring of cognitive states, studies of motor imagery, sleep analysis, emotion recognition, and recognition of imagined speech [4]. BCI systems provide a direct communication channel between the human brain and an external device without requiring any physical movement or muscle activity. One of the important research areas in BCI is the imagined speech recognition [10]. Imagined speech is a mental rehearsal of words without vocalization or movement of the speech organs. Automatic imagined speech recognition (AISR) [10, 11] systems attempt to recognize these imagined words from EEG signals. These systems can improve communication for people with paralysis, profound speech impairment, locked-in syndrome, pseudo coma, and other neurological conditions. Although AISR has been gaining increasing attention, it is still hard to classify the imagined speech signals from EEG accurately. EEG signals are weak, nonstationary, nonlinear and often contaminated by noise [8, 10]. Multichannel EEG recordings also have overlapping frequency components and strong relationships across channels. Because of these problems, traditional signal processing approaches frequently fail to extract useful information from EEG data. Conventional methods like Fourier transform (FT) and short-time Fourier transform (STFT) assume stationarity of the signal and are not appropriate for EEG analysis where the signal behavior changes over time. The wavelet transform (WT) improves time-frequency analysis by multiresolution decomposition [20], but it relies on pre-defined basis functions and may not

perfectly match complex EEG patterns. As a result, adaptive signal decomposition methods have been increasingly popular in EEG analysis. Methods such as empirical mode decomposition (EMD) [24, 26], empirical wavelet transform (EWT) [27, 29], variational mode decomposition (VMD) [30, 31] and iterative filtering (IF) [20, 26] can be used to decompose nonlinear and nonstationary signals into oscillatory components. They are adapted to the signal itself and do not require the basic functions to be defined as a priori. However, when separately applied to multichannel EEG signals, problems such as mode mixing, unequal decomposition, spectral leakage and poor alignment between channels may occur. To solve these problems, multivariate adaptive decomposition methods were used for the analysis of multichannel signals. These methods consider all the EEG channels together, thus keeping the common oscillatory information and channel relationships. The multivariate empirical mode decomposition (MEMD) [24], multivariate empirical wavelet transforms (MEWT) [27, 33], multivariate variational mode decomposition (MVMD) [30, 31] and multivariate iterative filtering (MIF) [34, 36, 38] methods yield more consistent synchronization and mode alignment among channels. Among these methods, MIF has been proven to be an important one due to its numerical stability, reduced mode mixing, improved convergence and efficient multichannel decomposition capability. MIF is an iterative moving average filtering approach to decompose multichannel EEG signals into multivariate intrinsic mode functions (MIMFs). The extracted components contain common frequency information across all EEG channels, which makes MIF suitable for imagined speech recognition tasks. We propose a MIF EEG-based automatic imagined speech recognition framework. The main purpose of this work is to improve the decomposition process and classification accuracy of the imagined speech EEG signals using effective multivariate signal analysis and feature extraction methods.

1.2 Problem overview

EEG-based AISR is difficult because brain signals are complex and EEG recordings are usually very noisy. Blinks, muscle movement, electrical interference, and poor electrode contacts all add disturbances. Imagined speech

EEG is especially hard: it is nonlinear and nonstationary, and its frequency bands often overlap. Many existing AISR systems treat each EEG channel separately using single-channel methods, which miss the shared and synchronized information across channels. That can lead to problems like mode mixing, misaligned components, and uneven decomposition, all of which hurt feature quality and classification accuracy. Another big challenge is extracting reliable features: imagined speech classes typically produce only subtle differences in brain activity, making them hard to tell apart. For these reasons, we need effective multivariate decomposition methods that separate components correctly while preserving common frequency information across channels. In this work, we use MIF to decompose multichannel EEG into MIMFs, then extract features from those components for imagined-speech classification. The proposed framework aims to improve synchronized feature analysis and boost AISR performance for BCI applications.

1.3 Motivation

The rapid development of BCI technology has increased the need for accurate and reliable imagined speech recognition systems. While conventional communication systems based on motor imagery or eye movements are useful, they offer limited flexibility for individuals with severe physical disabilities. Compared with imagined speech based BCI systems, the users only need to imagine speaking words in a mental way without any physical movement, which provides a more natural communication way. The success of the AISR systems largely depends on the quality of EEG signal decomposition and the effectiveness of the features extracted. Many existing methods apply univariate decomposition techniques to each EEG channel independently. Such methods cannot fully take advantage of the shared information and relations among multiple EEG channels. Due to this limitation, the analysis of EEG is taking an increasing interest in multivariate adaptive signal decomposition techniques. MIF offers several advantages over conventional decomposition techniques. It enhances the mode matching between channels and mitigates mode mixing. It also offers better stability on decomposition and convergence behavior. Moreover, it is capable of extracting oscillatory components efficiently while

maintaining the important characteristics of multichannel EEG signals.

1.4 Objectives of thesis

The main aim of this thesis is to study multichannel EEG signals and to understand their behavior for the applications of imagined speech recognition. In this work we study adaptive signal decomposition methods for analyzing nonlinear and nonstationary EEG signals. MIF is employed to decompose the multichannel EEG signals into MIMFs. After decomposition, EEG signals are processed through appropriate signal processing techniques to extract significant features to characterize the imagined speech patterns. Also, a framework of AISR based on machine learning and multivariate decomposition approaches is developed. The performance of the proposed framework is tested and compared for different classes of imagined speech. The study also studies the improvement of signal decomposition quality by MIF and the improvement of classification accuracy of AISR system.

1.5 Research contributions

A detailed study of multivariate adaptive signal decomposition methods for EEG signal analysis. We propose a MIF-based framework to decompose the multichannel imagined speech EEG signals. The proposed method is able to extract MIMFs and keep the synchronized behavior between different EEG channels. After the decomposition, useful features are extracted from the MIMFs to better represent imagined speech EEG signals. We also develop a classification framework for AISR using these extracted features. The decomposition quality and classification performance of different decomposition methods are compared. Experimental results show that the MIF-based approach can enhance the performance of AISR systems based on multichannel EEG signals.

Chapter 2

Literature Survey

2.1 Introduction

EEG-based AISR [39] has become an important topic in BCI research since it can provide people with severe physical disabilities with easier communication. Imagined speech happens when you think of saying words without actually making any sounds or moving your speech muscles. The challenge in recognizing imagined speech from EEG signals is that the EEG signals are weak, nonlinear, nonstationary and often contaminated by noise and artifacts. Therefore, efficient signal decomposition, feature extraction and classification techniques are to be developed to improve the performance of AISR systems. In recent years, many researchers have proposed different signal processing and machine learning methods for EEG-based AISR systems. Numerous studies have addressed adaptive signal decomposition, multichannel EEG analysis, feature extraction and deep learning models to enhance classification accuracy and reliability. In this chapter, the previous work related to EEG-based imagined speech recognition, adaptive decomposition methods, multivariate signal analysis and machine learning approaches relevant to this thesis are presented.

2.2 EEG-based imagined speech recognition

EEG-based AISR has attracted considerable attention, as it offers a direct communication channel between the human brain and external devices [41]. AISR systems attempt to find brain activity that corresponds to words the user is silently thinking and turn it into commands or text, unlike traditional speech recognition. Several researchers have studied different methods of EEG processing for imagined speech classification. Nguyen et al. created an EEG dataset for imagined speech and used common spatial pattern features with a relevance vector machine classifier for recognizing imagined words [41]. Their study showed that multichannel EEG signals contain useful neural information; however, the performance is still limited due to the high variability of the EEG

signals and the difficulty of feature extraction. Min et al. classified imagined vowels using statistical feature extraction and machine learning classifiers [42]. They have shown that statistical features can be used to separate imagined speech classes. However, these traditional features may not represent the complex oscillatory patterns of EEG signals completely. Deng et al. proposed an imagined syllable classification method based on Hilbert-Huang transform and linear discriminant analysis [43]. Their approach improved feature representation by adaptive decomposition and instantaneous frequency analysis. Although the method led to better classification results, there remained problems such as mode mixing and higher computation complexity.

