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Hybrid Electroencephalogram (EEG) - Functional Near-Infrared Spectroscopy (FNIRS) Brain-Computer Interface (BCI) Classification of Motor Imagery Tasks

THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
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MUSTAFA HASAN

A MASTER OF SCIENCE THESIS
IN
THE DEPARTMENT OF MECHATRONICS ENGINEERING

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THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES
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MUSTAFA HASAN

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Approval of the Graduate School of Natural and Applied Sciences, Atilim University.

Prof. Dr. Ali KARA
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I certify that this thesis satisfies all the requirements as a thesis for the degree of **Master of Science Engineering in Mechatronics Atilim University**.

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This is to certify that we have read the thesis Hybrid Electroencephalogram (EEG) - Functional Near-Infrared Spectroscopy (FNIRS) Brain-Computer Interface (BCI) Classification of Motor Imagery Tasks submitted by Mustafa Hasan and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

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I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ABSTRACT

HYBRID ELECTROENCEPHALOGRAM (EEG) – FUNCTIONAL NEAR-INFRARED SPECTROSCOPY (FNIRS) BRAIN-COMPUTER INTERFACE (BCI) CLASSIFICATION OF MOTOR IMAGERY TASKS

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Hybrid Brain Computer Interface, a combination of two or more neurophysiological signals, is getting attention for its ability to complement a single modality drawbacks and in achieving reliable results by extracting harmonizing features. A hybrid EEG-fNIRS BCI system achieved through the fusion of simultaneously recorded functional Near-Infrared Spectroscopy (fNIRS) and Electroencephalography (EEG) signals, is used to overcome the limitations of uni-modality and to achieve high motor tasks classification. Although, hybrid BCI approach enhanced the performance of the system, yet the improvements are still modest because of the lack of computational methods to fuse the two modalities. The contributions of this thesis is twofold: a novel channel selection correlation coefficient approach to select the most representative channels and a novel fusion approach using Multi-resolution singular value decomposition (MSVD). MSVD is utilized to achieve both system-based and feature-based fusion for the optimal EEG-fNIRS channels. Another contribution of this thesis is to utilize canonical correlation analysis (CCA) for feature-based fusion. Correlation analysis is used primarily to study the relationship between the two modalities. CCA feature-based fusion improved performance through maximizing the inter-subject covariance across the two modalities. Through simulation results, it can be witnessed that the proposed approaches help to achieve optimal performance while reducing the computational complexity.

Keywords: Hybrid BCI, fNIRS, EEG, Multi-resolution Singular Value Decomposition, Canonical correlation analysis, Multi-modal fusion, Channel selection, Classification.

ÖZ

MOTOR GÖRÜNTÜ GÖREVLERİNİN HİBRİT ELEKTROENSEFALOGRAFİ (EEG)- İŞLEVESEL KIZILÖTESİNE YAKIN SPEKTROSKOPİ (fNIRS) BEYİN BİLGİSAYAR ARA BİRİMİ (BCI) SINIFLANDIRMASI

Hasan, Mustafa
M.S., Mekatronik Mühendisliği Bölümü Yüksek Lisansı
Danışman: Yard. Prof. Dr. M. Umer Khan

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Hibrid Beyin Bilgisayar Ara Birimi, iki ya da daha fazla nörofizyolojik sinyalin birleşimidir ve tek modalite sakıncalarını tamamlama yeteneği ile uyumlu hale getirici özellikleri ortaya çıkarmada güvenilir sonuçlar elde etmesiyle dikkat çekmektedir. Simultane biçimde kaydedilen işlevsel kızılötesine yakın spektroskopi(fNIRS) füzyonu ve Elektroensefalografi (EEG)aracılığı ile elde edilen hibrid bir EEG-fNIRS BCI sistemi, tek-modalite sınırlarını aşmak ve yüksek motor görevlerinin üstesinden gelmek üzere kullanılmaktadır. Her ne kadar hibrid BCI yaklaşımı sistemin performansını başarıya ulaştırsa da, hala ilerlemeler iki modaliteyi birleştirmek üzere hesaplama olmaması nedeniyle henüz makul düzeydedir. Bu teze katkılar iki yönlüdür: en çok temsili kanalları seçme konusundaki roman kanal seçim katsayı korelasyonu ve Çoklu çözünürlük tek değerli dekompozisyan kullanan roman füzyon yaklaşımı (MSVD). MSVD' den, optimal EEG-fNIRS kanallar için hem sistem-temelli ve hem de özellik-temelli füzyon elde etmekte yararlanılır. Bu teze diğer bir katkı da, özellik-temelli füzyon için kanonik korelasyon analizinden (CCA) yararlanmaktır. Korelasyon analizi, öncelikle iki modalite arasındaki ilişki üzerinde çalışmak üzere kullanılmaktadır. CCA özellik-temelli füzyon, iki modalite üstünden inter-konulu orta değişikliği maksimize ederek performansı arttırdı. Simülasyon sonuçları vasıtasıyla, hesaplama karmaşıklığını azaltırken, amaçlanan yaklaşımların optimal performansı elde etmeye katkı sağladığına tanık olunabilmektedir.

Anahtar Kelimeler: Hibrid BCI, fNIRS, EEG, Çoklu çözünürlük tek değerli dekompozisyon, Kanonik korelasyon analizi, Çokul-modal füzyonu, Kanal seçimi, Tasnif.

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To my family, friends and loved ones…

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LIST OF ABBREVIATIONS

BCI	Brain Computer Interface
fNIRS	functional Near Infrared Spectroscopy
fMRI	functional Magnetic Resonance Imaging
MEG	Magnetoencephalography
EEG	ELECTROENCEPHALOGRAPHY
BOLD	Blood Oxygen Level Dependent
HbO	Oxygenated Hemoglobin
HbR	Deoxygenated Hemoglobin
ITR	Information Transfer Rates
SSVEP	Steady State Visual Evoked Potential
LDA	Linear Discriminant Analysis
GLM	General Linear Model
CCA	Canonical Correlation Analysis
PPMCC	Pearson Product Moment Correlation Coefficient
MSVD	Multi-resolution Singular Value decomposition
FIR	Finite Impulse Response Filter
IIR	Infinite Impulse Response Filter
KNN	K-Nearest neighbor
DWT	Discrete Wavelet Transform
ICA	Independent Component Analysis

CHAPTER 1

INTRODUCTION

BCI technology is an effective communication tool between a machine and a user. It utilizes the brain signals generated through certain events that can help to predict the intention of the user in order to interact with the environment. BCI systems have applications in many fields like medical, military, industry, just to name a few. Such systems are frequently used to control a computer or to drive a humanoid robotic device in real time. Currently, several invasive and non-invasive BCI approaches are being used to read the brain activities. Invasive BCI is achieved through a neurosurgery of implanting microelectrodes on the shape of microchips attached to the cranium to record the neuron-generated signals. Electrocorticography (ECOG), an example of invasive BCI techniques, places electrodes on the cortex surface, which differs from, Intra-cortical neurons that is another invasive BCI technique in which the electrodes are placed inside the cortex during a neuro-surgery. Though the invasive BCI techniques have the highest signal quality, they also have the highest risk. Such problems need to be addressed before they are engaged in long-term applications. First, microelectrode tissues acceptance need to be resolved in a way that it improves the biocompatibility. Secondly, link between the hardware device and the electrodes should be strengthened to reduce the risk of infection; and finally, the plugging/un-plugging processes are not matured enough, hence, may lead to system failure or tissue damage. Due to these or similar restrictions, researchers mainly focused on exploring non-invasive BCI techniques rather than invasive.

Non-invasive BCI record the human brain signals from outside. At present, there are two types of signals that can be recorded through a non-invasive BCI, electrophysiological and hemodynamic. Electroencephalography (EEG), an electrophysiological technique is used to sense the brain activity by means of thousands of neurons. Hemodynamic signal is generated through Blood-oxygen-level-dependent (BOLD) measurement which can provide important information for brain investigation activity, whereas, functional magnetic resonance (fMRI) and functional near-infrared spectroscopy (fNIRS) are used to measure the Hemodynamic signals.

Generally, BCI applications consist of five steps: signal acquisition, signal processing, feature extraction, classification and application’s control. In signal acquisition, the brain signal is acquired either in the form of electrophysiological or hemodynamic activity. By means of pre-processing, the effects of biological noises, such as heartbeat, muscle movements, and eye-blinking can be reduced. Feature extraction helps to reduce the dimensionality, where the original set of signals are transformed to a more manageable set. Through classification, specified pattern in the signal is decoded into a control signal by utilising the features extracted in the previous step. Lastly, based upon the command generated by the classifier, some control action is performed.

This chapter is structured as follows: section 1.1 introduces the motivation behind using Brain Computer Interface (BCI), the problem statement is presented in section 1.2, the following section introduces the contributions made through this study, section 1.4 presents the organization of the thesis, whereas, section 1.5 highlights the potential research areas.

1.1 Motivation

The power to guide a robot, a computer and a car using human brain signals alone would provide a significant mechanism for communication between human and robot. Such innovation is also featured in futuristic narratives, where a robotic hand works flawlessly with the human nervous system as in Star Wars. Unfortunately, I have spent most of my life in a war torn country where many people lost their limbs due to explosions. My motivation is to enable them to lead a healthy and normal life. Brain computer interface can be used as a tool to empower those people so that they can communicate and control their surroundings using their brain signals.

1.2 Problem statement

The ultimate goal for hybrid EEG-fNIRS BCI is to overcome the drawbacks of single modality and achieve an improvement in classification accuracy while reducing the computational time. However, this technique generate an extensive computational complexity. Furthermore, the lack of computational approaches to achieve a true integration at the system level to get the maximum benifits of a hybrid EEG-fNIRS BCI system.

1.3 Contributions

a) This study presents a novel approach for hybrid BCI channel selection using Pearson product-moment correlation coefficient (PPMCC). The determination of a correlation coefficient is a statistical method that allows to quantify the strength of a linear relationship between two channels. The calculation yields the association which is used to identify the most dominant channels. Based upon the correlation coefficient, rank matrix is developed. The highest ranked channels are classified as the dominant channels or the channels that can produce true motor imagery signal, whereas, the lowest ranked channels are assumed to be noisy, non-representative or the ones that are un-correlated with the motor imagery tasks. To the best knowledge of the author, PPMCC has never been utilized for channel selection in hybrid BCI paradigm before. Therefore, this study will introduce a completely new perspective for channel selection in a hybrid BCI systems.

b) Another contribution of this study is a novel hybrid BCI fusion approach using Multi-resolution singular value decomposition (MSVD) to perform EEG-fNIRS fusion for the selected channels from each hemisphere. MSVD performs the first level of decomposition by processing the signals through two consecutive layers of low pass finite impulse response filter and high pass finite impulse response filter. This study also examines the MSVD multi-modal fusion on both feature and system level.

c) This thesis also works upon the feature-based fusion using CCA which is a statistical method that defines the linear association between two sets of data by determining the covariance between the subjects. The approach helps to maximize the correlation between the pairs of canonical variates- EEG and fNIRS. Through results, it is exhibited that the proposed approach has played its role effectively when used in conjunction with two different classifiers to attain reduced computational time, improve classification accuracy and higher number of control commands.

1.4 Organization of the Thesis

This thesis consists of six chapters: introduction, literature review, dataset and processing, optimal channels selection using correlation coefficient, data fusion, discussion and conclusion.

In chapter 2 (Literature review); an introduction to BCI technology, ELECTROENCEPHALOGRAPHY (EEG) and functional Near-Infrared Spectroscopy (fNIRS) with their advantages and dis-advantages are presented. This chapter also highlights the related work on most closely related hybrid BCI studies.

In chapter 3 (Dataset and processing); the experimental setup, procedure, and pre-processing steps—filtering, feature extraction and classification—are discussed in detail.

Chapter 4 (Optimal channels selection using correlation coefficient) discusses the proposed correlation coefficient approach that has been utilized to select the most representative channels from both EEG and fNIRS systems. Moreover, the effect of channel selection on the computational time and classification accuracy has also been investigated.

Chapter 5 (Data fusion) looks into three different approaches— Concatenation, CCA and MSVD—to achieve the fusion on feature and system level. Their performance comparison based upon the classification accuracy is also explored.

Chapter 6 (Discussion) discusses the results and highlights the major findings of the proposed approaches.

Chapter 7 (Conclusion) provides an overview of the proposed hybrid EEG-fNIRS BCI approaches and presents the findings.

1.5 Future work

In future work, the author is interested in investigating new approaches for the channel selection using weighted average or similar. Furthermore, the focus can be on the validation of the results using online data and the investigation of the performance of the entire system using bigger dataset (more trials per class).

CHAPTER 2

LITERATURE REVIEW

2.1 Brain Computer Interface

In 1924, Hans Berger, a neurologist, recorded human brain signals through EEG for the first time. This actually encouraged other researchers to further investigate the human brains and record their activity in computer through Brain Computer Interface (BCI). BCI is a technology that decodes user intentions and transform it to commands that can drive devices like mobile robots and quadcopters without the involvement of the peripheral nervous system and muscles [1]. This provide the means for the disabled patients to control and communicate with the surroundings solely through their brain activities. Several techniques have been utilized to study brain activities such as near-infrared spectroscopy (NIRS) [2], functional magnetic resonance imaging (fMRI) [3], and magnetoencephalography (MEG) [4]. In the last decade or so, most BCI studies mainly focused on EEG.

2.2 ELECTROENCEPHALOGRAPHY (EEG).

EEG can record a variation in voltage over time between two different brain locations associated with neuronal activity using electrodes, positioned on the scalp. EEG is one of the most common non-invasive techniques used to study the brain still to date. After pre-processing steps such as removal of artifacts due to eye-blinking or muscle movement. The temporal and spectral analysis are used to extract the features from EEG data. Though EEG signal has an advantage of high temporal resolution, yet it suffers from low signal to noise ratio and low spatial resolution [5]. Likewise, visual EEG-BCI systems demonstrated high and reliable performance, but it suffers from inter-subject’s variation. [6] reported that some users do not generate classifiable sensorimotor rhythms or produce noisy signals, that cannot be classified easily using given algorithms. With pre-processing steps, biological noises due to heartbeat, eye-blinking, and muscle movements can be removed. Whereas, electrical noises such as individual variation cannot be removed through this step; hence, it can still affect BCI system's performance. Therefore, optical BCI system that uses fNIRS signal has been introduced [7], since then many studies have been conducted on this technique [2].

2.3 functional Near-Infrared Spectroscopy (fNIRS)

functional Near-Infrared Spectroscopy (fNIRS) is another non-invasive BCI system based upon detecting the hemodynamic response to achieve portable and cost effective solution. This technology measures the number of photons using light in the visible and near-infrared range (700–1000 nm). Modified Beer-Lambert law is the most commonly used approach to quantify the chromophore concentration and its relative changes into two different infrared frequencies [8]. Optical properties of Oxygenated (HbO) and de-oxygenated hemoglobin (HbR) i.e., concentration change of these molecules is considered as the main feature of fNIRS. Contrary to EEG, NIRS is considered to have strong tolerance against electrical noises and motion artifacts. Despite its ability to measure hemodynamic response, it suffers from long delay in the hemodynamic response. The response time in order to generate the execution command for NIRS is almost 9 times of EEG [9]. Additionally, it suffers from low spatial and depth-resolution. Over the last decade, investigations have been carried out to increase information transfer rates (ITR) and to overcome the limitations of uni-modal system. This leads to the multi-modal systems that is now formally known as the hybrid BCI.

2.4 Previous Hybrid BCI studies

The research performed on hybrid BCI is still far from completion. This technology is used to overcome the limitations of single modality, to improve the classification accuracy [10], and to increase the number of control commands [11]. For these reasons, in 2012, [10] conducted the first study of hybrid EEG-fNIRS BCI to improve the performance of motor execution and imagery. The authors recorded EEG-fNIRS data simultaneously, 14 subjects were advised to perform hand gripping and visual feedback-controlled motor imagery. They used Laplacian filtered band-power, oxygenated (HbO) and de-oxygenated hemoglobin (HbR) as the main features for both EEG and fNIRS, respectively. Classification accuracies in motor execution and imagery tasks for 14 healthy subjects improved by 5% on average using simultaneous

EEG and fNIRS when compared to single modality. In 2015, an online self-paced motor imagery task was performed, fNIRS signals were classified by [12] using threshold-based discrimination, while SVM-based classification was used for EEG signals. Alpha-band powers and oxygenated hemoglobin (HbO) were the main features for both EEG and fNIRS to achieve 88% accuracy with a new system to block light leakage from fNIRS. In addition to motor imagery, [13] combined two modalities in a steady-state visual evoked potential (SSVEP). This study investigated an optimal time window for hybrid BCI. fNIRS signal in the occipital region was used as a brain trigger to activate the SSVEP BCI. SSVEP, HbO and HbR were the main features extracted from EEG-fNIRS. Extracted features were then classified using a joint classifier. Their results showed improvements in the classification performance and a reduction in error rates for the 13 subjects. Although, the improvements were observed, yet it is important to design a true self-paced BCI system that significantly reduce the error rate and to investigate a subject intention in a more naturalistic BCI. Though the improvements in classification accuracy was achieved, the number of extracted control commands were still limited. The following section will review the studies that focused on increasing the number of extracted control commands.

[11] achieved an increase in the number of extracted control commands by simultaneously decoding EEG and fNIRS activities that were recorded from sensorimotor and prefrontal brain regions. LDA was used as a classifier for EEG and fNIRS, whereas peak amplitudes, HbO, and HbR were the main features for both EEG-fNIRS. Mental arithmetic and motor imagery tasks were decoded using fNIRS, left- and right-hand tapping were coded using EEG. Another study where hybrid EEG–NIRS system was used to decode four motor tasks, namely right- and left-arm movement and right- and left-hand movement was investigated by Buccino (2016) [14]. The authors developed slope indicator function as a new feature, which is the difference between the current time segment average and that computed from a previous time segment. Band-powers, HbO and HbR were used as the main features for both EEG and fNIRS. LDA classifier was used to perform the classification for four motor movements (Left arm, right arm, left hand and right hand). Buccino's hybrid EEG-fNIRS BCI achieved an increase in classification accuracy for all four motor tasks compared to single modality. The new feature developed by the authors, slope indicator, helped to reduce the delay in peak classification accuracy up to 2

seconds in fNIRS signal. The increase in the extracted control commands created a computational complexity and dimensionality problems. In previous studies, [10], [14] and [15], all available channels from both hemispheres were considered for the feature extraction and classification. This not only increases the system complexity but also the computational cost.

To reduce the computational time and system complexity, several researches suggested a channel selection approach to select the most representative channels. Yet most of the literature focused on crude analysis as to pick few channels, manually [16, 17, 18]. This approach may work in some cases, but the generalization of such methods is limited by the self-analysis as well as due to excessive time required in order to analyse each individual channel. Other researchers strived for the sophisticated channel selection approaches to determine the most representative channels. [19] proposed the selection of singular channel of both EEG and FNIRS from both hemispheres using General Linear Model (GLM). Although high classification accuracy of 91.02% was achieved, yet channels selection approach was not very convincing. The analysis was fNIRS-based, where EEG channels were picked based upon their position from the selected fNIRS channels, this might end up picking bad or noisy EEG channels for some cases. Recently, researchers looked for more sophisticated fusion approaches to achieve true integration between the two modalities.

[15] introduced a feature combination and optimization approach using joint mutual information (JMI) in a study performed on motor imagery tasks to decode the force and speed of hand clenching. The feature optimization method was utilized to remove excess information that might affect the classification accuracy. They achieved an improved performance by 5% when compared to previous studies. [20] proposed a canonical correlation analysis (CCA) to perform feature-based fusion. The study examined the effects of mental stress on prefrontal cortex (PFC) sub-regions based upon simultaneously recorded EEG-fNIRS signals. CCA is a statistical method that works as a linear association model which maximizes the correlation between the features of brain signals recorded by each modality EEG-fNIRS. The results showed an improvement in the detection rate of mental stress of 7.9% and +12.1% as compared to sole EEG and sole fNIRS modality, respectively. Though the improvements achieved by JMI and CCA were satisfactory, yet the fusion was applied on feature

level, where the two modalities were processed separately. Therefore, a true system level fusion is needed in order to reduce the computational complexity since the analysis is performed on fused signal instead of processing each signal separately and to achieve maximum benefits of the hybrid BCI system.

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CHAPTER 3

DATASET AND PROCESSING

3.1 Dataset source and processing

The dataset is taken from an online repository (https://doi.org/10.6084/m9.figshare.1619640.v1,2) provided by [14]. This dataset is simultaneously recorded through EEG and fNIRS for motor tasks of left-arm, left-hand, right-arm, and right-hand. For motor imagery tasks, fifteen healthy subjects took part in the experiment, which lasted for an hour. During the experiment, the subjects were instructed to perform four movements—right-left hand gripping, right-left arm raising— as per the visual instructions displayed on the laptop screen placed 1m away. For each subject, trials were initiated with a rest, followed by the movement, according to the screen instructions where each action lasted for six seconds. Raw EEG signals obtained at 250Hz through twenty-one channels were baseline corrected by subtracting the mean value of channels, afterwards, filtered at (1-50 Hz) by 4th order IIR Butterworth filter. The fNIRS signals were recorded at a sampling frequency of 10.42 Hz for two wavelengths—760nm and 850nm, equipped with 12 sources and 12 electrodes on 34 channels. The raw data is then decomposed into Oxyhemoglobin and Deoxyhemoglobin concentration changes through Modified Beer-Lambert law. This study considers HbO as the main feature for fNIRS, referred as fNIRS from here on. The fNIRS data is then filtered by a 4th order band pass IIR Butterworth filter between (0.01-0.2 Hz) to remove artifacts. Initialization trials prior to the motor tasks was segmented out for both EEG and fNIRS. Filtered EEG and fNIRS data are then normalized by subtracting the mean and dividing by the standard deviation. To reduce dimensionality and to improve parity, the EEG-fNIRS data were downsized through a 0.096 s averaged moving window.

3.2 Feature extraction

3.2.1 Statistical Features

Six different statistical features—mean, peak, skewness, kurtosis, standard deviation, and variance—are extracted using spatial averaging of selected channels.

Signal mean for all channels involved is calculated as follows:

$$SM = \frac{1}{N}\sum_{i=1}^{N} X_i \tag{3.1}$$

Where N is the total number of observations and X_i represents fNIRS for each observation.

Skewness is calculated according to the asymmetry of single values relative to the normal distribution:

$$Sk(X) = E\left[\left(\frac{X-\mu}{\sigma}\right)^3\right] \tag{3.2}$$

Kurtosis of the signal is a statistical measure that is used to describe the distribution:

$$Kr(X) = E\left[\left(\frac{X-\mu}{\sigma}\right)^4\right] \tag{3.3}$$

Standard deviation is a measure to quantify the amount of variation or dispersion of the data:

$$SD(X) = \sqrt{\frac{\sum_1^N (X-\bar{X})^2}{n-1}} \tag{3.4}$$

Variance is the expectation of the squared deviation of a variable from its mean:

$$Var(X) = \frac{\sum_1^N (X-\bar{X})^2}{n-1} \tag{3.5}$$

3.2.2 Discrete Wavelet Transform (DWT)

DWT decomposes the time series data of a signal by processing it using consecutive layers of a series of low-pass filter and high-pass filter, named as quadrature mirror filters. Outputs of the low pass and high pass filters are the approximation (A1) and detail (D1) coefficients from the first level of decomposition, respectively. Second level decomposition can be achieved by repeating the same procedure as before to get the second level coefficients. At each level of this decomposition, the frequency resolution is doubled through filtering and the time resolution is halved through down sampling.

In the recent study, [19] proved that the last layer approximation coefficients of DWT carries the main power of the event-related oscillation of the EEG signal in brain activity based on the assumption of [21]. EEG signal is decomposed with a 4-layer Symlet wavelet, resulting in four approximation coefficients that are assumed as the main feature of the signal. The procedure of multi-resolution decomposition of a signal x[n] is schematically shown in Figure 3.1. Each stage of this scheme consists of two digital filters and two down samplers.

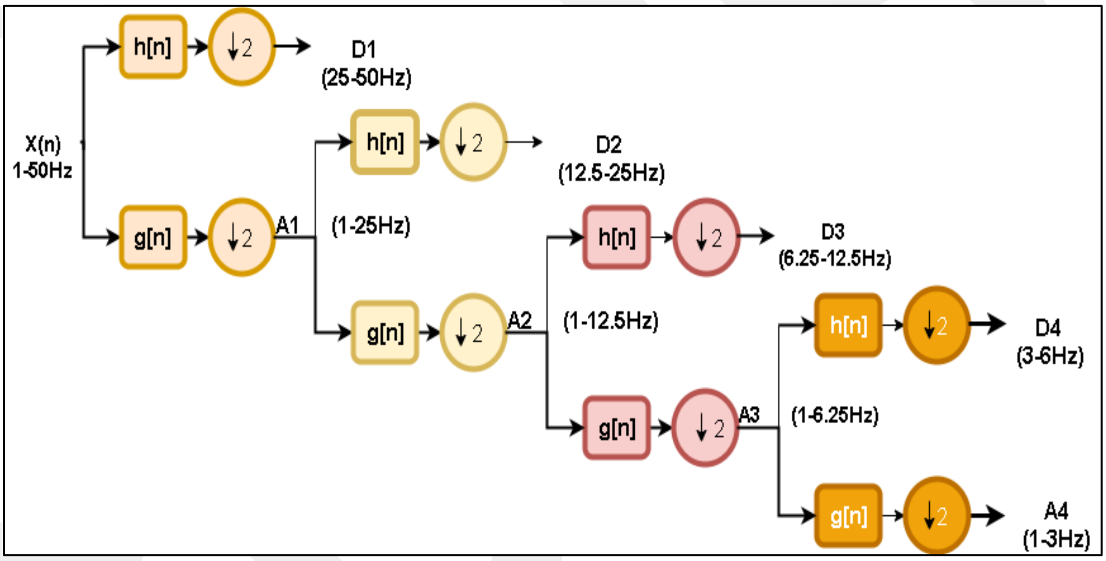


Figure 3.1 Sub-band decomposition of DWT. h[n] is the high pass filter, g[b] is the low pass filter.

The extracted features for both EEG and fNIRS systems are then rescaled between 0 and 1 using:

$$X_{new} = \frac{X_i - \min(X_i)}{\max(X_i) - \min(X_i)} \tag{3.6}$$

3.3 Classification

The goal of this thesis is to compare the performance of three different feature sets: EEG-only, fNIRS-only, and hybrid EEG-FNIRS for the selected channels based upon correlation coefficient. To evaluate, classification is performed on two trials of dataset for the four motor execution tasks versus rest. The classification accuracy of 100% refers to the perfectly separated motor tasks, whereas, 50% refers to the poor performance of the classifier. The movement of the subjects are recorded through twenty-one EEG channels and thirty-four fNIRS channels. For classification between 4 motor tasks and rest, two classifiers are employed, namely: K-Nearest neighbor (KNN) and Decision Tree classifier and are implemented through MATLAB Machine learning toolbox.

3.3.1 K-Nearest neighbor (KNN)

KNN classifier proximate the nearest observation points from training data into a single class, given a data set X= $(X_1,\ldots,X_n)$ as a collection of N marked instances. A point X_1 is connected to its closest neighbor in X which is assigned by the nearest neighbor classifier. Figure 3.2 shows how KNN classifier defines the nearest neighbor instances.

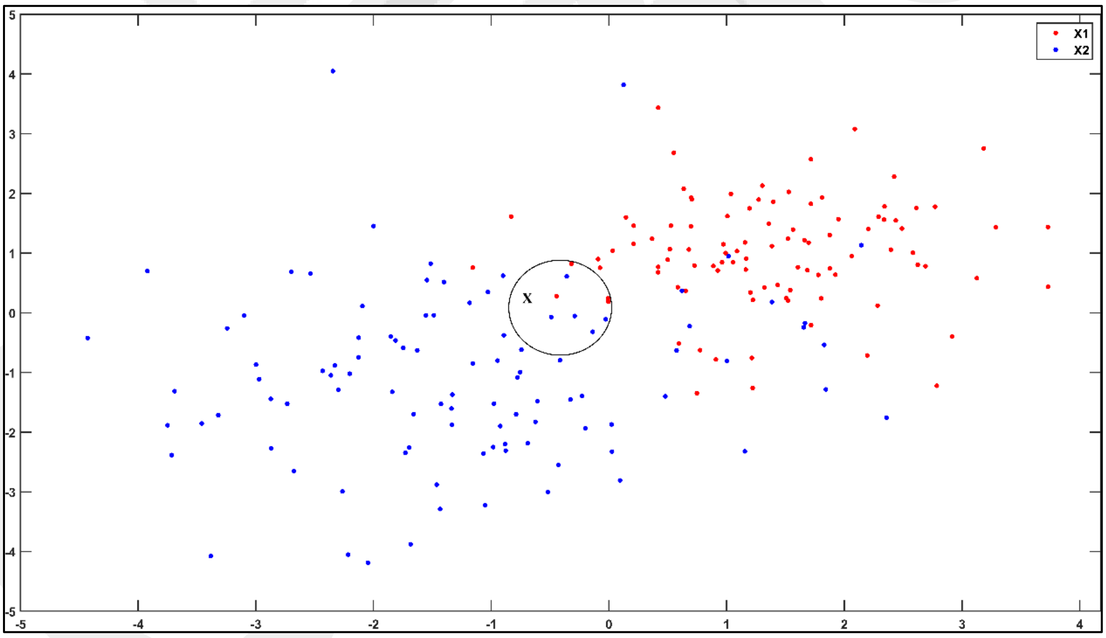


Figure 3.2 K-nearest neighbor form a spherical region around the data instance X to define its nearest neighbor instances.

The closeness defined by a distance function can be defined using Minkowski metric, Manhattan, City block distance or Euclidean distance. This study considers Euclidean distance to calculate the distance between instances.

$$L(X_1,X_2) = \left(\sum_{i=1}^{d}|X_1 - X_2|^2\right)^{\frac{1}{2}} \qquad (3.7)$$

KNN is used due to its simplicity, easiness to implement, the ability to classify multiple tasks of motor imagery and high classification performance [22].

3.3.2 Decision Tree classifier

Decision tree algorithm, falls under the supervised learning, can be used to solve problems in both regression and classification domains. The classifier construct decision tree with branches and nodes based on the extracted features. Each node carries either a single feature or several features that can be considered to minimize the entropy labels of the class [23]. Figure 3.3 shows the structure of decision tree classifier.

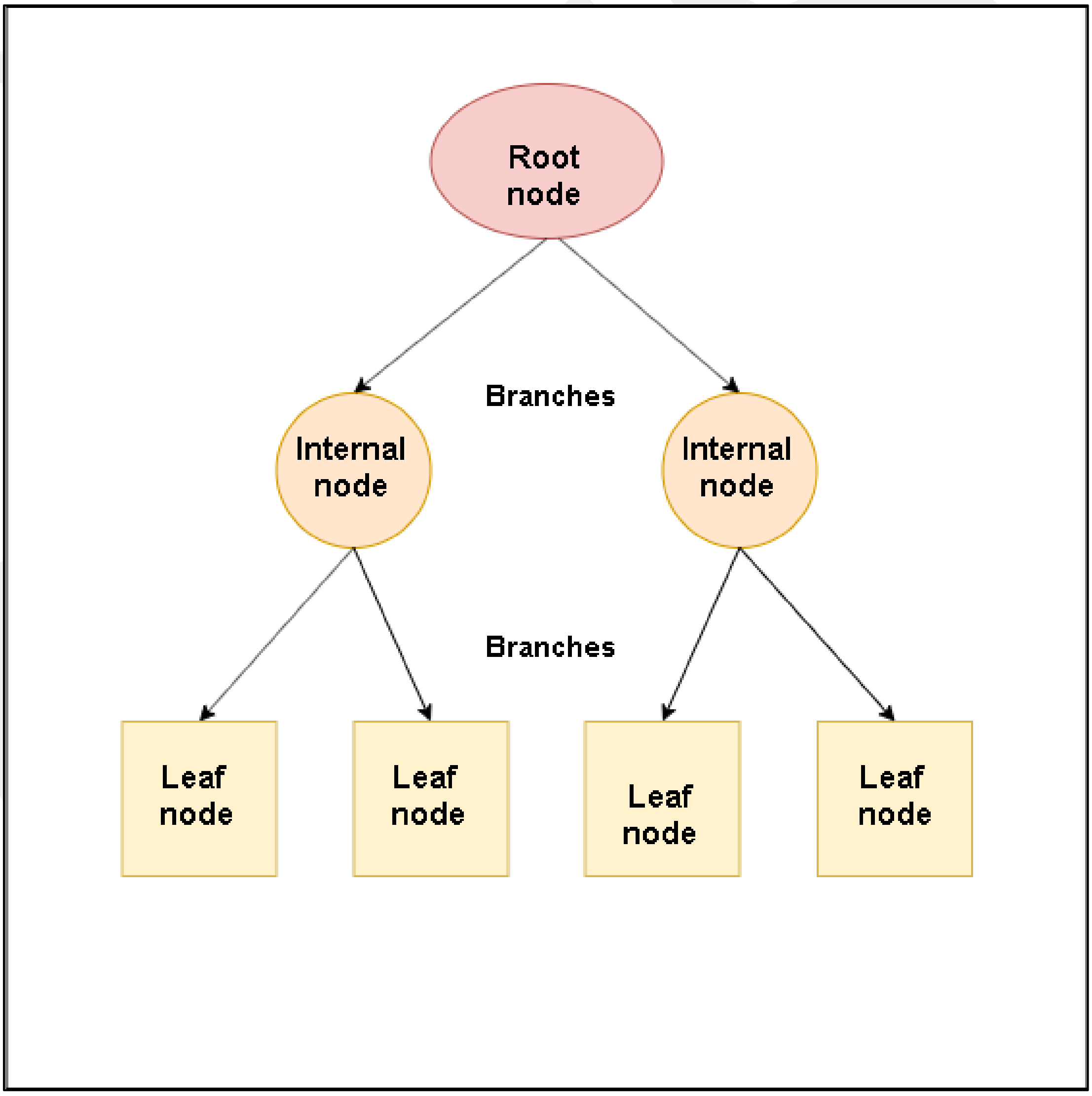


Figure 3.3 Decision tree classifier structure.

Decision Tree classifier has the tendency to achieve fast and accurate classification performance. A 10-fold cross-validation paradigm implemented to each feature set is split into ten subsets where nine subsets are used to train the classifiers and the remaining one subset is used to test the classification accuracy.