Cooney et al. studied deep learning methods for imagined speech EEG classification using convolutional neural networks (CNN) [45]. Their work showed that deep learning models can automatically learn important spatial and temporal features from EEG data. However, deep learning models usually need large datasets and high computational power for effective training. Even though many improvements have been made in AISR research, achieving highly reliable classification is still difficult because EEG signals are nonlinear and nonstationary. Therefore, effective signal decomposition and feature extraction remain very important for improving AISR performance.

2.3 Adaptive signal decomposition techniques

Traditional signal processing techniques such as FT and WT are commonly used for EEG analysis. However, these methods have limitations when applied to EEG signals because brain activity is nonlinear and nonstationary. FT assumes stationarity, while WT depends on predefined basis functions. This may not always be able to correctly analyze complex EEG signals. Adaptive methods of signal decomposition have been widely used in biomedical signal processing to overcome these limitations. These techniques decompose complex signals into simple oscillatory components while maintaining the original behavior of the signal. They are data-driven and do not need a pre-specified set of basic functions but can adapt to the signal. The usual adaptive decomposition methods are EMD, VMD, EWT, and IF. These techniques are

widely used in EEG analysis for the extraction of features, reduction of noise, decomposition of signals, and interpretation of biomedical signals.

2.4 Empirical mode decomposition (EMD)

The EMD is a popular adaptive method for the analysis of nonlinear and nonstationary signals [46, 48, 49]. In EMD, a signal is decomposed into oscillatory components called IMFs. The process is based on locating local maxima and minima and then applying sifting operations repeatedly. The advantage of the EMD is that it is fully adaptive and does not need predefined basis functions. It also provides good time-frequency analysis and is suitable for signals whose characteristics change over time, like EEG signals. EMD possesses several important advantages for the analysis of EEG signals. It is an adaptive decomposition technique, which can automatically adapt according to the characteristics of the signal without any predefined basis functions. This makes EMD very effective in studying complex EEG signals that change with time. Another important feature of EMD is its good time-frequency representation ability that allows the identification of different oscillatory patterns present in the signal. Since EEG signals are nonlinear and nonstationary in nature, EMD becomes an appropriate choice for biomedical signal analysis and related applications. EMD has some limitations affecting its performance in real EEG analysis. One of the major problems is the mode mixing, in which oscillatory components with different frequencies may coexist in the same IMF or similar frequency components may be distributed across multiple IMFs. Furthermore, the method is sensitive to noise and may lead to incorrect decomposition in presence of disturbance in the signal. Also, EMD is subject to end effects near the signal boundaries that can distort the extracted components. Furthermore, the lack of a firm mathematical basis can sometimes make the decomposition process less stable and reproducible.

2.5 Empirical wavelet transform (EWT)

EWT is an adaptive decomposition method based on wavelet analysis and data-driven design [27, 29]. Unlike the traditional WT, EWT does not employ fixed wavelet functions. It builds wavelet filter banks that are dependent on the

frequency content of the signal. Compared with EMD, EWT has better frequency separation and better localization in the frequency domain. It can therefore better analyze the signal components. However, EWT strongly depends on the proper detection of spectral boundaries. Inaccurate boundary detection can result in improper decomposition and mode splitting into noisy EEG signals. As a result, the extracted components may not be a good representation of the original signal. To improve the frequency resolution further, researchers have also proposed EWT methods based on Fourier–Bessel series expansion (FBSE-EWT) [53, 55, 57]. These methods have the potential to improve the quality of decomposition for biomedical signals but also lead to increased computational complexity and processing time.

2.6 Variational mode decomposition (VMD)

VMD is an optimization based adaptive decomposition method [30, 31]. The signal is split into modes, each with a compact frequency range. VMD, in contrast to EMD, poses the decomposition as a mathematical optimization problem. In the VMD algorithm, the different parameters are updated continuously in the process of decomposition to obtain the accurate signal components. These parameters are mainly the mode functions, the center frequencies and the bandwidth values of the decomposed modes. VMD decomposes a signal into a collection of various oscillatory modes with limited frequency bandwidths by means of iterative optimization to improve the quality of the signal decomposition. VMD has a number of important advantages over traditional decomposition approaches. It can effectively reduce the mode mixing and provides a better separation of frequency components, so that the extracted modes become more distinct and meaningful. Furthermore, the method shows better robustness to noise, which is highly advantageous for the analysis of noisy biomedical signals, e.g., EEG recordings. Moreover, VMD is backed by a robust mathematical framework derived from variational optimization, which enhances the stability and dependability of the decomposition process. Although VMD is better than EMD, it also has limitations. It has to specify the parameters (number of modes, penalty factors, etc.) in advance. When applied to multichannel EEG signals the computational

cost also increases considerably.

2.7 Iterative filtering (IF)

IF is a method of adaptive decomposition to signals, developed as an alternative to EMD [20, 26]. IF uses iterative moving average filtering instead of envelope interpolation to separate signal components. The IF decomposition process consists of the design of a moving average filter, the calculation of the local moving average, the extraction of oscillatory fluctuations, and the repetition of the filtering operation until convergence is obtained. This iterative process leads to the decomposition of the signal into meaningful oscillatory components. IF has better numerical stability, better convergence behavior, less noise sensitivity and more efficient decomposition performance than EMD. Such advantages make IF very suitable for biomedical signal processing applications, particularly for the nonlinear and nonstationary EEG signal analysis.

2.8 Multivariate signal decomposition techniques

Modern EEG systems are typically based on multichannel recordings to record the brain activity of different brain regions at the same time. However, since the univariate decomposition methods are applied separately on each EEG channel, problems like improper mode alignment, unequal number of decomposed modes, loss of inter-channel information and reduced synchronization between channels may arise. To overcome such limitations, multivariate adaptive decomposition techniques have been proposed for a fast analysis of multichannel EEG signals while maintaining the relations among channels.

2.8.1 Multivariate empirical mode decomposition (MEMD)

MEMD is an extension of EMD for multichannel signal decomposition [24, 58, 61]. All the EEG channels are decomposed simultaneously instead of one by one. The method computes multivariate envelopes through projections on several direction vectors on hyperspheres, which maintains the inter-channel relations during the decomposition. Advantages of MEMD are better mode alignment, joint decomposition of multichannel EEG signals, and retain

common oscillatory information of multichannel EEG signals. However, this approach still suffers from some limitations such as mode-mixing, high computational complexity and noise sensitivity that could impair the decomposition performance in complex EEG recordings. The EEG signal is decomposed using MEMD method and the MIMFs are shown in Fig 2.1. The figure contains three columns which are channel 1, channel 2 and channel 3 of the EEG signal. The top row in each column is original EEG signal, and remaining rows are extracted MIMFs.