CHAPTER 4

OPTIMIAL CHANNEL SELECTIONS USING CORRELATION COEFFICIENT

In hybrid BCI studies, numerous channels are involved in recording data, this led many to work on the channel selection algorithms. The channel selection is considered as the key element that directly affects the system's performance. The main objective is to improve the efficiency by reducing time consumption and dimensionality. Pearson correlation coefficient has been investigated by few researchers [24, 25] in order to solve practical problems for medical. Though, it has given some promising results, it has never been tested for hybrid BCI systems before. This thesis proposes a novel approach to ensure optimal performance by involving only the most dominant channels using the Pearson product-moment correlation coefficient. The correlation coefficient is a statistical method that helps to calculate the strength of a linear association between two channels, denoted by ρ , and can hold any value between [-1,1]. The basic idea is to associate the data of two channels through the best fit line. The Pearson correlation coefficient, ρ , is an indicator of the location of these data points in reference to the line of best fit. A higher positive value indicates stronger association, whereas the more the negative value the stronger is the negative association. Third possibility is of absolute no association between the variables, i.e., $\rho = 0$.

EEG-fNIRS channels are distributed into two groups based upon their placement in the right and left hemispheres, shown in Figure 4.1.

The correlation coefficient between two channels in each hemisphere is a measure of their linear association:

$$\rho_{I,J} = \frac{\mathrm{E}\left[\left(I-\mu_I\right)\left(J-\mu_J\right)\right]}{\sigma_I \sigma_J} \tag{4.1}$$

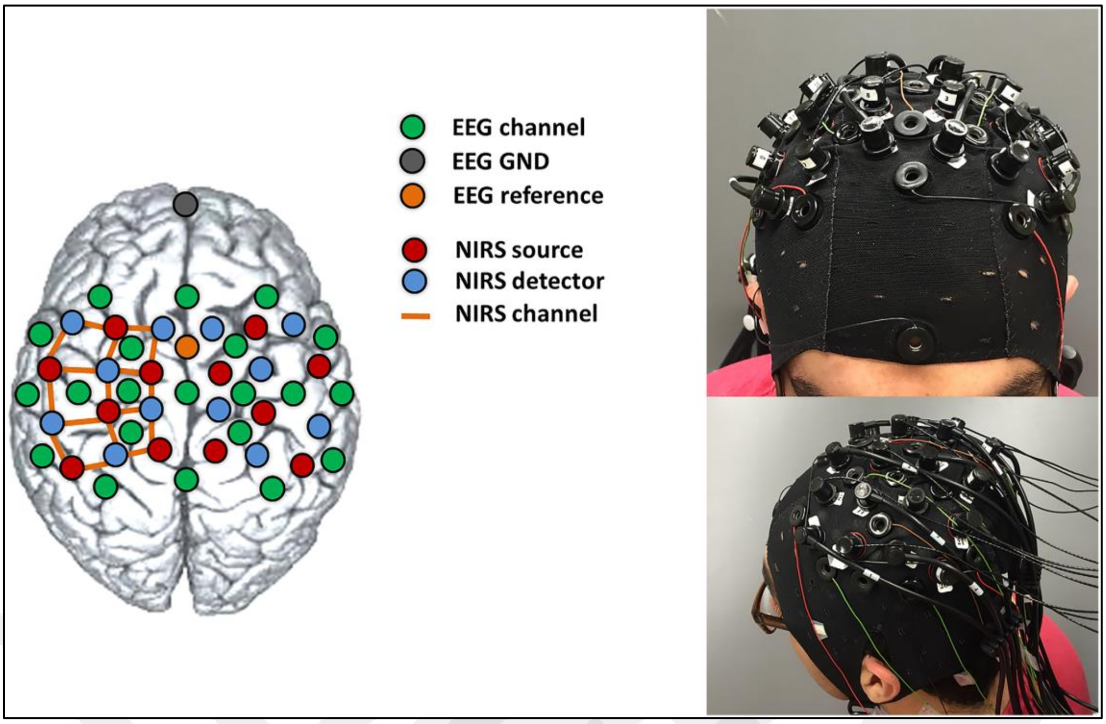


Figure 4.1 EEG-fNIRS channels placement [14].

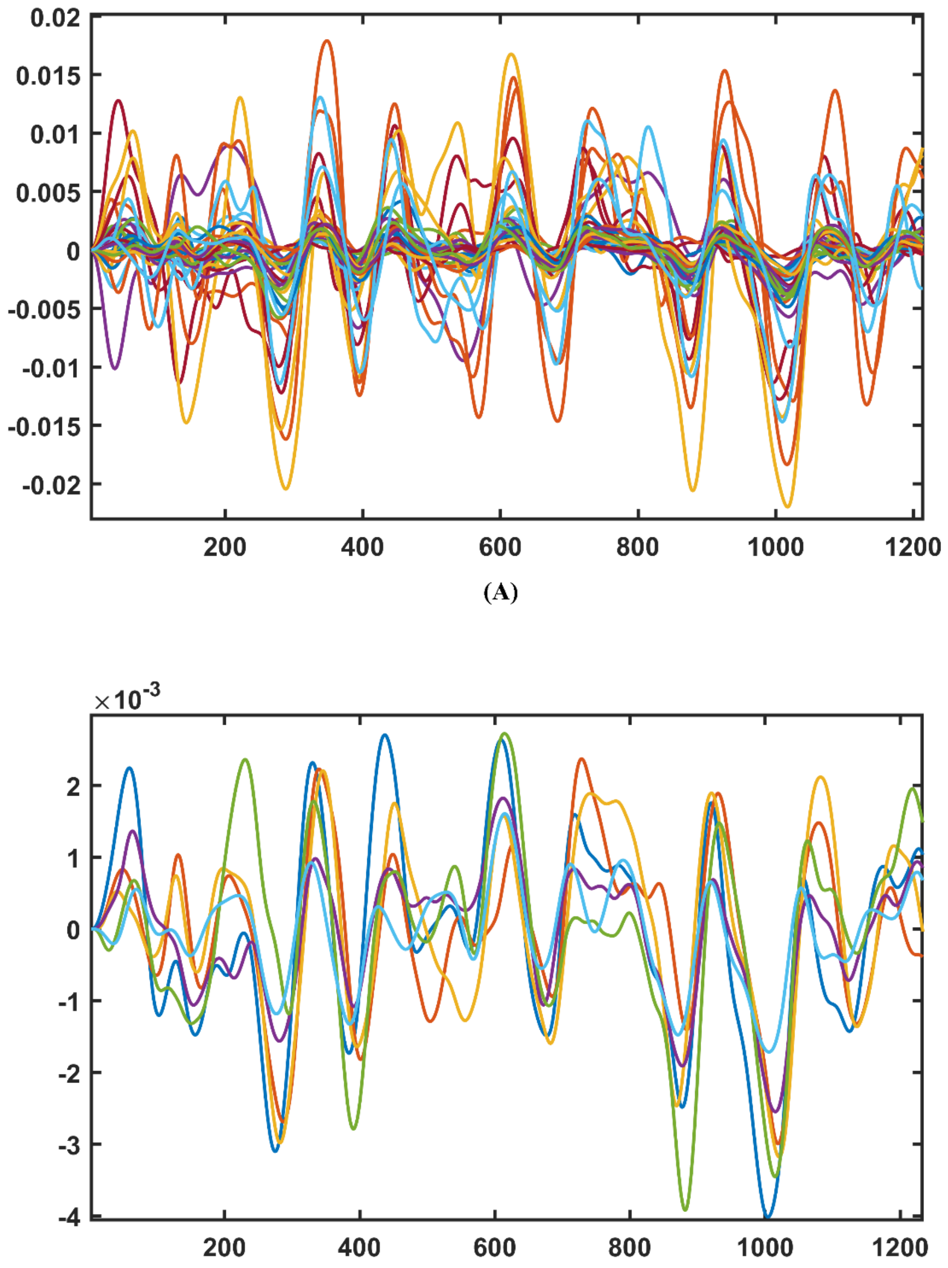
The reference guideline as how to interpret the strength of association based upon the correlation coefficient is given in Table 4.1.

With the help of novel correlation coefficient-based method, only those channels are picked that contain most relevant motor imagery information. Figure 4.2 depicts the

Table 4.1 Correlation coefficient *[26]*

Strength of linear Association	ρ	
	Positive	**Negative**
Small	0.1 to 0.3	-0.1 to -0.3
Medium	0.3 to 0.5	-0.3 to -0.5
Large	0.5 to 1.0	-0.5 to -1.0

comparison between fNIRS data; a) For all channels, and b) After the utilization of channel selection, where 6 channels from both modalities are chosen.



(A)

(B)

Figure 4.2 fNIRS data A) Before channel selection B) After channel selection.

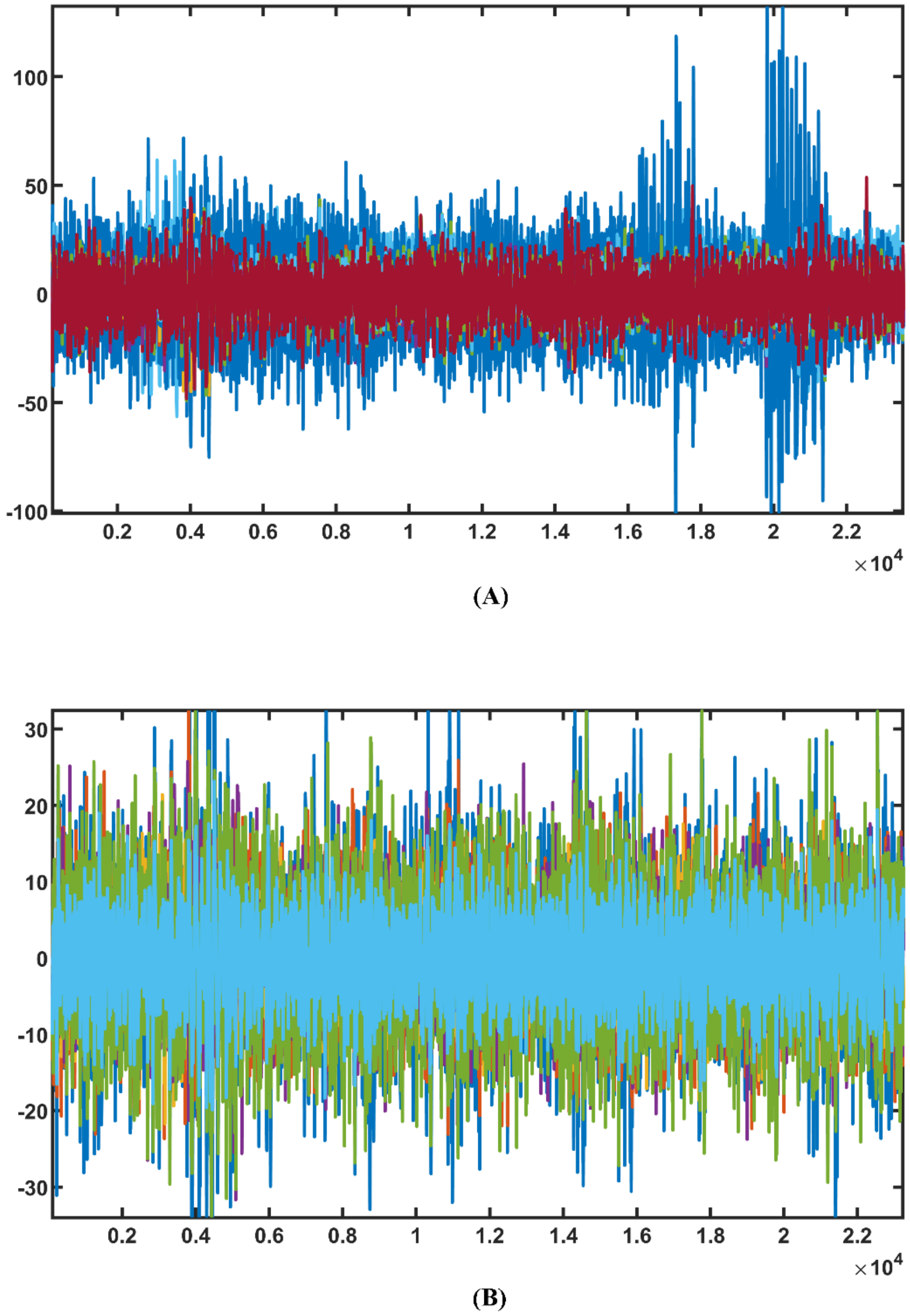
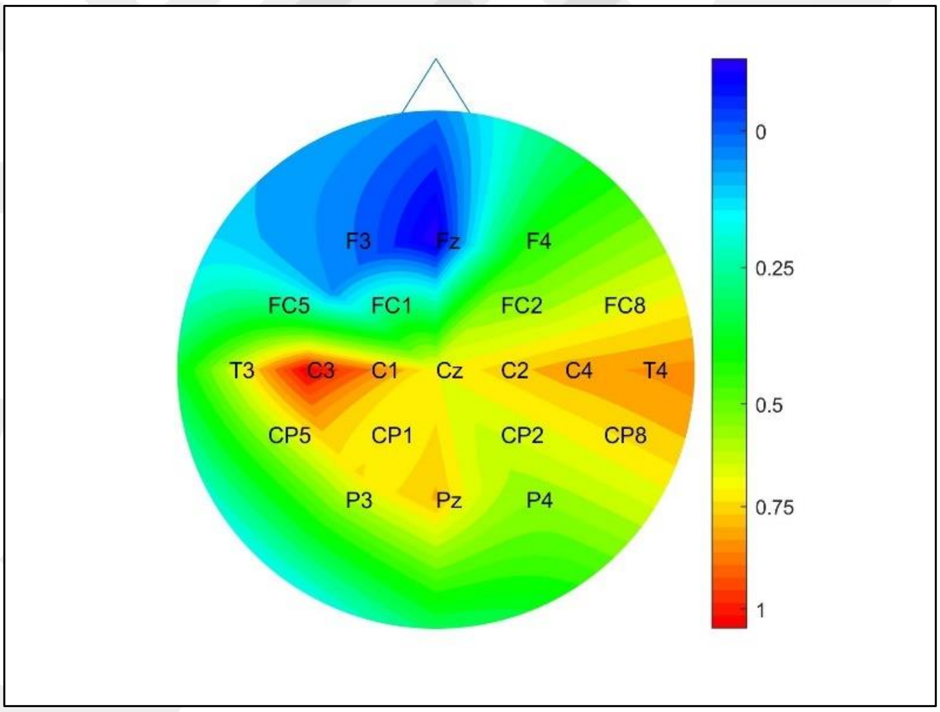


Figure 4.3 EEG data A) Before channel selection B) After channel selection.

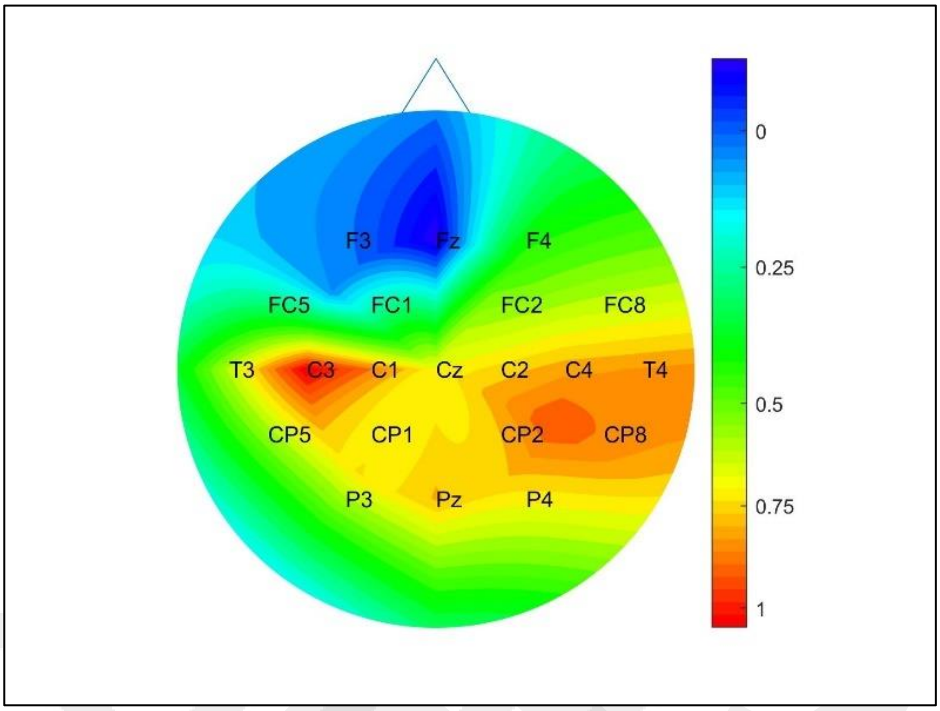
Figure 4.3 show a comparison between EEG data; a) For all channels, and b) After the selection of the dominant channels. Channels are selected based upon the correlation coefficient ranking defined for the channels. For selecting most representative channels with most meaningful performance and to eliminate signals with unnecessary information and noise, highly correlated EEG-fNIRS channels from each hemisphere are picked. This might not be clear from Figure 4.3 due to the high density of EEG data, but it is more obvious from Figure 4.2, where bad performing and noisy channels are dropped and only high ranked channels are kept.

Figure 4.4 shows the probability for selection of channels based upon the correlation results obtained for subject 1, 4 and 15, when all channels are considered. The highest correlation coefficients are obtained in the motor cortex region in the right and left hemisphere. This seems also true, because the movements considered are of the right and left hand. The highest correlation coefficient helps to separate the optimized channels from the rest. Once the channels are selected, next task is to train the classifiers on the given data set from different sources to produce accurate results.