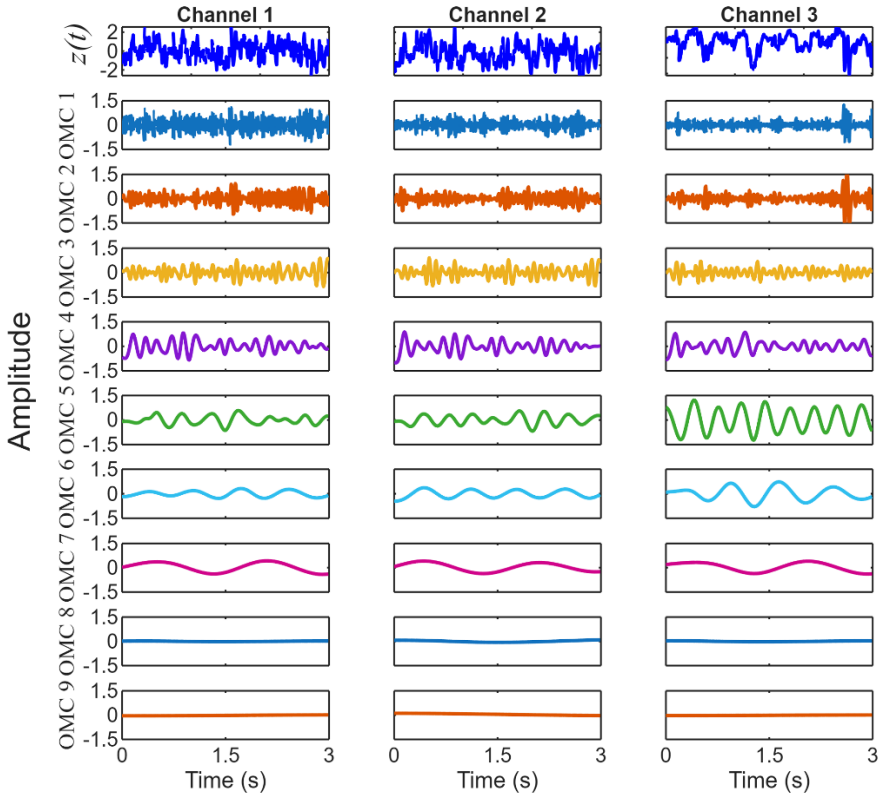

Fig 2.1: MIMFs corresponding to EEG Signal obtained from MEMD

2.8.2 Multivariate empirical wavelet transform (MEWT)

MEWT is a multichannel extension of EWT for signal analysis [27]. It employs common spectral information among all EEG channels to create adaptive wavelet filter banks, which leads to synchronized decomposition and better

spectral matching among channels. This allows MEWT to offer enhanced frequency localization for multi-channel EEG signal analysis. This method can lead to mode splitting and boundary detection errors especially when analyzing noisy EEG signals. Moreover, the computational complexity is greatly increased for the applications of multichannel signal processing. The MEWT method is used to decompose the EEG signal into multiple MIMFs as shown in fig 2.2. The figure is arranged in 3 columns for the 3 channels of the EEG signal channel 1, channel 2, and channel 3. The first row of each channel contains the original EEG signal, and the subsequent rows are the extracted MIMFs after decomposition.

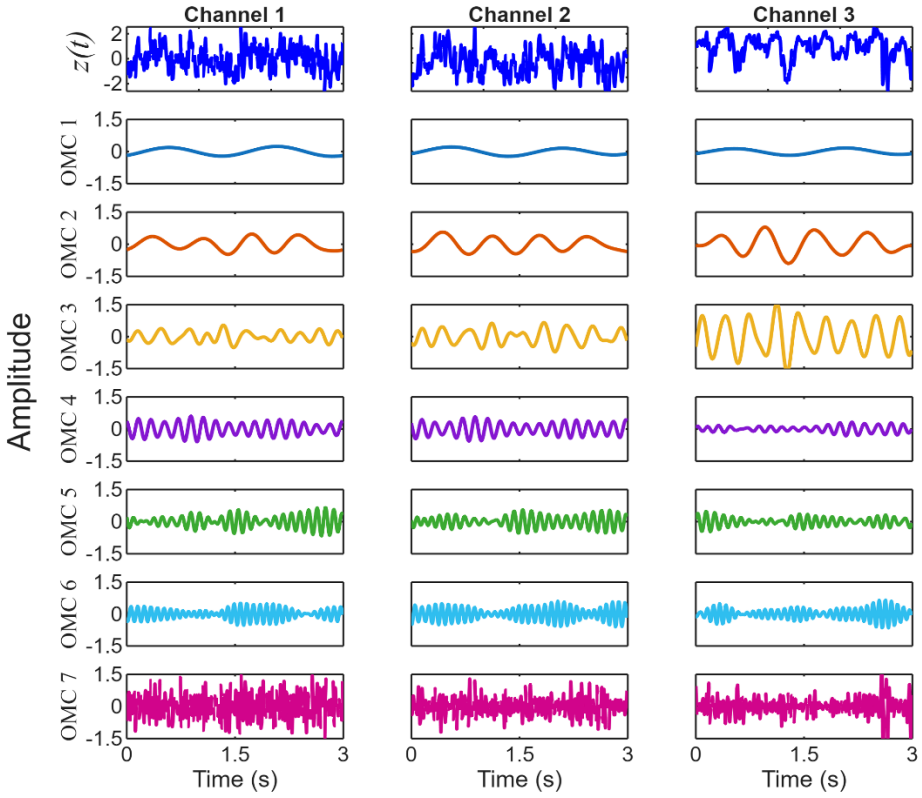

Fig 2.2: MIMFs corresponding to EEG Signal obtained from MEWT

2.8.3 Multivariate variational mode decomposition (MVMD)

MVMD is an extension of VMD for the analysis of multichannel signals that decompose all EEG channels together, while preserving common frequency structures across channels [31]. This joint processing allows the preservation of

synchronization and inter-channel relationships during decomposition. MVMD has several advantages such as better mode alignment, better robustness to noise, and better spectral separation of oscillatory components. These properties make MVMD useful for multichannel EEG signal analysis. However, the method still faces challenges, including high optimization complexity and sensitivity to parameter selection. The MVMD technique is used to decompose the EEG signal and the extracted MIMFs are shown in fig 2.3. The figure shows three columns corresponding to channel 1, channel 2 and channel 3 of EEG signal. In each column, the first row is the original EEG signal, and the subsequent rows are the decomposed MIMFs obtained using MVMD method.

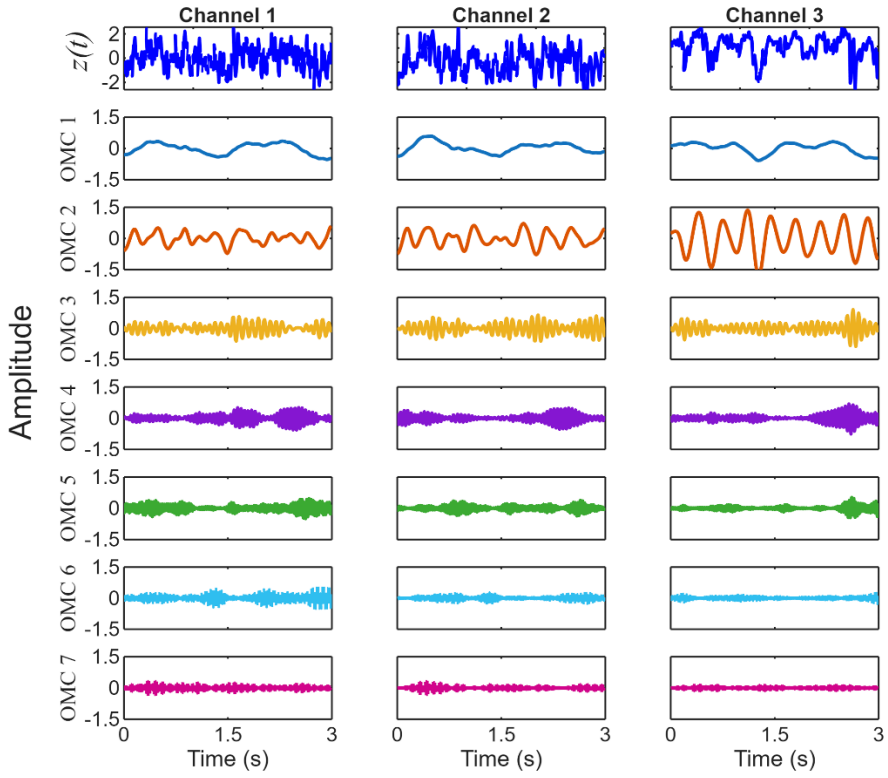

Fig 2.3: MIMFs corresponding to EEG Signal obtained from MVMD

2.9 Multivariate iterative filtering (MIF)

MIF is an extension of the IF technique to analyze multivariate signals such as EEG recordings, with a multichannel version [34, 36, 38]. In this method, all the EEG channels are processed simultaneously, and the signals are decomposed into MIMFs by an iterative moving average filtering approach.

This joint decomposition helps in keeping the relationship among different EEG channels in the signal analysis. The MIF algorithm has several important advantages: correct alignment of oscillatory modes among channels, less mode mixing, better convergence characteristics and better decomposition stability. It also preserves the oscillatory patterns present in multichannel EEG signals in a synchronized manner. The method calculates a common moving average filter based on the extrema information of all the EEG channels. Therefore, the extracted MIMFs have similar frequency characteristics among channels. Due to these advantages, MIF is well conceived as a highly effective method for multichannel EEG analysis and imagined speech recognition, hence it has been applied in EEG decomposition and feature extraction.

2.10 Machine learning techniques for AISR

Machine learning techniques play a significant role in the classification of imagined speech signals in the AISR systems [63]. Different classifiers are used by researchers to recognize the imagined speech patterns from EEG recordings. Some of the common machine learning methods are SVM, K-nearest neighbor (KNN), random forest (RF), relevance vector machine (RVM), and CNN [65, 70]. KNN is one of these methods that is widely preferred due to its simplicity and effective performance for lower dimensional EEG feature spaces. RF provides better robustness and also helps to identify important discriminative features from the data. Recently, deep learning methods such as CNNs have attracted much attention because of their ability to automatically learn the spatial and temporal information from EEG signals and their promising performance in the imagined speech recognition tasks. However, the overall performance of these classifiers highly depends on the quality of extracted EEG features. Thus, adaptive signal decomposition and efficient feature extraction techniques are very important to improve the accuracy and reliability of AISR systems.

2.11 Research gaps

The literature review reveals that there are still a number of challenges in EEG-based imagined speech recognition. However, traditional univariate decomposition methods cannot preserve the relationship among multiple EEG channels, which often leads to problems such as mode mixing and poor mode alignment. In addition, the classification accuracy of AISR systems is still limited due to the difficulty in extracting meaningful features from EEG signals. Therefore, better synchronized EEG analysis requires more reliable multivariate decomposition and feature extraction methods. Furthermore, there is a limited amount of research on MIF-based AISR systems.

Chapter 3

MIF for Multichannel EEG Signal Analysis

3.1 Introduction

EEG signals are non-linear, non-stationary and contain multiple frequencies. These are different brain and cognitive activities that occur simultaneously. It is important to decompose these signals into meaningful oscillatory components to extract useful features for classification in AISR systems [72]. The traditional decomposition methods often fail to preserve the synchronized behavior among EEG channels, which may decrease the classification accuracy. Multivariate adaptive signal decomposition methods were developed as a solution to these problems for the analysis of multichannel EEG. Such methods treat all EEG channels as a whole. These methods help to preserve common information and relations between channels. MIF has become one of the reliable and efficient methods among them for the multichannel EEG signal analysis. In this chapter, we introduce the mathematical description of the multichannel EEG signals and the basic concept of adaptive signal decomposition. Details of the MIF algorithm, including the working principle, implementation steps, benefits, and applicability for processing imagined speech EEG signals are also explained [34, 36, 38].

3.2 Multivariate signal representation

A multichannel EEG signal can be represented as a multivariate time series consisting of multiple correlated channels recorded simultaneously from different scalp locations. The multichannel EEG signal can be represented as [73],

$$x(t) = \begin{bmatrix} x_1(t) \\ x_2(t) \\ x_3(t) \\ \vdots \\ x_C(t) \end{bmatrix} \tag{3.1}$$

where (C) denotes the total number of EEG channels and $x_c(t)$ represents the EEG signal corresponding to the cth channel.

Each EEG channel contains multiple oscillatory components with different amplitudes and frequencies. Therefore, a multivariate oscillatory signal can be represented as a combination of several amplitude and frequency modulated components [75, 77, 81]. The general form of an oscillatory component is given by,

$$u(t) = a(t)e^{j\emptyset(t)} \tag{3.2}$$

where $a(t)$ represents the instantaneous amplitude and $\phi(t)$ denotes the instantaneous phase of the signal.

For a multicomponent multivariate signal, the overall signal can be expressed as,

$$x(t) = \sum_{p=1}^{P} u_p(t) \tag{3.3}$$

where P represents the total number of oscillatory components and $u_p(t)$ denotes the p^{th}oscillatory mode.

The main objective of adaptive signal decomposition is to separate these oscillatory components while preserving the important characteristics of the original signal.

3.3 Adaptive signal decomposition

Adaptive signal decomposition methods are data-driven techniques widely used for analyzing nonlinear and nonstationary signals such as EEG recordings. Unlike conventional methods like FT and WT, these approaches do not rely on predefined basis functions. Instead, they adapt according to the characteristics

of the signal itself and extract meaningful oscillatory components automatically. The main goals of adaptive decomposition are to separate different frequency components, maintain time-varying characters of the signal, suppress noise and interference, and extract useful oscillatory information from complicated signals. For the analysis of EEG signals several adaptive decomposition techniques have been developed, including EMD [24], EWT [33], VMD [30] and IF [26]. These methods work well for single channel signals. Direct application of these approaches to multi-channel EEG recordings could lead to problems such as bad mode alignment and uneven decomposition across channels. To address these limitations, for efficient multichannel EEG signal analysis, multivariate versions of these decomposition methods have been proposed.

3.4 Need for multivariate decomposition

EEG-based imagined speech recognition systems usually employ multichannel EEG recordings to capture neural activity from different brain regions. Since these channels contain related and synchronized oscillatory patterns, processing each channel separately may cause loss of important information between channels. It can also cause problems such as mode misalignment, unequal numbers of decomposed modes, reduced synchronization between channels, spectral inconsistency and increased mode mixing. Multivariate decomposition techniques process all EEG channels together to keep common frequency information between channels to resolve these problems. This approach allows us to maintain the correct mode alignment and to consistently extract oscillatory components with similar frequency ranges from all EEG channels.

3.5 Multivariate adaptive signal decomposition techniques

Several multivariate decomposition techniques have been introduced for multichannel signal processing.

3.5.1 Multivariate empirical mode decomposition (MEMD)

MEMD extends EMD for multichannel signals by computing multivariate envelopes using projections along multiple direction vectors [24]. This method provides synchronized decomposition across channels and improves mode alignment. However, MEMD suffers from mode mixing, sensitivity to noise, and high processing time for large EEG datasets.

3.5.2 Multivariate empirical wavelet transform (MEWT)

MEWT constructs adaptive wavelet filter banks based on the common spectral information of all EEG channels [27]. It improves the frequency localization and the separation of oscillatory components. However, MEWT may suffer from problems such as inaccurate spectral boundary detection and mode splitting problems in multichannel EEG signal analysis.

3.5.3 Multivariate variational mode decomposition (MVMD)

MVMD decomposes multichannel signals into modes with compact bandwidths through constrained optimization [65,102]. The method provides better and reduced mode mixing. However, MVMD requires prior parameter selection, optimization-based iterative processing and takes longer time as compared to others.

3.6 Iterative filtering (IF)

IF is an adaptive signal decomposition method developed as an alternative to EMD for analyzing nonlinear and nonstationary signals [61, 26]. Unlike EMD, which uses spline interpolation to compute the envelope, IF decomposes oscillatory components based on iterative moving average filtering. The decomposition process is done by calculating the local moving average, extracting signal fluctuations and repeating the filtering operation until the convergence condition is satisfied. IF is more numerically stable than EMD, less sensitive to noise, better convergence behavior and lower computational

complexity. These advantages make IF a suitable method for biomedical signal decomposition applications, especially for EEG signal analysis.