A



B



C

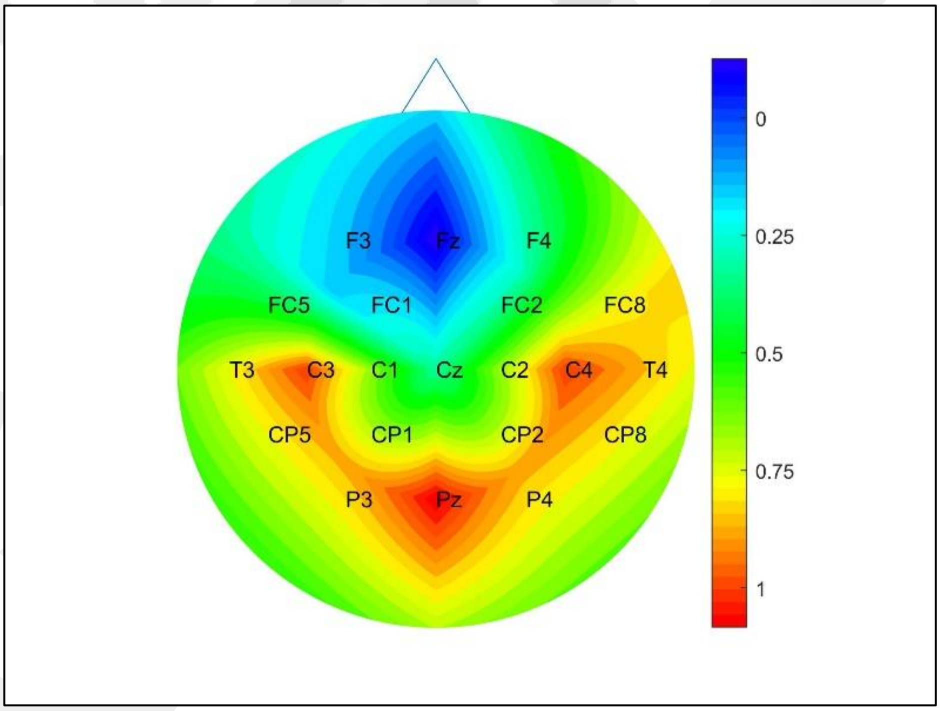


Figure 4.4 Probability of selecting channels based upon correlation coefficient from subject 1 (A), subject 4 (B) and subject 15 (C).

Figure 4.4 (C) illustrates the probability of selecting EEG channels from both hemispheres for subject number fifteen, where C3, T3, and P3 are selected from left hemisphere, and C2, C4, and T4 are selected from the right hemisphere. The selected channels are not generalized for all subjects, yet, the selected channels are mostly picked from C3 and C4 regions for most subjects as they attain the highest rank correlation. This seems also true as previous studies recommended to pick channels from C3 and C4 area to generate execution commands based upon the motor imagery tasks [14, 10]

Through the proposed correlation coefficient approach, only highly correlated channels are selected. For EEG, only 6 channels were selected out of 21 channels and, for fNIRS, only 6 channels were selected of 34. It has been observed that if the number of selected channels are lesser than 25% of the total for EEG and 15% for fNIRS: the accuracy will start deteriorate with not much improvement recorded in the computational time. In the following section, it will be explained that only those channels are dropped that contain less significant information as compared to the rest. This help to get rid of the outliers, noise variation that may have been introduced in some channels at the time of data acquisition.

In order to examine the performance of the classification accuracy against the varying number of channels, five subjects are considered. Figure 4.5 displays the EEG average accuracy for five subjects when evaluated for 6-21 channels against randomly selected (sr) channels set. It is observed that increase in number of channels has not produced any noticeable effect on the classification accuracy. But with this increase, computational cost is increased. On the other hand, the accuracy starts to drop sharply if the number of selected channels are lesser than the safe bound.

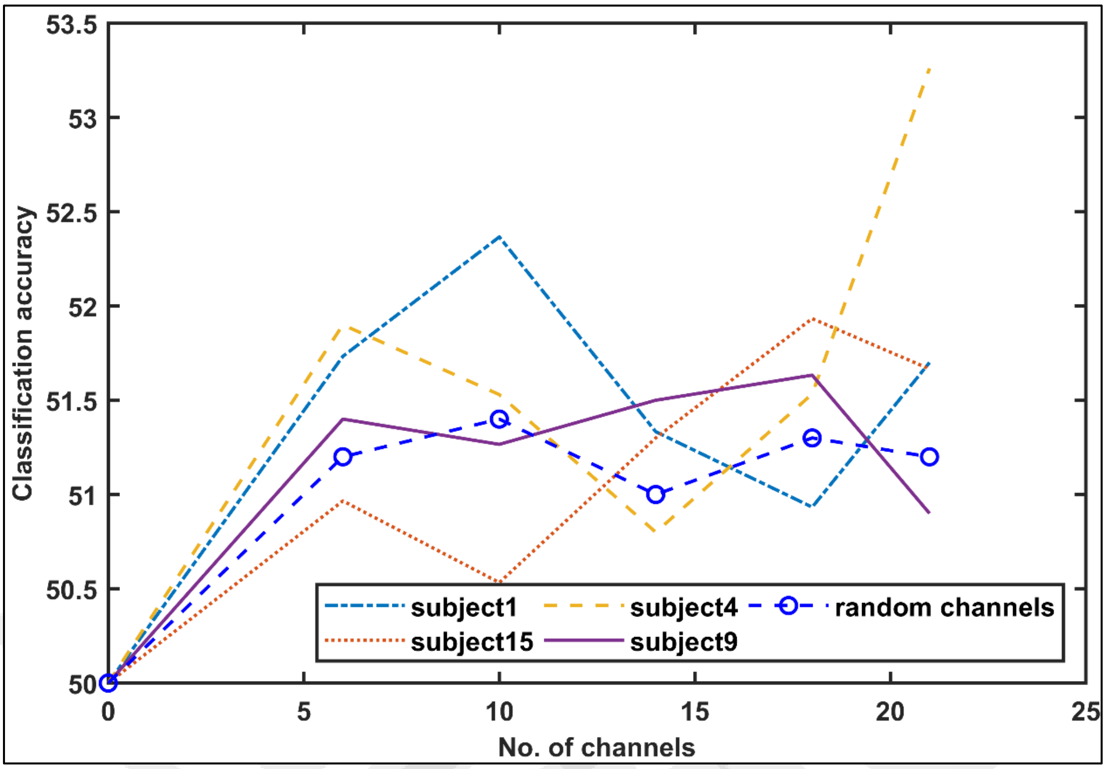


Figure 4.5 EEG classification accuracy for 5 subjects including randomly selected channels (sr) against number of channels.

Figure 4.6 shows fNIRS average accuracy for five subjects when evaluated for 6-34 channels against randomly selected (sr) channels set. It is observed that subject nine has been able to perform best as compared to others. The classification accuracy using the proposed channels selection is higher than the random selection approach for all except for subject one, which is categorised as a bad performing subject. The increase in the number of channels hasn't played much role in improving the accuracy; rather, if we select lesser than 15% of the total number of channels, then the accuracy drops.

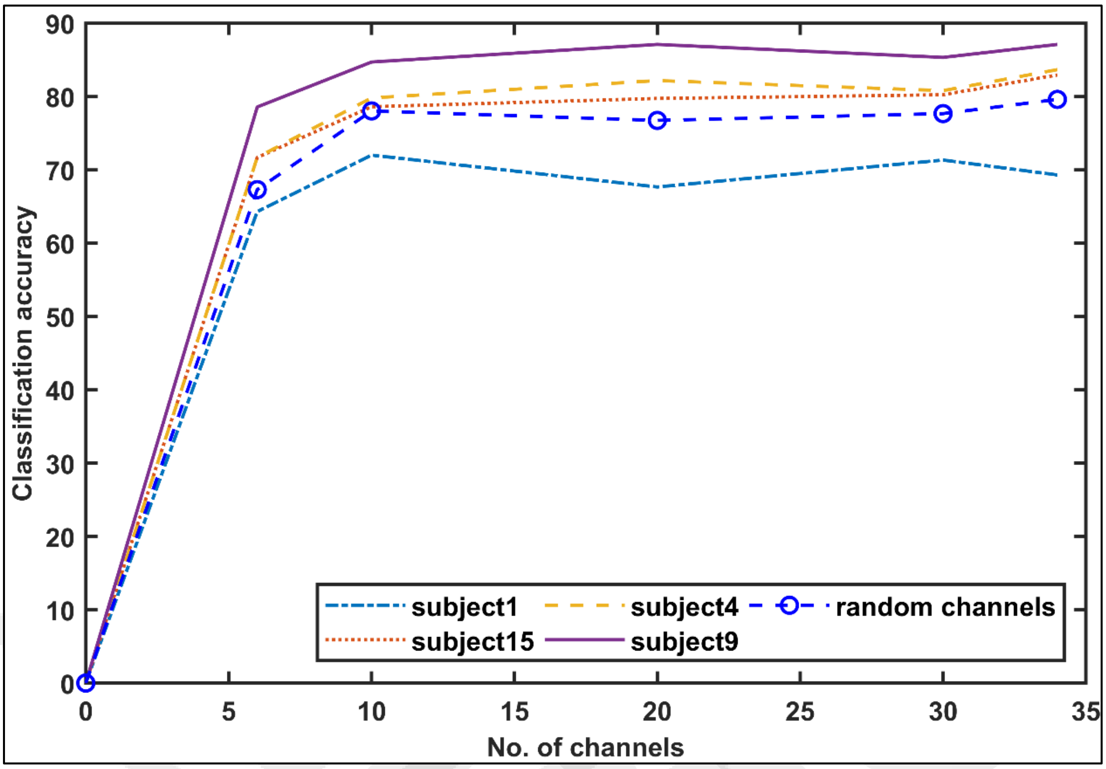


Figure 4.6 fNIRS classification accuracy for 5 subjects including randomly selected channels (sr) against number of channels.

To analyse reduction in the computational time, temporal distance between the filtration step and feature extraction is recorded as an evaluation time. Through the proposed approach, only highly correlated channels are obtained and processed. The comparison is made for one second of sampled data, obtained through EEG and fNIRS. For EEG, six channels are selected out of twenty-one and for fNIRS six channels are selected out of thirty-four. The response time is reduced by around 40% for EEG and more than 40% for fNIRS, respectively. Figure 4.7 illustrates the required computational time in order to process ten samples of fNIRS and two-hundred-and-fifty samples of EEG using six channels versus all channels.

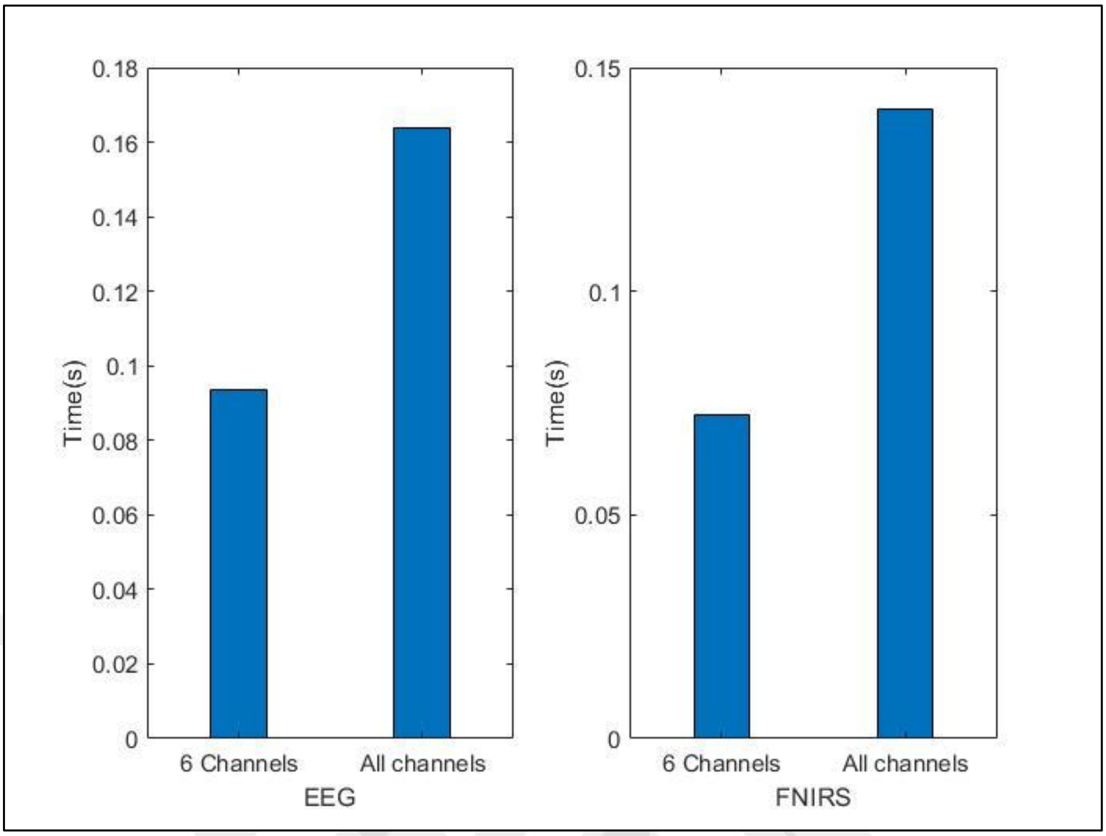


Figure 4.7 Performance comparison of EEG and fNIRS

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CHAPTER 5

DATA FUSION

Multimodality data-fusion is a particularly challenging problem as the nature of information from brain is intrinsically different, which makes it difficult to analyse. Instead of using a complex analysis to fuse the data sets, researchers tend to reduce both modalities to a feature level which has lower dimensionality and then investigating the associations across this information through variations among individuals. Feature space is a lower-dimensional representation of the recorded brain signals. Most of the literature focused on feature-based level fusion through concatenating EEG and FNIRS features $[f_{EEG}: f_{FNIRS}]$ [10] [15]. In this thesis, three different fusion approaches are used to fuse EEG and fNIRS data, namely: concatenation, Canonical correlation analysis (CCA) and Multi resolution singular value decomposition (MSVD). To better understand the improvement in hybrid BCI EEG-fNIRS fusion, it is better to discuss the performance of sole EEG and sole fNIRS systems first.

5.1 Sole EEG system

For the EEG data, two different sets of features are extracted: statistical features and DWT approximation coefficient. The movement of the subjects are recorded through twenty-one EEG channels.

5.1.1 Using Statistical features

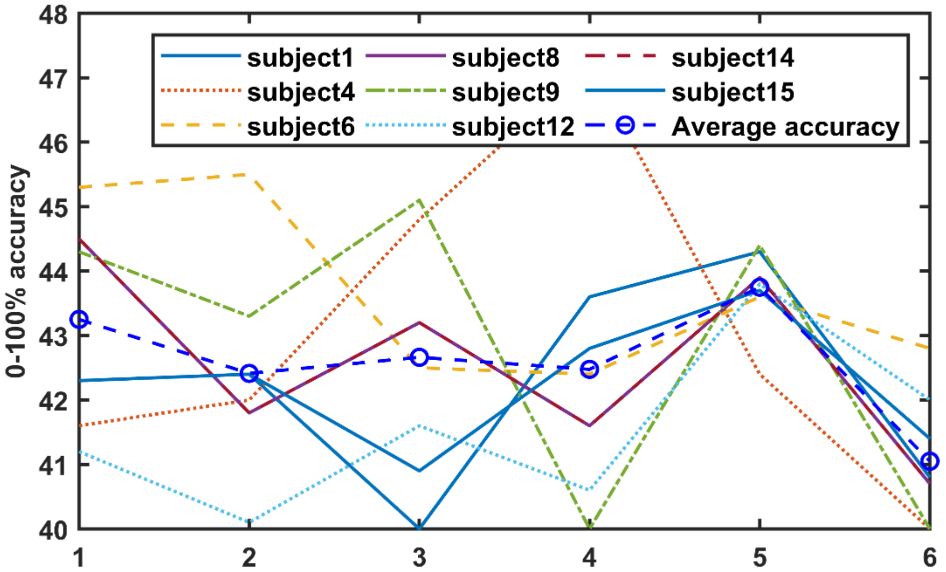
The average classification accuracies for five different classes—four movements and one rest— are obtained using KNN and Tree classifiers and shown in Table 5.1. Mean (M), Peak (P), Kurtosis (KR), and Skewness (SK) are used as the statistical features. The feature set contains one-one every possible combination of the features.

Table 5.1The average classification accuracy for 8 subjects of EEG-only features set filtered by Butterworth filter between the Hand, Arm and Rest tasks calculated through KNN and Tree classifiers when statistical features are used

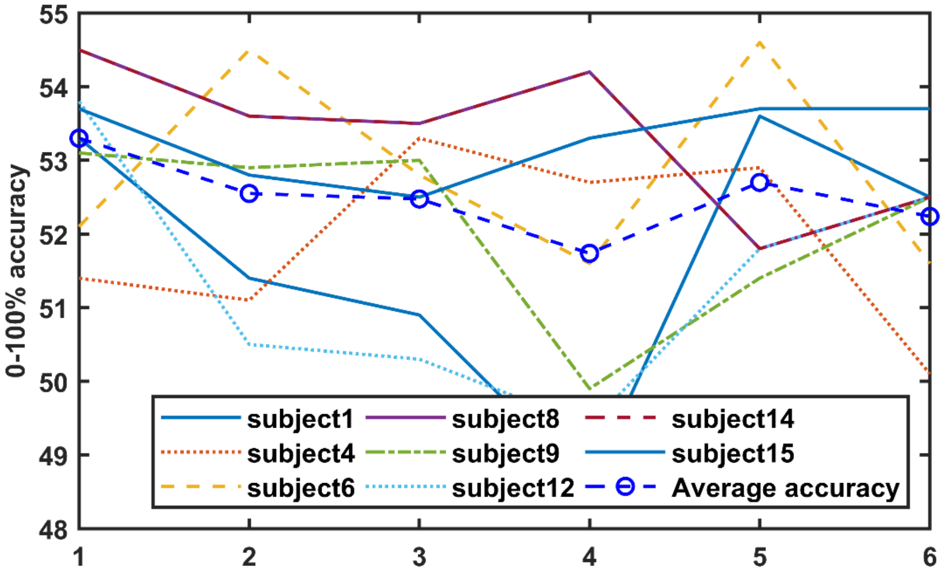
Features set	**EEG**	
	KNN	Tree
M, P	**44.5**	**53.30**
M, SK	41.8	52.55
M, KR	43.2	52.47
P, SK	41.6	51.73
P, KR	43.9	52.70
SK, KR	41.37	52.23

The Tree classifier has produced acceptable results when evaluated against the given features set as compared to KNN. The average classification accuracy obtained through KNN is well below the defined acceptable threshold of 50%. This drop in accuracy is probably due to the less engagement from same subjects. This urges to get rid of such channels that are directly effecting upon the accuracy. Figure 5.1 depicts the EEG average classification accuracy obtained through KNN and Tree classifiers.

The low classification accuracy of 52.49±4% achieved using statistical features can be observed through Figure 5.1. It can be stated that for sure there is a need to search for another features set that is more suitable according to nature of EEG data and helps to achieve higher classification accuracy. Figure 5.2 shows the EEG statistical features (Mean, Peak, Skewness, Kurtosis). DWT used for EEG data feature extraction is such an approach that can cater the mentioned concerns.



(A) Features set-KNN classifier



(B) Features set-Tree classifier

Figure 5.1 EEG classification accuracy classified through A) KNN classifier B) Tree classifier, using statistical features for 8 subjects.

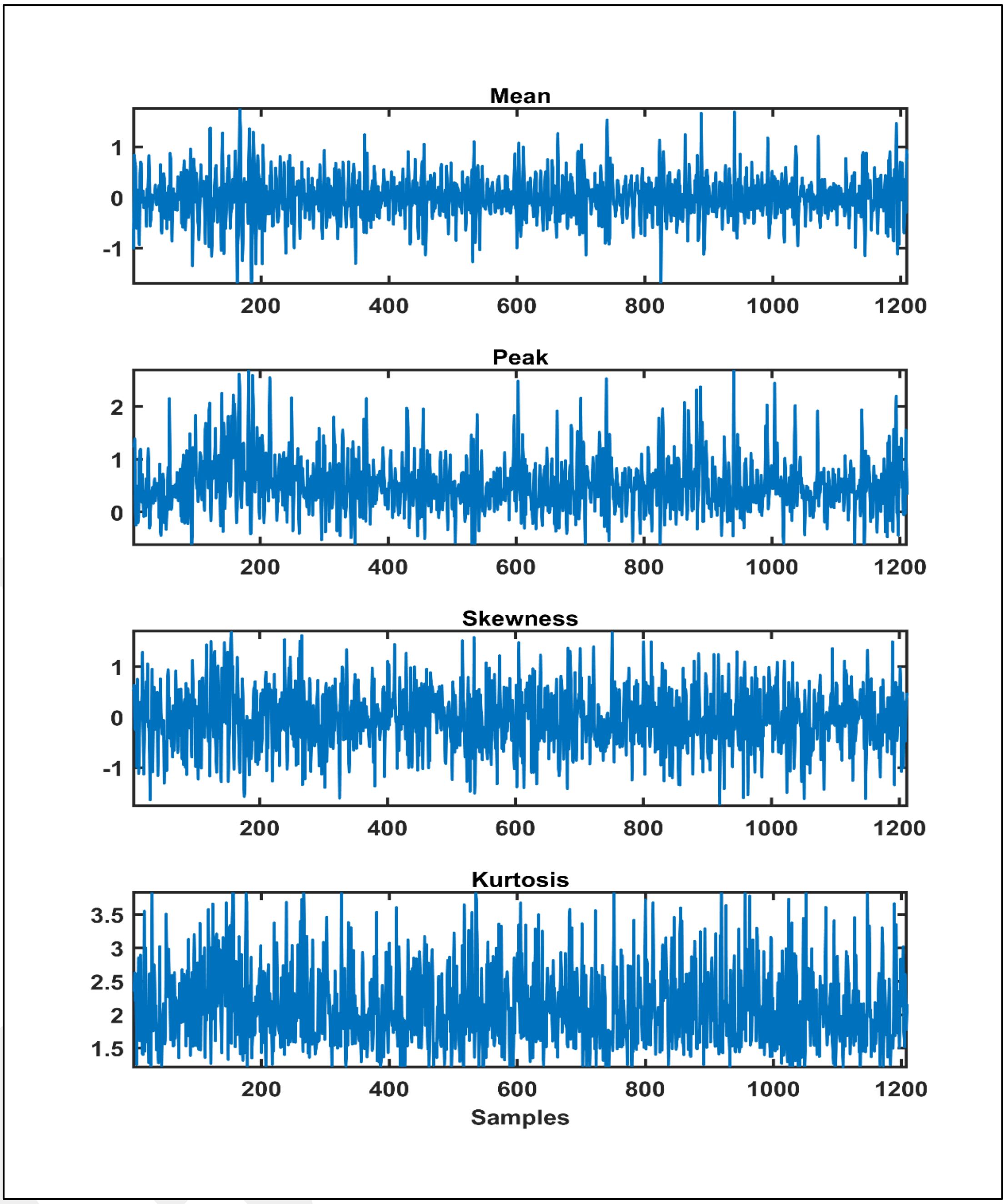


Figure 5.2 EEG statistical features (Mean, Peak, Skewness, Kurtosis).

5.1.2 Using Discrete wavelet transform (DWT)

DWT approximation coefficients are defined as the EEG features. The feature set contains one-one every possible combination of the features. Figure 5.3 shows the DWT decomposition of EEG signal into approximation and detailed coefficients.

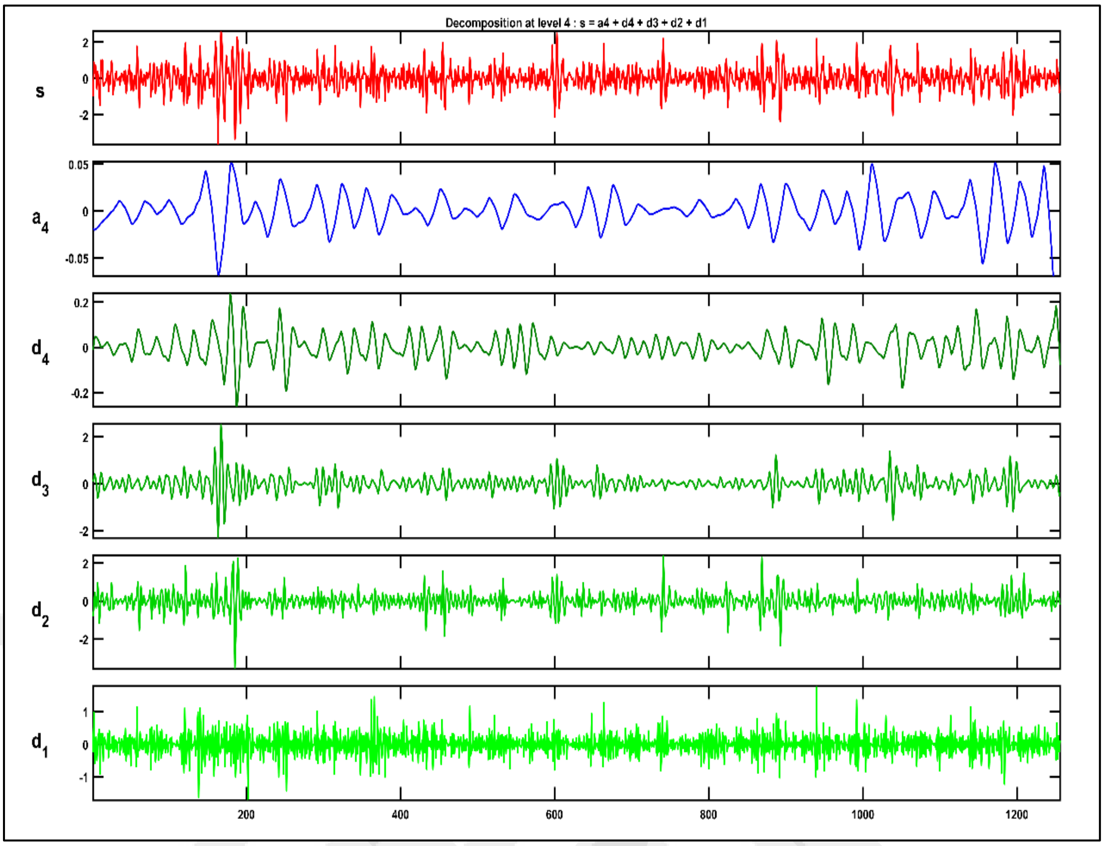


Figure 5.3 EEG DWT features (Approximation coefficients, Detailed coefficients).

The Tree classifier has produced decent results when evaluated against the given feature set as compared to the high accuracy achieved by KNN classifier. The average classification accuracy obtained through KNN using last layer DWT approximation coefficients is above 80%. This phenomenon is observed as DWT helps to decompose EEG signals into 4 layers, where approximation coefficients assumed to hold the most effective ERP of the brain activity [21]. The DWT decomposition also helped to reduce the dimensionality of the system. Table 5.2 shows the average classification accuracy for 8 subjects of EEG-only feature set when the Approximation Coefficients A1, A2, A3, A4 features are used.

Table 5.2 The average classification accuracy for 8 subjects of EEG-only features set, when the Approximation coefficients A1, A2, A3, A4 features are used

Features set	**EEG**	
	KNN	Tree
A1	44.45%	50.62%
A2	59.96%	53.10%
A3	70.83%	60.55%
A4	82.36%	71.32%

Figure 5.4 illustrates the EEG average classification accuracy obtained through Tree and KNN classifiers using DWT features. From Figure 5.4, it can be noticed that by selecting the highly optimized channels, average accuracy has now been improved and stays above the given threshold.

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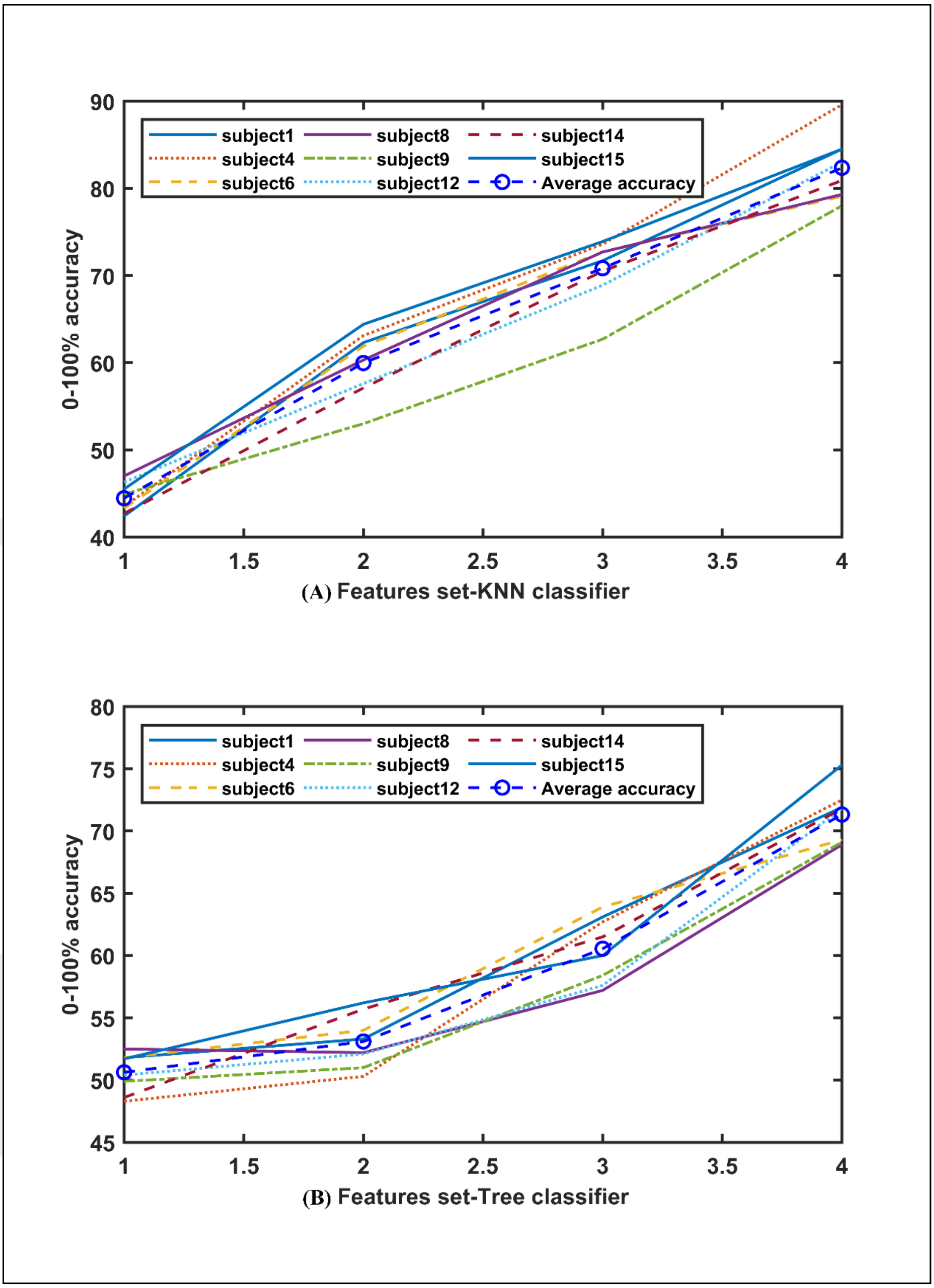

Figure 5.4 EEG classification accuracy through A) KNN classifier B) Tree classifier, using DWT features.

5.2 Sole fNIRS system

Table 5.3 shows the KNN and Tree classification results obtained for four-movements and one-rest activity.

Table 5.3 fNIRS classification accuracy obtained for 4-movements and 1-rest activity using statistical features through KNN and Tree classifiers.

Features set	**fNIRS**	
	KNN	Tree
M, P	66.87%	69.82%
M, SK	**71.90%**	**73.63%**
M, KR	69.42%	71.81%
P, SK	71.30%	73.27%
P, KR	67.32%	71.32%
SK, KR	57.42%	64.52%

From table 5.3, it is observed that the combination of peak and skewness has produced the highest accuracy for both KNN and Tree at three instances. The accuracy obtained through fNIRS is much higher as compared to EEG. When the most representative channels are picked and evaluated for 8 subjects, the accuracy trend for the Tree classifier has further improved and can be witnessed through Figure 5.5.