3.7 Multivariate iterative filtering (MIF)

MIF is a multivariate extension of IF developed for multichannel signal decomposition [85]. In this method, all EEG channels are processed together so that synchronized oscillatory behavior across channels can be preserved during decomposition. The MIF algorithm uses a common moving average filter obtained from extrema information of all EEG channels, which allows oscillatory modes with similar frequency characteristics to be extracted simultaneously from each channel.

The multichannel EEG signal can be represented as,

$$X(t) = \sum_{k=1}^{K} MIMF_k(t) + r(t) \tag{3.4}$$

where $MIMF_k(t)$represents the kth multivariate intrinsic mode function, K denotes the total number of extracted modes, and $r(t)$represents the residual trend component.

The extracted MIMFs preserve synchronized frequency characteristics across different EEG channels, making them highly useful for EEG feature extraction and imagined speech recognition applications.

3.8 Moving average filter in MIF

The moving average filter plays a crucial role in the MIF algorithm. The filter length is computed using extrema information obtained from all EEG channels [26].

The filter length is determined by,

$$L = \left\lfloor \frac{kN}{e} \right\rfloor \tag{3.5}$$

where k is a positive constant, N represents the total number of samples, e denotes the maximum number of extrema among all EEG channels, and $\lfloor . \rfloor$ represents the floor operator.

The moving average operation is defined as, M(x[n]) the fluctuation component is obtained by subtracting the moving average from the original signal, which can be written as,

$$x[n] - M(x[n])$$

This process is repeated iteratively until the stopping condition is satisfied.

3.9 Advantages of MIF

There are several advantages of MIF for the analysis of multichannel EEG signal. It is beneficial to maintain the oscillatory modes in good alignment across the different EEG channels and to preserve the synchronized signal patterns during decomposition. MIF can reduce the mode mixing, and the decomposition results are more stable and consistent than EMD-based methods. The method also demonstrates superior convergence behavior and can effectively extract important oscillatory components from EEG signals. Also, MIF is efficient in large EEG datasets and is robust even in the presence of noise in the signals. These benefits make MIF very suitable for the decomposition and feature extraction of the imagined speech EEG. MIF retains the common oscillatory structures of different channels, which makes the extracted features more discriminative and suitable for imagined speech classification.

Chapter 4

Proposed Methodology for AISR

4.1 Introduction

AISR systems are developed to recognize silently imagined words or speech patterns from EEG signals without any actual speech or physical movement [10, 11]. One of the major challenges in AISR is extracting useful information from multichannel EEG signals because these signals are nonlinear and nonstationary in nature. Therefore, effective signal decomposition and feature extraction methods are required to improve classification performance. This chapter presents the proposed methodology for imagined speech recognition using multichannel EEG signals. In the proposed framework, MIF is used to decompose EEG signals into MIMFs. Important features are then extracted from the decomposed components, and machine learning techniques are used to classify different imagined speech classes. The proposed AISR framework mainly consists of EEG dataset acquisition, signal preprocessing, MIF-based decomposition, feature extraction, and classification of imagined speech signals.

4.2 Dataset description

The EEG dataset used in this work is publicly available and was developed by the Human-Oriented Robotics and Control (HORC) Laboratory at Arizona State University [88]. The dataset contains multichannel EEG recordings collected during different imagined speech tasks. The experiment includes four imagined speech categories: vowels, short words, long words, and short–long words. During the experiment, multiple subjects were asked to silently imagine speaking specific words or vowels without making any actual sound or physical movement. Throughout the recording process, the subjects remained relaxed and repeatedly performed the imagined speech tasks mentally.

Table 4.1: Imagines speech categories used in the dataset

Imagined speech category	**Classes**
Vowels	/a/, /i/, /u/
Short words	in, out, up
Long words	independent, cooperate
Short–long words	cooperate, in

The EEG signals were recorded using multichannel electrodes with a sampling frequency of 1000 Hz. Later, the signals were down sampled to reduce computational complexity while still preserving important brain activity information.

4.3 Proposed AISR framework

The proposed AISR framework is designed to improve classification accuracy through efficient multivariate signal decomposition and feature extraction. The framework jointly processes multichannel EEG signals to preserve inter-channel relationships and synchronized oscillatory behavior. The proposed methodology is illustrated conceptually as,

$EEG\ Signal \rightarrow Preprocessing \rightarrow MIF \rightarrow Feature\ Extraction \rightarrow Classifier \rightarrow AISR\ Output$

4.4 EEG signal preprocessing

EEG signals are highly sensitive to different types of noise and artifacts, including eye blinks, muscle movements, electromagnetic interference, power-line noise, and electrode disturbances [91]. These unwanted components can influence the quality of EEG recordings and decrease the performance of imagined speech recognition systems. Thus, preprocessing is required before signal decomposition and feature extraction. Preprocessing generally consists of bandpass filtering, noise reduction, artifact suppression, and signal normalization. A Butterworth bandpass filter is applied to retain the EEG frequency components corresponding to imagined speech and to remove low-frequency drift and high-frequency noise. Also, a notch filter is used to remove

power-line interference from the recordings. After filtering, the EEG signals are normalized to maintain the amplitude levels of all channels and subjects [38].

Algorithm 1 IF

Input : x (univariate signal)

Output: IMF

1: IMF = {}

2: while e ≥ 2 do // e is the number of extrema of x

3: $m = 1$

4: $x_m = x$

5: while stopping criterion is not satisfied do

6: compute the filter length l_m for $x_m(n)$

7: design moving average filter $w_m(n)$of length l_m

8 $x^{m+1}(n) = x^m(n) - \sum_{k=-l_m}^{l_m} x^m(n+k)w_m(k)$

9: $m = m + 1$

10: end while

11: IMF = IMF ∪ $\{x_m\}$

12: $x = x - x_m$

13: **end while**

14: IMF = IMF ∪ $\{x\}$

4.5 MIF for EEG decomposition

After preprocessing, MIF is applied to decompose multichannel EEG signals into MIMFs. The MIF algorithm jointly analyzes all EEG channels and extracts synchronized oscillatory modes across channels. This helps preserve common frequency characteristics and mutual information among the EEG channels.

The multichannel EEG signal is represented as,

$$X(t) = \sum_{k=1}^{K} MIMF_k(t) + r(t) \tag{4.1}$$

Where $MIMF_k(t)$ denotes the kth MIMFs, k represents the total number of

extracted modes and r(t) denotes the residual trend component. The MIF algorithm iteratively computes moving average filters using extrema information from all channels and extracts oscillatory fluctuations from the signal.

The moving average filter length is computed as [26],

$$L = \left\lfloor \frac{kN}{e} \right\rfloor \tag{4.2}$$

where k is a positive constant, N denotes total number of samples and e represents maximum extrema count among all channels.

The extracted MIMFs preserve the synchronized oscillatory structures over channels and demonstrate better decomposition consistencies than univariate approaches. The details of MIF are shown in algorithm 2 [93]. In algorithm 2, the outer loop gives one MIMF after a single iteration, and the inner loop is for properly extracting a particular MIMF. The flowchart of MIF is represented in Fig. 4.1.

Algorithm 2 MIF

Input: x (multivariate or multichannel signal)

Output: MIMF

1: MIMF = {}, c is number of channels

2: Compute **E** of x, $\mathbf{E} \in \mathbf{R}^{cx1}$ // **E** is the number of extrema

3: **while** any value in **E** ≥ 2 **do**

4: $m = 1$ // m counts the number of inner loop iteration

5: $x^m = x$

6: **while** stopping criterion is not satisfied **do**

7: Compute **E** of x

8: Compute the l_m based on maximum (E) for x^m

9: design moving average filter w_m (n) of length l_m

10: $x^{m+1}(n) = x^m(n) - \sum_{k=-l_m}^{l_m} x^m(n+k) w_m(k)$

11: $m = m + 1$

12: **end while**

13: MIMF = MIMF $\cup$ { x^m}

14: $x = x - x^m$

15: Compute E of x

16: **end while**

17: MIMF = MIMF ∪ { x }

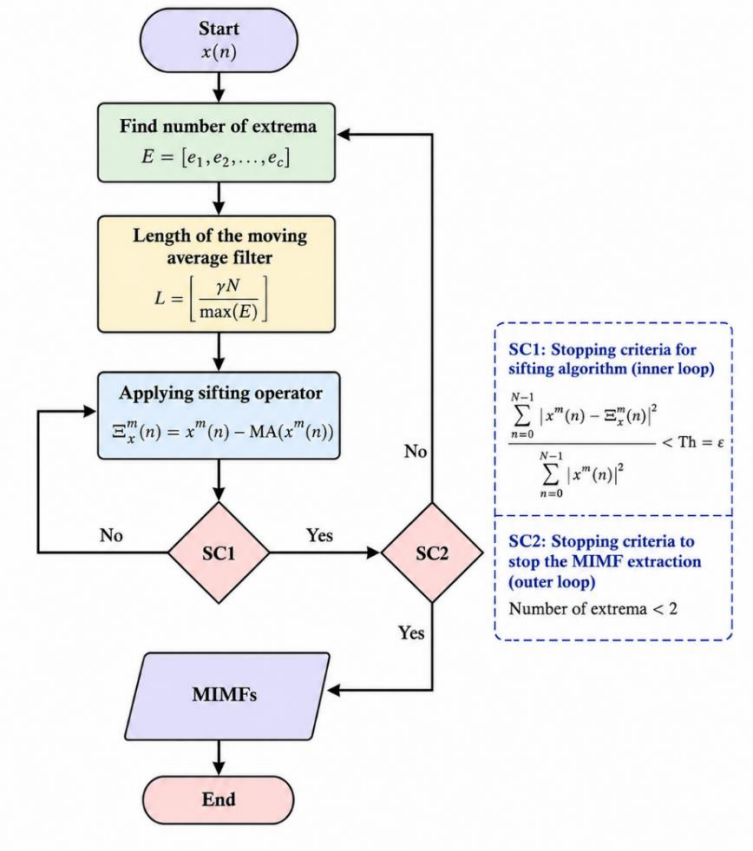

Fig 4.1: Flowchart for MIF

4.6 Extraction of MIMFs

The MIF algorithm decomposes EEG signals into multiple MIMFs associated with different oscillatory frequency ranges. The extracted MIMFs are rich in neural information like time-varying oscillatory behavior, frequency-related characteristics and synchronized patterns among different EEG channels. The extracted MIMFs contribute to the separation of the high-frequency neural oscillations, the low-frequency brain rhythms, the noise components and the residual trends. Speech EEG signals imagined are several cognitive activities running in parallel. Thus, these decomposed components have valuable information for feature extraction and classification. This process of decomposition continues iteratively until the residual signal has very small

oscillatory information left. The MIF-based decomposed components of the EEG signals are shown on Fig 4.2. The figure contains three columns which are channel 1, channel 2 and channel 3 of the EEG signal. The top row in each column is original EEG signal, and the subsequent rows extracted MIMFs after decomposition.

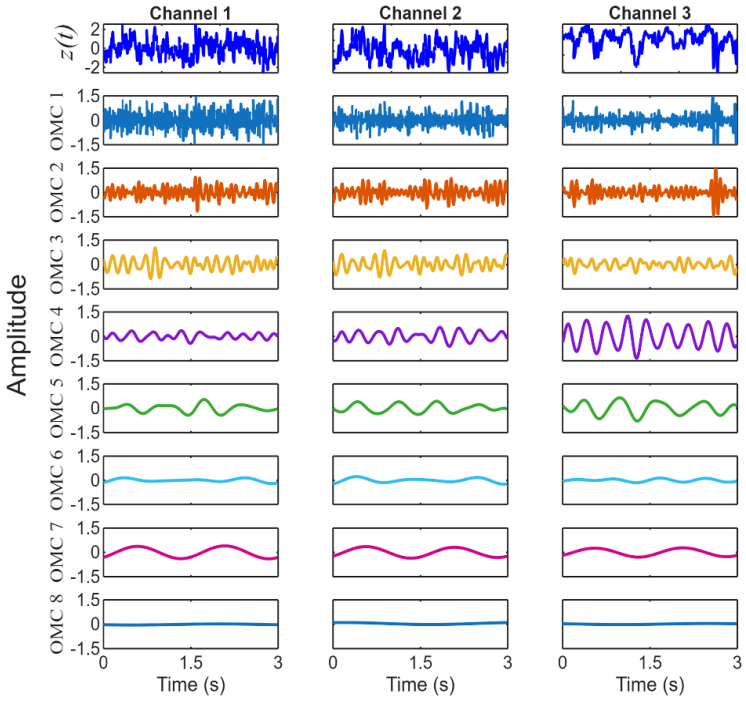

Fig 4.2: MIMFs corresponding to EEG signal obtained from MIF.

4.7 Feature extraction

Feature extraction is one of the most important steps in AISR systems because the classification accuracy mainly depends on the quality of the extracted features [97]. After applying MIF decomposition, several useful and discriminative features are obtained from the extracted MIMFs. These features mainly include spectral features, statistical features, power-based features, and time-domain characteristics, which help represent important patterns present in imagined speech EEG signals.

4.7.1 Power spectral density (PSD) features

PSD analysis is used to estimate the frequency-domain energy distribution of EEG signals [99]. PSD features help identify dominant oscillatory frequency bands associated with imagined speech activity. The PSD of the signal is computed using spectral estimation techniques such as the Welch method and

Fourier spectral analysis. Frequency-domain energy extracted from different MIMFs improves the distinction between imagined speech classes.

4.7.2 Hjorth parameters

Hjorth parameters provide compact statistical information about the characteristics of EEG signals [101]. The commonly used Hjorth parameters are activity, mobility, and complexity. These parameters describe important signal properties such as signal variance, frequency behavior, and oscillatory complexity. Hjorth features extracted from the decomposed MIMFs provide meaningful representations of EEG signals and are useful for imagined speech classification tasks.

4.7.3 Statistical features

Statistical measures extracted from EEG components include mean, standard deviation, variance, energy, entropy, root mean square value. These features characterize amplitude distribution and signal variability associated with imagined speech patterns.

4.8 Classification framework

These extracted features are utilized to classify different categories of imagined speech [65]. Machine learning classifiers analyze EEG feature vectors to identify different imagined speech patterns. In the classification stage, the primary target is to discriminate the vowel, short word, long word and short-long word classes from EEG signals. Different machine learning algorithms such as KNN, SVM, RF and CNN can be used to implement AISR systems [65, 70]. The classifier is trained on the extracted feature vectors and their corresponding class labels. During testing, the trained model is used to predict the category of the imagined speech signal for unknown EEG signals.

4.9 Performance evaluation metrics

The performance of the proposed AISR framework is evaluated in terms of the standard classification metrics. Common evaluation measures are accuracy, precision, recall, F1-score and confusion matrix analysis. These metrics are

used to test the effectiveness of the proposed framework for classification of different imagined speech categories.

Classification accuracy is calculated as,

$$Accuracy = \frac{Number\ of\ correct\ prediction}{Total\ number\ of\ prediction} \times 100\ \% \qquad (4.3)$$

The higher accuracy indicates that the proposed decomposition and feature extraction framework performs better. Besides, the class-wise prediction performance of classifier is analyzed using confusion matrix analysis.