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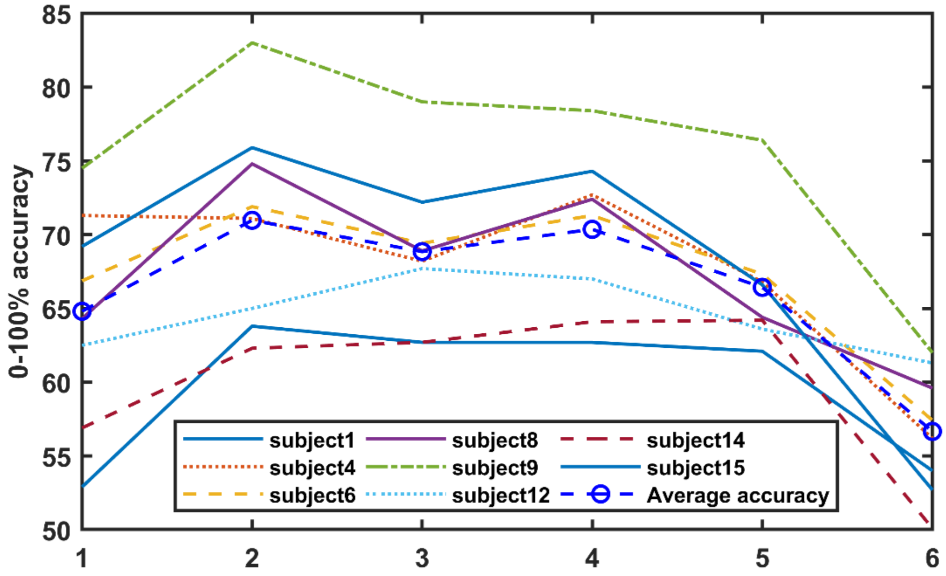
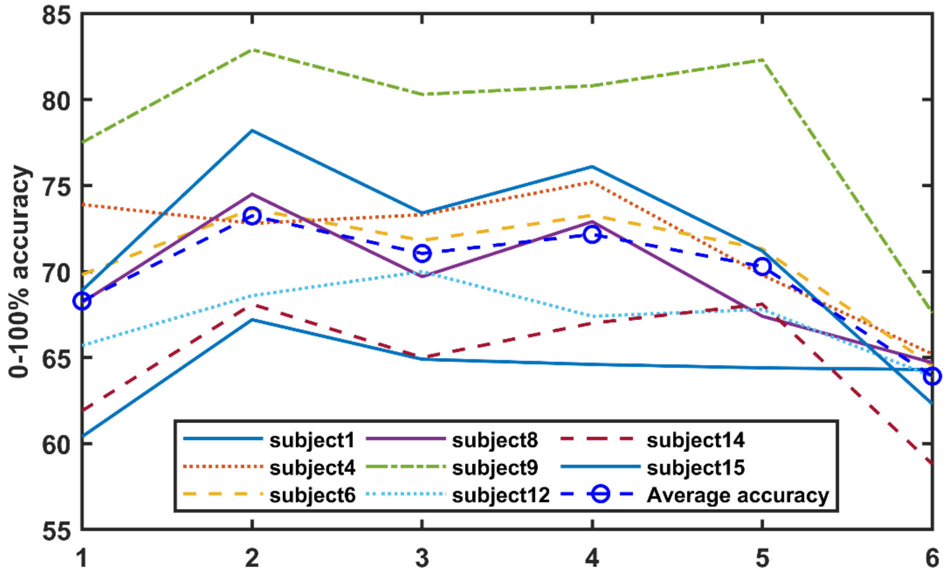


(A) Features set-KNN classifier



(B) Features set-Tree classifier

Figure 5.5 fNIRS classification accuracy through A)KNN classifier B) Tree classifier, filtered by IIR between the Hand, Arm and Rest tasks evaluated for 8 subject

For some healthier subjects, such as S9, the average accuracy achieved is above 80% using [M, SK] feature set. The average classification accuracy obtained for 8 subjects is also above the given threshold. Through the Figure 5.6, it can be observed that the feature set [M, SK] and [P, SK] have performed best as compared to other feature sets. Moreover, S9 is considered as the most reliable subject in terms of accuracy.

5.3 Hybrid EEG-fNIRS

Sole EEG and sole fNIRS systems have shown decent classification accuracy—70% or higher—to discriminate among four different motor tasks and rest. The hybrid EEG-fNIRS system helps to improve the classification accuracy of sole EEG and fNIRS systems and can be used to resolve the drawbacks of the two modalities. This thesis presents three different fusion approaches to fuse EEG and fNIRS systems, namely: Concatenating, Canonical correlation analysis (CCA) and Multi resolution singular value decomposition (MSVD).

5.3.1 Concatenating Statistical-only Feature-based fusion:

For the hybrid EEG-fNIRS, the EEG feature set containing six feature vectors are combined with the fNIRS feature set also containing the same number of feature vectors, in order to generate a total of thirty-six feature vectors. Table 5.4 shows the average classification accuracy for eight subjects obtained through KNN and Tree classifiers. No absolute judgement can be made based upon the most desired feature set, however, [M, SK] has performed well as compared to the rest at multiple instances. The highest and the lowest average classification accuracy of 78.2% and 64.58% is obtained through Tree and KNN classifiers, respectively.

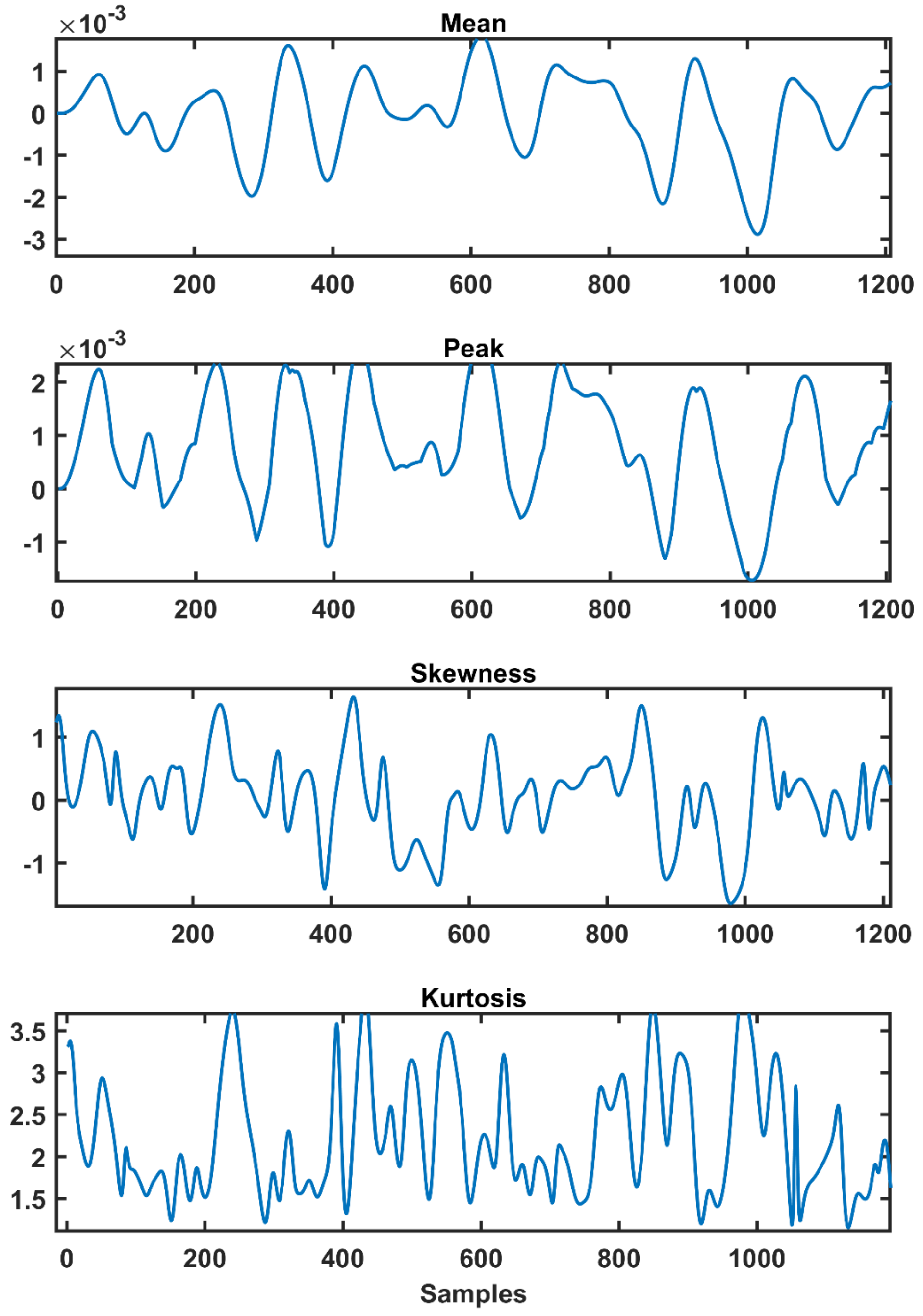


Figure 5.6 fNIRS statistical features (Mean, Peak, Skewness, Kurtosis).

Table 5.4 The Classification accuracy of hybrid EEG-fNIRS filtered by IIR Butterworth for the hand, arm and rest tasks are calculated through [KNN, Tree] classifiers

Features set fNIRS	**M, P**	[73.82, 76.75]	[67.46, 76.45	[66.85, 75.38]	[67.36, 74.72]	[65.68, 74.85]	[62.08, 73.4]
	M, SK	[**75.28**, 76.91]	[69.25, **78.2**]	[67.93, 75.5]	[**69.43**, **76.02**]	[67.37, 75.2]	[**64.58**, **73.7**]
	M, KR	[74.32, 74.53]	[68.98, 74.6]	[67.82, 74.02]	[68.51, 73.62]	[67.31, 73.38]	[63.03, 70.6]
	P, SK	[73.83, **77.63**]	[67.36, 77.4]	[67.5, **77.03**]	[67.2, 74.83]	[**67.63**, **75.76**]	[62.55, 73.7]
	P, KR	[74.2, 76.53]	[**69.68**, 75]	[**68.75**, 74.65]	[69.3, 73.6]	[67.6, 73.78]	[63.8, 72.32]
	SK, KR	[71.81, 69.88]	[67.03, 69.9]	[65.38, 69.25]	[66.2, 69.2]	[62.16, 69.3]	[60.76, 66.7]
		M, P	M, SK	M, KR	P, SK	P, KR	SK, KR
		Features set EEG					

Figure 5.7 shows the classification accuracy for eight subjects obtained through KNN and Tree classifiers, and the latter achieved an accuracy of 76.75±11% using [M, P] features set for both EEG-fNIRS. The average classification accuracy for eight subjects is recorded as 76.75%, where subject fourteen being the highest achieved an accuracy of 88% and subject one being the lowest reached an accuracy 66% using the same feature set.

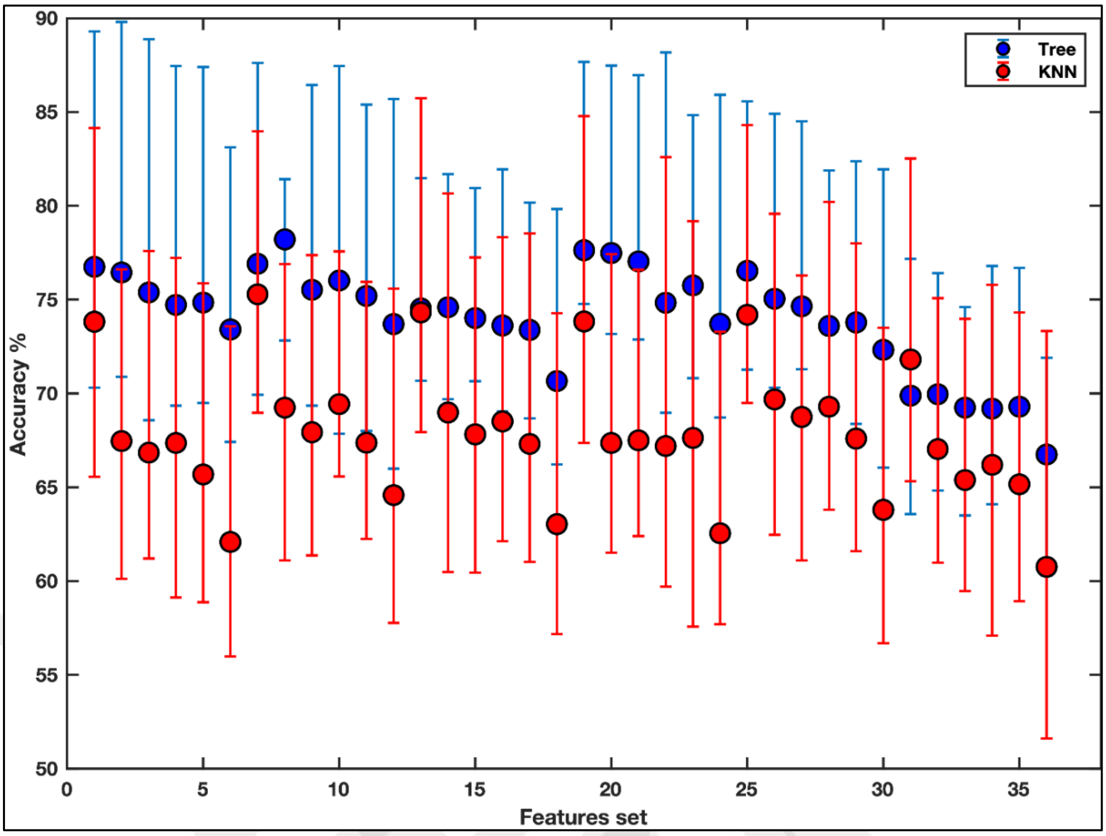


Figure 5.7 The Classification accuracy of hybrid EEG-fNIRS filtered by Butterworth filter between the hand, arm and rest tasks calculated through KNN and Tree when hybrid features set were used.

The average classification accuracy for EEG-only feature set achieved using Butterworth filter is KNN=42.728%, Tree=52.49%. For fNIRS-only feature set, filtered by Butterworth filter, achieved an average accuracy of KNN=71.40%, Tree=72.42%, while an improved accuracy of KNN=67.85%, Tree=74.02% is achieved by the hybrid EEG-fNIRS feature set.

5.3.2 Concatenating DWT-Statistical Feature-based fusion:

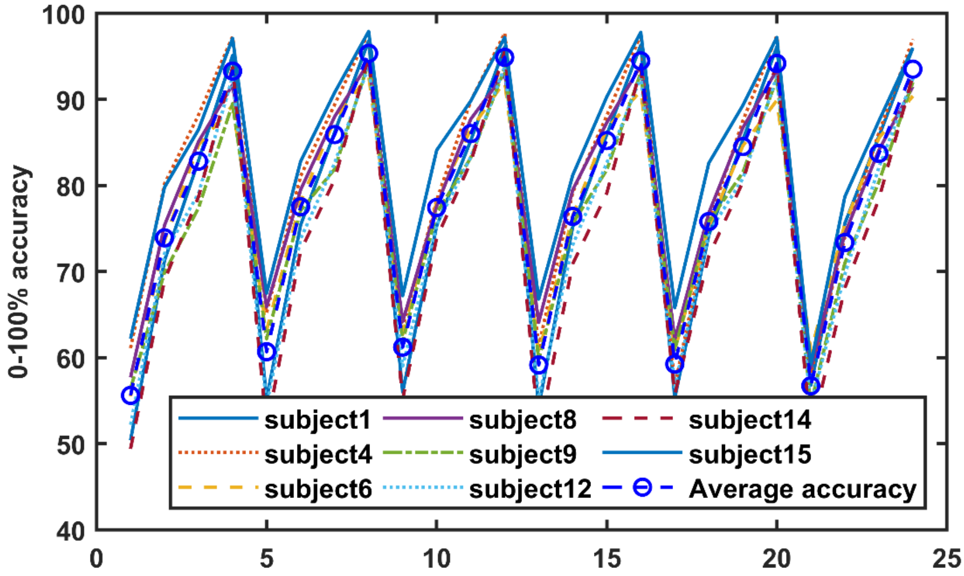
For the hybrid EEG-fNIRS, the EEG feature set containing four feature vectors are combined with the fNIRS feature set containing six feature vectors in order to generate a total of twenty-four feature vectors. Table 5.5 shows the performance in terms of the average classification accuracy for eight subjects obtained through KNN and Tree classifiers. It is clear that the approximation coefficient of the last layer of DWT i.e., A4 achieved a high classification accuracy which is also in accordance with the assumption made by Li, Potter, Huang, & Zhang, (2017)—who stated that A4 contains the primary power in event-related oscillation of brain activities. The highest and the lowest average classification accuracy of 93.38% and 86.65% is obtained through Tree and KNN, respectively.

Table 5.5 The Classification accuracy of hybrid EEG-fNIRS filtered by IIR Butterworth for the hand, arm and rest tasks are calculated through [KNN, Tree] classifiers

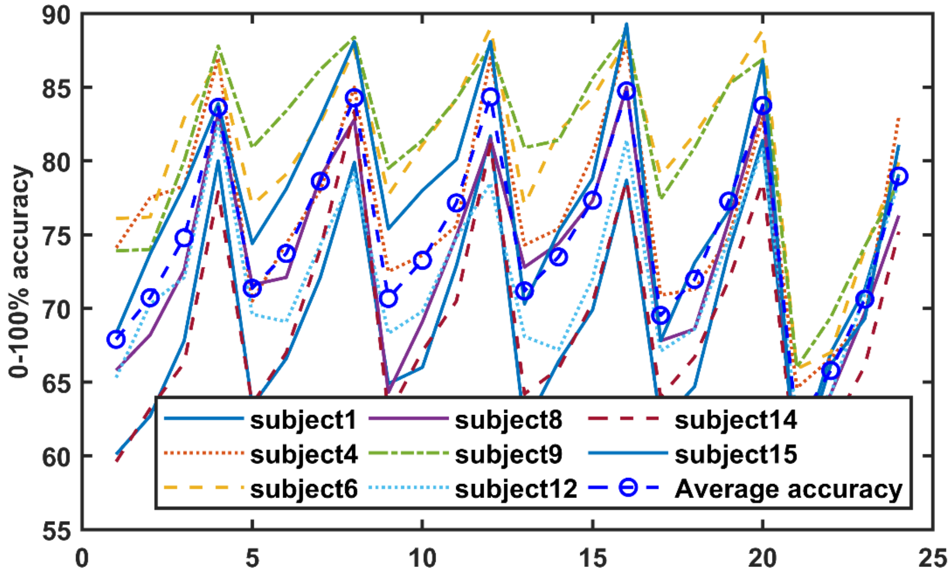
Features set fNIRS	M, P	[93.28, 83.63]
	M, SK	[**95.35**, 84.28]
	M, KR	[94.88, 84.33]
	P, SK	[94.47, **84.75**]
	P, KR	[94.17, 83.76]
	SK, KR	[93.51, 78.97]
		DWT Last layer approximation coefficient A4
		Features set EEG

Figure 5.8 shows the classification accuracy for eight subjects obtained through KNN and Tree classifiers when statistical features from fNIRS are fused with DWT approximation coefficients (A1, A2, A3, A4) from EEG.

The fusion between statistical features from fNIRS and DWT last layer approximation coefficients from EEG using concatenating approach achieved a significant improvement in performance of the hybrid EEG-fNIRS feature of accuracy average of KNN=95.35%, Tree=84.75%.