4.10 Advantages of the proposed framework

The proposed AISR methodology offers several advantages for the analysis of imagined speech EEG. It efficiently decomposes nonlinear EEG signals and preserves synchronized oscillatory information between channels. The use of MIF reduces the mode mixing and improves the quality of extracted signal components. Furthermore, the extracted MIMFs offer better feature representation that contributes to enhancing the discrimination between different imagined speech classes. The proposed framework is also more robust to EEG noise and signal artifacts.

Chapter 5

Results and Discussion

5.1 Introduction

This chapter describes the experimental analysis and performance evaluation of the proposed AISR system based on multichannel EEG signals. In the proposed approach, MIF is applied to decompose EEG signals into MIMFs, and then machine learning techniques are used to extract and classify important features. The framework is evaluated on synthetic speech EEG datasets with different categories such as vowels, short words, long words, and short-long words. The experiments are designed to examine the performance of MIF in preserving synchronized oscillatory information across EEG channels and in improving classification accuracy. The contents are mainly on the EEG decomposition analysis, the MIMF extraction results, the feature analysis, the classification performance evaluation, the comparative study and the discussion of the experimental results.

5.2 Experimental setup

The developed AISR framework was implemented using multichannel EEG recordings obtained from a publicly available imagined speech dataset. Experiments were conducted using MATLAB and Python based signal processing and machine learning tools. The general process included mainly EEG preprocessing, MIF based decomposition, feature extraction and classification. Before decomposition, the EEG signals were first filtered to remove noise and unwanted artifacts. All EEG channels were preprocessed and then MIF was applied to extract synchronized oscillatory modes Then, the acquired MIMFs were employed for the feature extraction and classification of different classes of imagined speech.

5.3 EEG signal decomposition using MIF

The multichannel EEG signals were decomposed using the proposed MIF algorithm, which generated multiple MIMFs associated with different oscillatory frequency ranges. The extracted MIMFs preserved synchronized oscillatory behavior across all EEG channels and effectively separated high-frequency oscillations, low-frequency components, residual trends, and noise components from the EEG signals. The decomposed MIMFs showed clear oscillatory patterns suitable for imagined speech analysis. The results also indicated that similar frequency components remained properly aligned across channels, oscillatory modes were separated effectively, and the effect of mode mixing was significantly reduced. These observations show that MIF effectively preserves inter-channel relationships during EEG decomposition.

5.4 Analysis of extracted MIMFs

The extracted MIMFs contain different neural oscillatory characteristics related to imagined speech. The lower-order MIMFs mainly relate to the high frequency EEG oscillations, fast neural activities and fast signal variations. On the other hand, the higher order MIMFs contain the low frequency oscillatory behavior, slowly varying neural components and residual trends present in the EEG signals. The extracted MIMFs exhibited distinct separation of the oscillatory modes corresponding to various EEG frequency bands. Decomposition quality was verified both visually and by spectral analysis. Results showed improved mode alignment, increased separation between oscillatory components, consistent decomposition behavior and decreased spectral overlap between the EEG channels.

5.5 Feature extraction analysis

Several discriminative features are extracted from the obtained MIMFs after decomposition. These include PSD features, Hjorth parameters, statistical features and energy-based features [97, 101, 104]. The features were calculated from different MIMFs to get important information related to frequency characteristics, time domain behavior, oscillatory patterns and signal complexity. The extracted features effectively represented the important

properties of the imagined speech EEG signals and helped to improve the separation between different imagined speech classes. PSD was used to analyze the decomposed MIMFs to investigate the frequency-domain features of the EEG signals. Spectral energy showed different patterns for different classes of imagined speech and important oscillatory frequency bands were clearly visible after decomposition. The decomposed MIMFs have better frequency localization and better spectral separation than those of the original EEG signals. This helped to extract more meaningful and discriminative spectral features and hence helped to improve the overall classification accuracy of the proposed system.

5.5.1 Hjorth parameter analysis

The complexity and oscillatory nature of the EEG signals were analyzed by calculation of Hjorth parameters from the extracted MIMFs [104]. The analysis was done by using three commonly used Hjorth parameters i.e. Activity, Mobility and Complexity. These parameters were useful in terms of signal variance, frequency characteristics and dynamic neural behavior that exists in the imagined speech EEG signals. The extracted Hjorth features successfully classified the different classes of imagined speech and were found to be effective for classification tasks based on EEG.

5.6Classification results

The extracted features were used for classification of different imagined speech categories using machine learning classifiers [65, 70]. The classification framework was trained and tested on different imagined speech classes such as vowels, short words, long words and short-long word categories. The trained classifier successfully recognized different imagined speech patterns from multi-channel EEG signals. The experimental results demonstrated that the MIF-based decomposition improved the quality of extracted features and the separation between different imagined speech classes. Thus, the proposed framework resulted in better classification performance than the direct analysis of raw EEG signals.

Table 5.1: Comparison of classification accuracy for long words

Long words (independent & co-operate)						
Method/participation number	**Subject-2**	**Subject-3**	**Subject-6**	**Subject-7**	**Subject-9**	**Subject-11**
CSP + RVM [5]	70.8±7.8	64.3±6.6	72±0.6	64.5±5.5	67.8±6.8	58.5±7.4
TS+ANN+ Bagging [18]	75	-	68	75	66	66
VMD + EBT [6]	63.63	71.73	69.96	69.35	84.59	83.18
MDMD + RF(Proposed)	88.6±2.7	88.01±2.72	88.9±2.44	85.31±2.5	86.99±2.	84.6±2.22
MDMD+ KNN (Proposed)	88.19±1.62	87.96±1.94	87.96±2.73	84.11±2.85	86.3±1.75	84.41±1.84
MIF + KNN	**89±1.62**	**85±1.94**	**85±2.73**	**84±2.85**	**80.5±1.75**	**84±1.84**

Table 5.2: Comparison of classification accuracy for short words

Short words (in, out, up)						
Method/participation number	**Subject-1**	**Subject-3**	**Subject-5**	**Subject-6**	**Subject-8**	**Subject-12**
CSP + RVM [5]	48±6.1	49.7±5.5	46.3±8.2	54±9.1	47.7±9.8	54.7±6.9
TS+ANN+ Bagging[18]	57	55	60	-	64	64
VMD + EBT [6]	71.82	56.77	49.91	68.53	61.17	74.26
MDMD + RF(Proposed)	82.06±2.13	83.45±2.06	83.05±2.01	83.29±2.05	81.18±2.05	83.64±2.11
MDMD+ KNN (Proposed)	81.98±2.72	83.14±1.71	83.63±2.14	82.27±2.53	81.51±1.36	84.35±1.37
MIF + KNN	**73.3±2.72**	**74.3±1.71**	**76.7±2.14**	**76.7±2.53**	**74.3±1.36**	**72±1.37**

Table 5.3: Comparison of classification accuracy for short-long words

Short-long words (in & cooperate)						
Method/participation number	**Subject-1**	**Subject-5**	**Subject-8**	**Subject -9**	**Subject-10**	**Subject-14**
CSP + RVM [5]	70.3±5.5	71.5±5.0	81.9±6.5	88±6.4	79.3±7.7	89.3±3.5
TS + ANN + Bagging [18]	77	71	77	85	78	83
VMD + EBT [6]	74.08	64..48	74.38	74.14	73.19	81.18
MDMD+ RF (Proposed)	81.88±2.7	87.89±2.18	86.33±2.6	85.28±2.6	80.56±2.22	82.83±2.22
MDMD+ KNN (Proposed)	80.11±2.66	87.78±2.3	85.42±3.15	84.4±3.59	80.3±2.45	78.22±2.72
MIF + KNN	**85.5±2.66**	**90.5±2.3**	**89.5±3.15**	**82±3.59**	**85.5±2.45**	**81.3±2.72**