(A) Features set-KNN classifier



(B) Features set-Tree classifier

Figure 5.8 The average Classification accuracy for 8 subjects of the hybrid EEG-fNIRS calculated through A) KNN classifier and B) Tree classifier, when the hybrid feature set is used.

5.3.3 Canonical Correlation Analysis (CCA)

This thesis proposes Canonical correlation analysis (CCA) to perform EEG-FNIRS feature-based level fusion. Given two signal X and Y, CCA finds the linear combination that maximizes the correlation between two information data sets. Suppose that a sample of instances X with the samples $(X_1, \ldots, X_n)$ and Y with the samples $(Y_1, \ldots, Y_n)$ is given. By selecting a direction w_x and projecting X in that direction, a new coordinate for X can be considered by Xw_x= $(X_1 w_x^T, ..., X_n w_x^T)$. The same procedure can be repeated for Y by selecting a direction w_y with the corresponding values of the new Y coordinate being Yw_y= $(Y_1 w_y^T, ..., Y_n w_y^T)$. Canonical correlation make a search for the canonical coefficients w_x and w_y that maximize the correlation of the two data sets. In other words, the function's result to be maximized is:

$$\rho = \max_{w_x, w_y} corr \left(Xw_x^T, Yw_y^T \right) \tag{5.1}$$

Then, the first pair of the canonical variates can be obtained by:

$$A1 = Xw_x^T \;\; , A2 = Yw_y^T \tag{5.2}$$

The CCA method can be posed as a restricted optimizing problem with Lagrange multipliers and the canonical covariates can be calculated by solving a generic eigenvalue solution as the columns of w_x and w_y are the eigenvectors of the two data sets. Then, transformed feature vectors are concatenated according to Nicolle M. Correa, (2010) as **F**= [A1:A2], where **F** is the discriminant features of the canonical correlation.

Compared with feature-based fusion using dataset concatenation, CCA feature-based fusion is more robust in identifying cross-dataset feature combination that can be used in different ways to generate group level inferences. Another advantage of CCA feature-based fusion is the dimensionality reduction that leads to a high classification accuracy achieved by KNN classifier. In Figure 5.9, CCA has shown reliability to be successful for the multi-modal fusion.

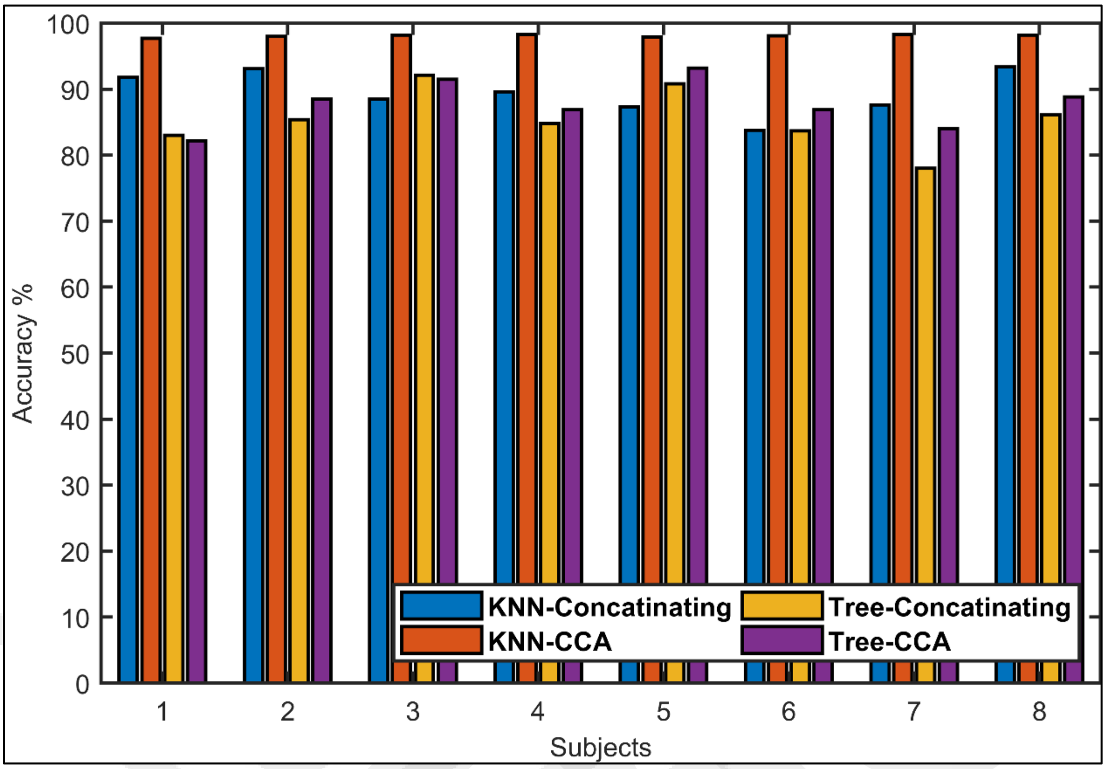


Figure 5.9 The Classification accuracy for 8 subjects of Hybrid EEG-fNIRS filtered by Butterworth filter between the Hand, Arm and Rest tasks calculated through KNN and Tree when Hybrid features-based fusion through Concatenating, CCA were used.

The results showed that CCA is a powerful fusion technique where multiple biomedical dataset can be analysed. The data fusion uses linear merging models to decompose the information into their latent components. If CCA feature-based fusion is compared to the feature concatenation, the former's performance is 10% higher using KNN. EEG-fNIRS features integration using suggested CCA method helps to enhance the association between the two modalities and estimate the essential components for this association. It jointly analyses the two modalities to fuse information without giving preference to either modality. The method identifies the relationship based on the natural inter-subject covariance between the modalities. CCA fusion approach also helps to reduce the dimensionality that leads to an improvement in the classification accuracy for all subjects, even for a bad performing subject such as S1, the accuracy has improved by +5% when compared against concatenation approach. Although, high classification accuracy is achieved using CCA, the two modalities are still processed separately. This adds computational complexity to the processing of the hybrid BCI system, it can be solved through system-based fusion, where signals from both modalities are fused and processed together as a single modality.

5.3.4 Multi-resolution Singular Value Decomposition

Another contribution of this thesis is a novel fusion approach using Multi-resolution singular value decomposition (MSVD) to achieve data fusion on both feature- and system-level. MSVD performs the first level of decomposition by processing the signal through two consecutive layers of low pass finite impulse response filter (FIR) and high pass finite impulse response (FIR) filter. The output of the filters form the first level of decomposition and is dismantled by a factor of two [27]. Second level of decomposition can be achieved by repeating the same procedure for the output of the dismantled low pass filter. This procedure can be repeated to achieve consecutive levels of decomposition.

Assume that $X = [x(1), x(2),..., x(N)]$ presents a 1D signal of length N, where N is divisible by 2. The samples are reshaped in a way that the odd indexed samples are re-arranged on the top row, and the even indexed samples are re-arranged in the bottom row. The resultant of this procedure is the data matrix:

$$X_1 = \begin{bmatrix} X(1) & X(3) & X(N-1) \\ X(2) & X(4) & X(N) \end{bmatrix} \tag{5.3}$$

By denoting the scatter matrix as:

$$T_1 = X_1 X_1^T \tag{5.4}$$

Let U_1 represent the eigenvector matrix which transforms T_1 into a diagonal matrix:

$$U_1^T T_1 U_1 = S_1^2 \tag{5.5}$$

The diagonal matrix

$$S_1^2 = \begin{bmatrix} S_1(1)^2 & 0 \\ 0 & S_2(1)^2 \end{bmatrix} \tag{5.6}$$

contains the squares of the singular values, with $S_1\,(1) > S_2(\,2)$.

Let $\widehat{X_1} = U_1^T X_1$, so $X_1 = U_1 \widehat{X_1}$. The top row of $\widehat{X_1}$, denoted as $\widehat{X_1}(1,:)$ contains approximation component corresponding to the largest eigenvalue. The bottom row of $\widehat{X_1}$, denoted as $\widehat{X_1}(2,:)$ contains detail component that corresponds to the smallest eigenvalue.

Let $\emptyset_1 = \widehat{X_1}(1,\ :)$ and $\varphi_1 = \widehat{X_1}(2,\ :)$ represents the approximation and detail components, respectively. The K times decomposition level can be achieved by repeating the procedure described above, where the approximation component $\emptyset_1$ is to be used in place of *X*.

Let $\emptyset_0(1,:)$ =*X* be the original signal, at the same time it also represents the first approximation coefficient. For each level *l* of decomposition, the approximation component vector has $N_l = \frac{N}{2^l}$. The K decomposition level MSVD for *l* =1,2,…,*K*-1 is achieved as follows:

$$X_l = \begin{bmatrix} \emptyset_{l-1}(1) & \emptyset_{l-1}(3) & \cdots & \emptyset_{l-1}(2N_l - 1) \\ \emptyset_{l-1}(2) & \emptyset_{l-1}(4) & \cdots & \emptyset_{l-1}(2N_l) \end{bmatrix} \tag{5.7}$$

Generally, it is sufficient to store the lowest resolution approximation component vector $\emptyset_l$, the detail component vectors φ_l for *l* =1,2,...,*L* and the eigenvector matrices U_l for *l* =1,2,..., *L* . Accordingly, the MSVD can be written as:

$$X \to \{\emptyset_l, \{\varphi_l\}_{l=1}^{L}, \{U_l\}_{l=1}^{L}\} \tag{5.8}$$

The original X signal can be reconstructed from the right-hand side, as the steps are reversible. Figure 5.10 shows the MSVD decomposition structure.

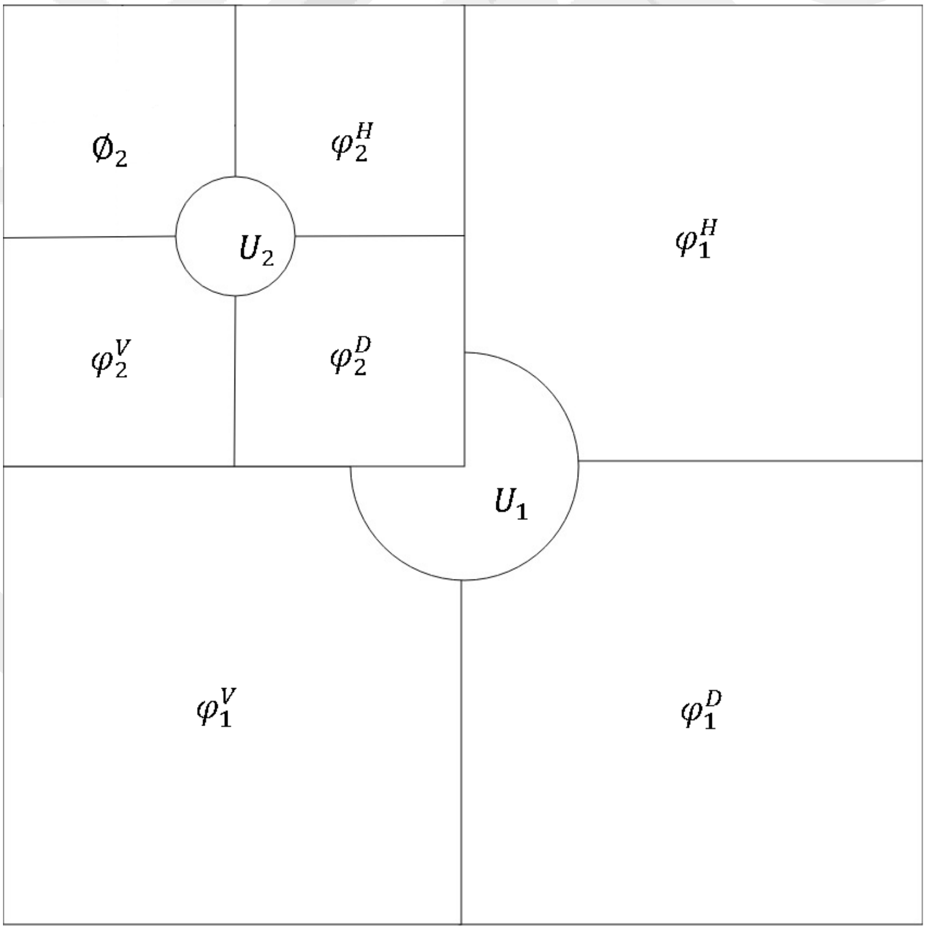


Figure 5.10 Multi resolution decomposition structures.

5.3.4.1 MSVD fusion scheme

The schematic diagram for the MSVD fusion scheme is shown in Figure 5.11. The signals to be fused S_1 and S_2 are decomposed into L (l =1, 2, ..., L) levels using MSVD. At each decomposition level (l =1, 2, ..., L) , the fusion rule selects the greater absolute value of the two detailed MSVD coefficients, as the detailed coefficients fluctuate around zero. The fusion rule takes average of the MSVD approximation coefficients at the final level of decomposition (l=L). Similarly, the fusion rule takes the average of the two MSVD Eigen matrices at each decomposition level (l =1, 2, ..., L).

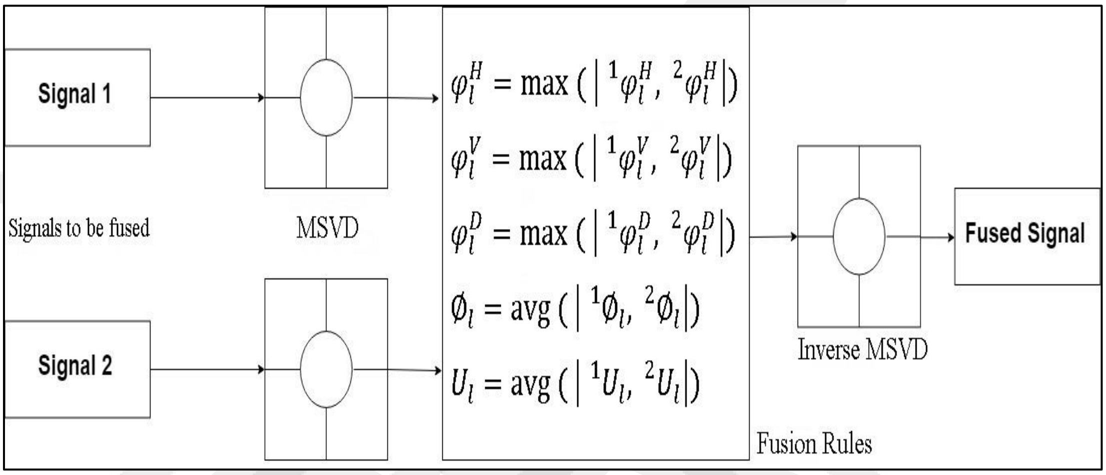


Figure 5.11 MSVD fusion scheme.

5.3.4.2 MSVD feature-based fusion

Proposed MSVD approach is used to perform EEG-fNIRS feature-based fusion. Six features for both EEG-fNIRS from the selected channels are first rescaled between [0-1]. Later, feature sets are decomposed into sub-bands through filtering it by two consecutive layers of low pass finite impulse response filter and high pass finite impulse response to achieve the first level of decomposition. After this process, fusion rules mentioned in Figure 5.11 are applied. To apply MSVD algorithm, EEG-fNIRS features must possess the same dimensions. For the hybrid EEG-fNIRS, the EEG feature set containing six feature vectors is merged with the fNIRS feature set containing six feature vectors using MSVD. The EEG approximation coefficient of the last layer of DWT namely, A4 with the highest classification accuracy is fused with the fNIRS statistical features–Mean, Peak, Skewness, kurtosis, Standard deviation, Variance.

The highest classification accuracy of 96.3% and 81.7% is obtained through KNN and Tree classifiers, respectively, whereas, the lowest classification accuracy of 82.6% and 66.2% is achieved through KNN and Tree classifiers, respectively. Figure 5.14 shows a comparison between feature-based fusion and system-based fusion.