Table 5.4: Comparison of classification accuracy for vowels

Vowels (a, i, u)								
Method/participation number	**Subject-4**	**Subject-5**	**Subject-8**	**Subject-9**	**Subject-11**	**Subject-12**	**Subject-13**	**Subject-15**
CSP + RVM [5]	47±4.6	48±7.2	51±6.7	47±5.5	53±4.0	51±6.3	46.7±8.2	48±7.2
TS+ ANN + Bagging [18]	-	-	62	62	54	54	58	62
VMD + EBT [6]	75.83	51.6	51.98	74.24	67.88	52.82	86.04	66.54
MDMD + RF (Proposed)	82.46±1.7	83.28±2.25	82.45±2.03	79±2.13	82.11±2.07	83.62±2.09	74.86±2.16	76.44±2.07
MDMD + KNN (Proposed)	81.65±1.9	82.99±2.39	82.86±2.9	78.52±1.88	81.32±2.03	82.89±2.67	73.93±2.86	75.95±2.17
MIF + KNN	**72.7±1.94**	**74.3±2.39**	**71.3±2.9**	**71.7±1.88**	**71±2.03**	**75±2.67**	**72.7±2.86**	**73.7±2.17**

5.7 Performance evaluation

The effectiveness of the proposed AISR framework was tested using conventional classification metrics like accuracy, precision, recall, F1-score and confusion matrix analysis. The performance of the proposed framework in classifying different imagined speech categories was evaluated using these evaluation measures.

The classification accuracy is calculated as,

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\ \% \tag{5.1}$$

where (TP) represents true positives, (TN) represents true negatives, (FP) denotes false positives, and (FN) represents false negatives.

The proposed framework achieved better classification performance due to effective multichannel decomposition, proper mode alignment and enhanced feature extraction from the EEG signals. The MIF helped to maintain the oscillatory information in sync across channels and also helped to better separate different imagined speech classes. In addition, the confusion matrix analysis indicated that most of the imagined speech categories were correctly classified with minor misclassification errors.

5.8 Comparative analysis

The presented MIF-based AISR framework was tested against various conventional signal decomposition methods including univariate decomposition approaches, MEMD-based techniques, and traditional EEG feature extraction methods. The comparison results showed that the proposed MIF framework can achieve more stable decomposition, better extraction of synchronized oscillatory patterns, less mode mixing, better quality of features, and higher classification accuracy. Unlike univariate methods, which analyze each EEG channel separately, MIF performs joint analysis of multichannel EEG signals and preserves important inter-channel relationships. This leads to better EEG representation and more stable decomposition results. It was found that, in

general, the decomposition performance based on MIF was better than the conventional decomposition methods.

5.9 Discussion

The findings obtained clearly show the effectiveness of MIF for the imagined speech EEG signal analysis. The experimental study demonstrated that MIF can effectively decompose multichannel EEG signals into synchronized oscillatory modes, while keeping the common frequency structures across channels. Compared with conventional methods, the proposed approach significantly mitigates the mode mixing and spectral overlap, thus, improves the quality of the signal decomposition. Moreover, the extracted MIMFs also enhanced the discriminative ability of the feature extraction process for imagined speech classification. In particular, spectral and Hjorth features provided meaningful neural representations of the EEG signals. The proposed framework outperformed AISR systems in terms of classification accuracy, robustness and overall performance. Moreover, the results showed that multivariate decomposition is more effective for EEG representation than independent channel-wise processing, suggesting that MIF is suitable for multichannel EEG analysis and imagined speech recognition applications.

5.10 Limitations of the current work

Although the proposed AISR framework has achieved better performance, some limitations still exist. Processing large EEG datasets may require higher computational complexity and the differences in EEG patterns across subjects might affect the classification performance. Other challenges are the limited availability of training data, sensitivity to EEG artifacts and inter-subject variability in the responses of imagined speech. Deep learning architectures with larger EEG databases in future work can improve the accuracy and overall performance of the suggested system.

Chapter 6

Conclusion and Future work

6.1 Conclusion

The use of EEG signals in AISR is an important field of research in BCI, as it has a potential application in communication support systems for people with speech and movement disabilities. However, accurate recognition of imagined speech is still challenging due to the nonlinearity, nonstationary, multiple frequency components and noise and artifact interferences of EEG signals. Thus, efficient signal decomposition and feature extraction methods are needed to boost the performance of AISR. This thesis provided a comprehensive study of multivariate adaptive signal decomposition methods for multichannel EEG analysis and imagined speech recognition. The main work is about the implementation of MIF to decompose the multichannel EEG signals into MIMFs. The proposed framework was developed for improving the performance of synchronous feature extraction and classification by preserving the common oscillatory information across EEG channels. First, mathematical representation of multichannel EEG signals and basic theory of adaptive signal decomposition were discussed. Various decomposition methods have been reviewed, including EMD, EWT, VMD, MEMD, MEWT, MVMD, MIF. Limitations of traditional univariate decomposition methods such as mode mixing, poor mode alignment and loss of inter-channel information showed the need for multivariate decomposition methods in EEG signal analysis. Then a multichannel imagined speech EEG signals based AISR framework was designed. Experimental analysis was performed using a publicly available imagined speech EEG dataset including vowels, short words, long words, and short–long words. Preprocessing was performed by filtering and normalization to reduce noise and to improve signal quality. The processed EEG signals were then decomposed using MIF algorithm. The MIF algorithm was successful in extracting synchronized MIMFs for different frequency bands. The extracted MIMFs preserved common frequency information across the EEG channels and reduced mode mixing. Thus, the quality of neural information extracted from EEG signals for imagined speech analysis was enhanced. The decomposed

MIMFs were used to extract different features such as PSD, Hjorth parameters and statistical features. These features described the spectral and temporal properties of the imagined speech EEG signals well. Then, machine learning-based classifiers were used to classify different imagined speech categories. Experimental results demonstrated that the proposed MIF-based AISR framework was better than the traditional signal decomposition methods in terms of decomposition consistency, oscillatory separation and classification performance. The results also verified that the multivariate decomposition aids in preserving the synchronized oscillatory information among EEG channels and enhances the feature extraction for the application of imagined speech recognition. The main contribution of this thesis is the thorough investigation of multivariate adaptive signal decomposition methods for the analysis of multichannel EEG. In this work, we have developed and implemented a MIF based decomposition framework for imagined speech EEG signals to obtain synchronized oscillatory components with less effect of mode mixing. Also, spectral and statistical feature extraction techniques were applied to obtain a better EEG signal representation. Also developed was an AISR framework with machine learning for classification of different imagined speech categories. The experimental analysis confirmed the effectiveness of MIF for multichannel EEG decomposition and imagined speech recognition tasks. The work presented demonstrates that MIF is an efficient and reliable approach for the analysis of multichannel EEG signals in general. The proposed methodology is a step towards the improvement of EEG-based imagined speech recognition systems and enables the progress of BCI technologies for assistive communication applications.

6.2 Future work

The proposed AISR framework showed promising results, but there are still several improvements to explore in future research.

6.2.1 Deep learning-based AISR systems

MIF-based decomposition can be combined with deep learning models such as CNN, RNN, long short-term memory networks and transformer-based

architectures to learn features and classify better. These models can automatically learn spatial and temporal patterns from multichannel EEG signals and may enhance accuracy further.

6.2.2 Real-time AISR implementation

The present work deals principally with the analysis of offline EEG signals. The proposed framework can be extended in the future work to real-time imagined speech recognition for practical BCI applications. The decomposition should be low latency for real-time use. Online classification methods should be efficient.

6.3 Final remarks

The works presented demonstrate the importance of multivariate adaptive signal decomposition for EEG-based imagined speech recognition. MIF is an effective decomposition framework that mitigates mode mixing while preserving the synchronized neural oscillatory behavior across EEG channels. The proposed methodology improves feature extraction and classification performance or AISR systems and helps to develop intelligent BCI technologies. The results of this work demonstrate the potential of multivariate EEG signal processing techniques for future assistive communication systems and intelligent biomedical applications.

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