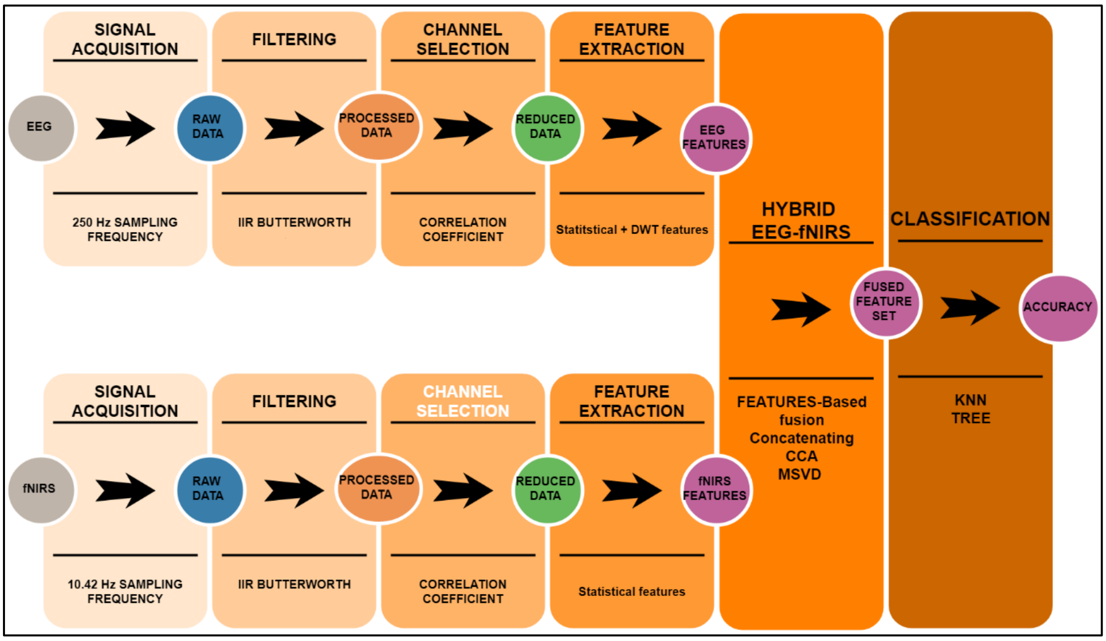


Figure 5.12 Hybrid BCI system using feature-based fusion

5.3.4.3 MSVD System-Based fusion

This thesis also proposes a system level fusion of the features obtained through hybrid EEG-fNIRS system. The fusion on system level has never been achieved due to some constraints, such as absence of suitable analytical methods for system-based fusion and the incompatibility between modalities in the recording regions. Previous studies mainly concentrated on feature-based fusion. Detailed step involved in System fusion approach is shown in Figure 5.13. Filtered signals for the selected EEG-fNIRS channels are rescaled between [0-1]. Six channels from both EEG-fNIRS are used. The MSVD fusion rules are applied to the filtered and rescaled signals. Feature extraction is then applied on the fused signal. Last layer DWT approximation coefficient and statistical feature are extracted from the fused signal. Features are arranged for the classification step in the form of F = [A4, statistical features, [A4: statistical features]].

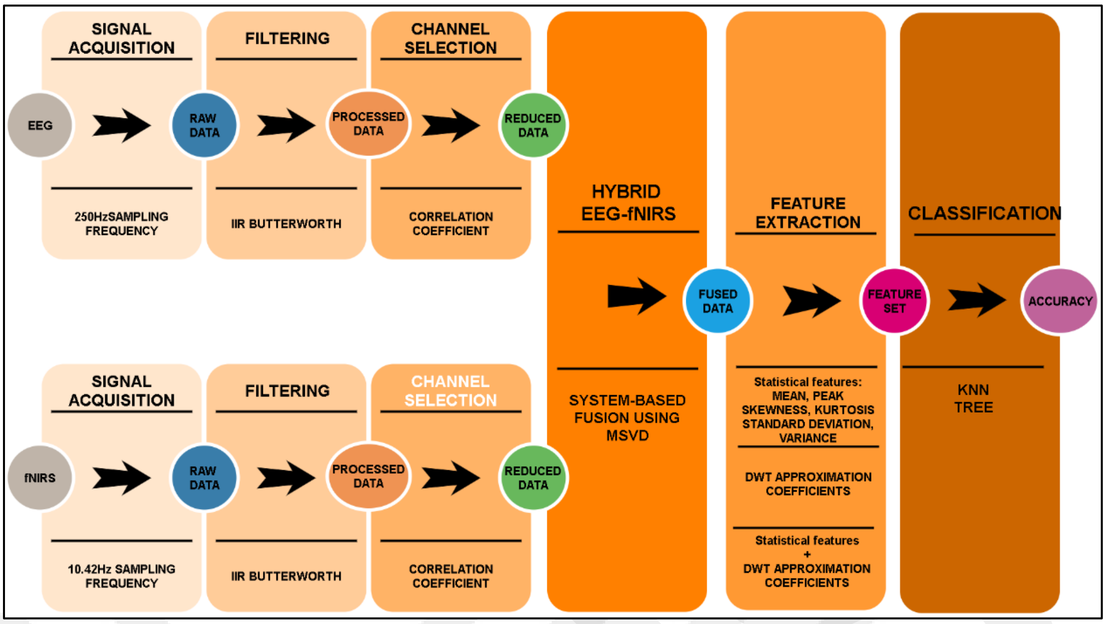


Figure 5.13 Hybrid BCI system using system-based fusion

Compared with feature-based level fusion, MSVD system-based fusion is more flexible in recognizing cross-dataset variants of the components that can be used in different ways to generate group level inferences. Moreover, it is less time consuming since the fusion is on signals level and the analysis is performed on fused signal instead of processing each signal separately. It is observed that MSVD fusion approach is computationally easy and it can be implemented for real time applications. Furthermore, Multi-resolution singular value decomposition does not have a fixed set of basis vectors like FFT and wavelet etc. and its basis vectors depends on the dataset only. Figure 5.14 shows the classification accuracy for both feature-based fusion and system-based fusion that are classified through KNN and Tree classifiers.

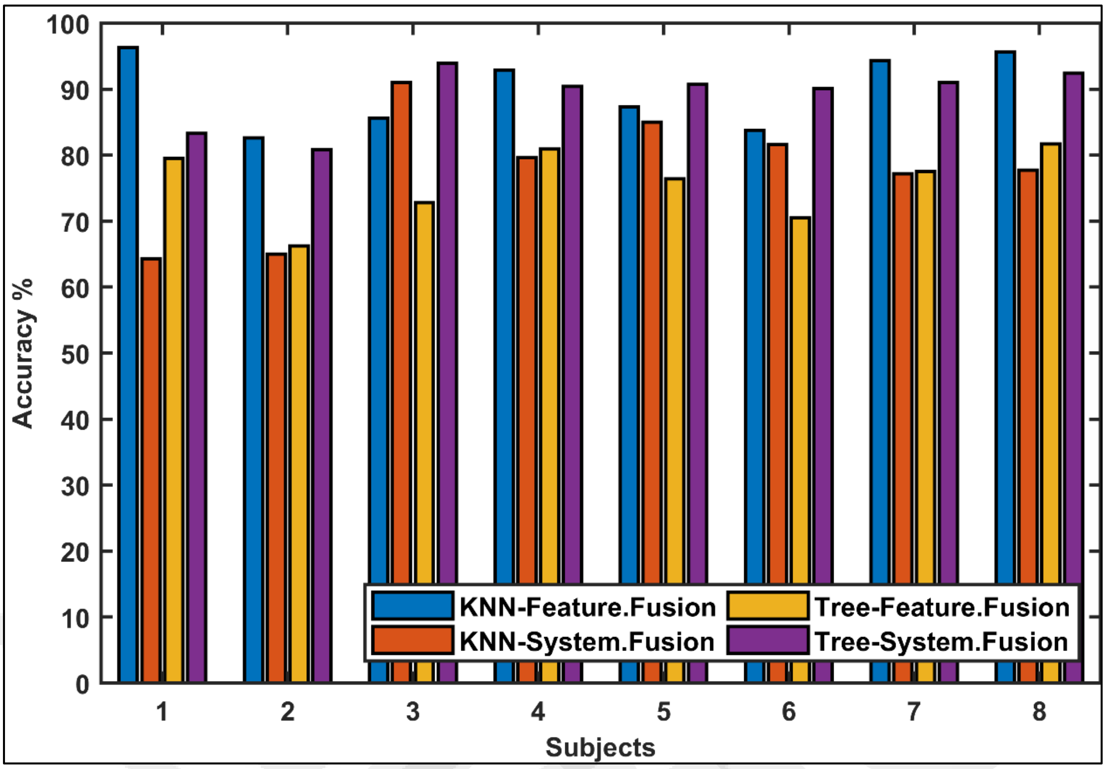


Figure 5.14 The Classification accuracy for 8 subjects of Hybrid EEG-fNIRS filtered by Butterworth filter between the Hand, Arm and Rest tasks calculated through KNN and Tree when Hybrid features-based fusion, system-based fusion is used.

From Figure 5.14, it can be observed that feature-based fusion using MSVD achieved better results using KNN classifier. On the other hand, system-based fusion for the same classifier achieved low accuracy, this can be due to the dimensionality problem. Figure 5.15 shows a comparison between feature set extracted from the fused signal, when [[A4: statistical features], A4, statistical features] are used in the analysis.

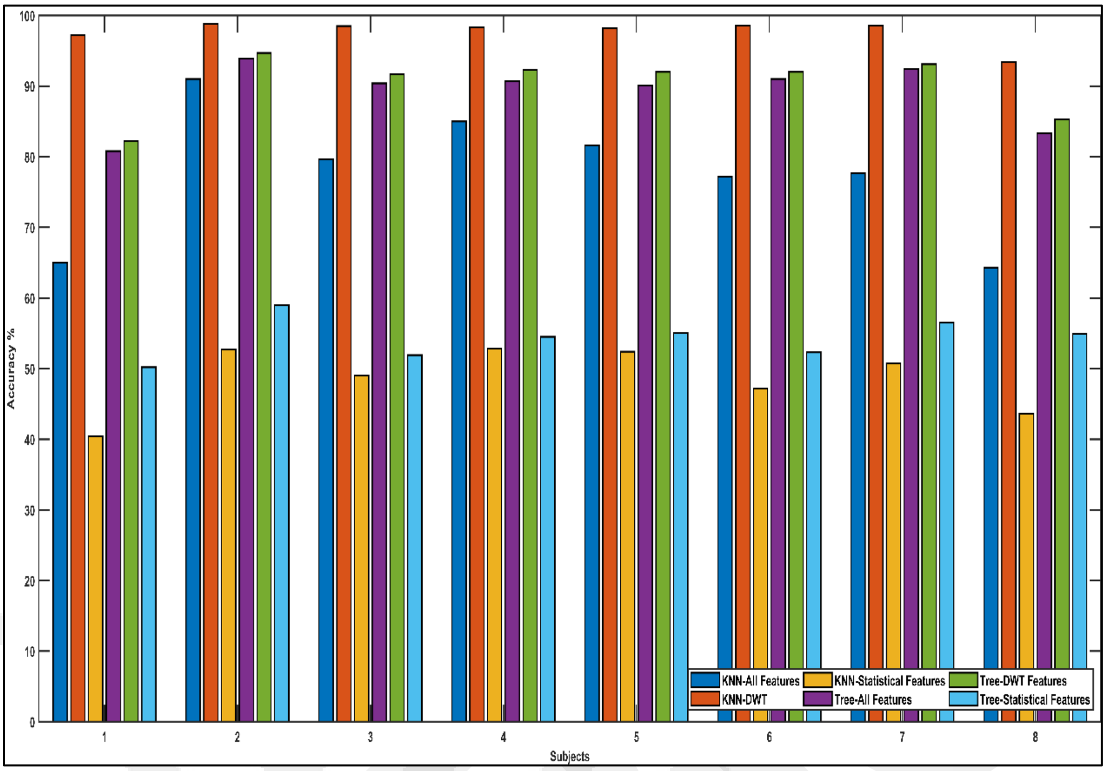


Figure 5.15 The Classification accuracy for 8 subjects of Hybrid EEG-fNIRS filtered by Butterworth filter between the Hand, Arm and Rest tasks calculated through KNN and Tree of Hybrid system-based fusion when DWT-only, Statistical-only and DWT-Statistical features are used

System-based fusion using MSVD achieved significant improvements in the classification accuracy. The improvement can be observed when spectral analysis is applied using last layer DWT approximation coefficient as the main feature for the fused signal. Though, the proposed approach has been able to give promising results as compared to the existing literature. Yet, there are some limitations that restricts its generalization, both modalities must be of the same dimensions (number of channels and recorded instances) for the algorithm to be able to utilize the fusion, this restriction makes channel selection a compulsory task. Another limitation is that additional two statistical features (Standard deviation, Variance) are added to the fNIRS analysis in feature level fusion to match the number of the EEG DWT features. In system level fusion any outliers and small noises accompanied in the processed signal can have a significant impact in dropping the classification accuracy of the system. Finally, temporal analysis achieved low accuracy, even below the threshold of 50% for some subjects, indicating that fused data suffers from dimensionality problem.

CHAPTER 6

DISCUSSION

The hybrid BCI using EEG-fNIRS improved the classification accuracy as compared to single-modality [10]. This thesis attempts to improve the classification accuracy of motor execution tasks as well as to reduce the computational cost. The results demonstrate that the EEG-fNIRS combination based upon the selection of most optimized channels has performed better as compared to the uni-modal approaches. It is widely accepted that the design and application of a BCI system strongly gets influenced by the selection of channels, their number and placement [19].

To generate execution commands based upon the motor imagery tasks, many researchers recommended to pick channels from C3 and C4 brain regions [14, 10]. But, this approach cannot be generalized due to the variation between subjects, as the most representative channels can be in different brain regions. Though, some researchers investigated the efficiency of different channel selection approaches [28, 9, 29], yet only few efforts have been made for the selection of most optimized channels. In this study, a set of channels from each hemisphere with high similarities based upon correlation coefficient have been chosen to ascertain that the most dominant channels are selected for the extraction and classification of the features. The obtained results show that not only the classification accuracy has improved but also computational complexity is reduced. Though few channels are used for the classification of the hybrid EEG-fNIRS, the accuracy achieved is decent as compared to previous studies where all channels were used for the classification process.

The classification performance of full channels set does not necessarily yield an optimal performance. Thus, it is desired that only those set of channels must be considered that actually contains the significant amount of information. The proposed channel selection approach based upon the ranking of the correlation coefficient can identify the optimal channels combination and enhance the classification performance. Six channels of both modalities are selected based upon their correlation rank. The selection of six channels from twenty-one channels for EEG and six fNIRS channels out of thirty-four helped to improve the response time. The response time for 1 sec long data, 250 samples of the EEG data and 10 samples of the fNIRS data has significantly improved the accuracy by 40% for the EEG data and more than 40% for the fNIRS. This helped to get rid of the outliers and noise variation; that may have been introduced in some channels at the time of data acquisition. The classification accuracy can be further improved by selecting more suitable and optimal features for the systems and using dimensionality reduction techniques. Signal mean, peak, skewness and kurtosis are used as the feature set for fNIRS classification, whereas discrete wavelet transform approximation coefficients, signal mean, peak, skewness and kurtosis are used as the feature set for EEG.

This study also proposes a CCA feature-based fusion approach for the data fusion of biomedical signals. Through results, it can be concluded that CCA is a powerful tool that allows the analysis of multiple signals. The fusion rule uses simple linear merging model for the data decomposition into their latent components. The classification performance of CCA feature-based fusion approach demonstrated a significant improvement—compared to the performance of EEG-only feature set and fNIRS-only features set modalities—with the highest classification accuracy of 98.35 and 89.98% using KNN and Tree classifiers, respectively. Furthermore, the highest classification accuracy achieved through sole EEG modality is 82.36 and 71.32% using KNN and Tree when last layer DWT approximation coefficient are used as the main feature set. By using statistical feature set for sole fNIRS modality, the highest classification accuracy of 71.90 and 73.63% is achieved using KNN and Tree, respectively. The results demonstrated that the CCA feature-based fusion achieved an accuracy improvement of 8% through feature concatenation when classified using KNN classifier, and an average increase in the classification accuracy of 3% when classified using Tree. EEG-fNIRS feature based fusion using suggested CCA approach helped to identify the association between the two modalities and predict the components responsible for these associations. This analyses the two modalities for information fusion without giving preference to either modality. The method identifies the relationships based on the natural inter-subject covariance between the modalities. Since, CCA are based on second-order statistics, it provides a relatively less constrained solution as compared to methods based on higher order statistics such as ICA [30].

Although, high classification accuracy is achieved by feature-based fusion approaches— feature concatenating and CCA—it still processes the two modalities in seperate windows before the fusion is applied. This adds computational complexity to the overall system that can be reduced by performing system-based fusion. It can decrease the computational cost by processing the fused signal instead of dealing with both modalities individually. System based-fusion is applied using the Multi resolution singular value decomposition (MSVD) approach. This thesis discusses the MSVD fusion on both system- and feature-level to improve the system performance, to reduce computational complexity, and to reduce dimensionality. The regions of interest within each subject are selected for individual modality (EEG and fNIRS) using the Pearson product-moment correlation coefficient (PPMCC), the channels with high correlation coefficient are used in the fusion of bimodality. It is evident from results that the hybrid EEG-fNIRS system fused on system- and feature-level using MSVD approach has performed better compared to single modality.

The classification performance of MSVD feature-based fusion approach demonstrated an improvement compared to the performance of sole EEG and sole fNIRS modalities, it achieved an average classification accuracy of 89.8-75.68% using KNN-Tree classifiers, respectively, compared to the highest average classification accuracy of the sole EEG modality of 82.36-71.32% using last layer DWT approximation coefficient and the highest average classification accuracy of the sole fNIRS modality of 71.90-73.63% using statistical features when classified using KNN-Tree classifiers, respectively. Yet, the MSVD feature-based fusion approach with the highest classification accuracy of 96.3% and 81.7% and the lowest classification accuracy of 82.6% and 66.2% achieved through KNN and Tree classifiers, respectively, yielded a lower classification accuracy when it is compared to the classification accuracy achieved using feature concatenating approach with a highest classification accuracy of 94.4-92.1% and a lowest classification accuracy of 83.8-78.0% using KNN-Tree classifiers, respectively, and lower than the classification of the CCA feature-based fusion approach with a highest classification accuracy of 98.3-93.2% and a lowest classification accuracy of 97.7-82.2% using KNN-Tree classifiers, respectively.

The results obtained through system-based fusion achieved a significant improvement in the classification accuracy with a highest classification accuracy of 98.8-94.7% and a lowest classification accuracy of 93.4-82.3% using last layer approximation coefficient of DWT as the main feature when classified through KNN-Tree classifiers, respectively. The system-based fusion using MSVD is a powerful fusion approach and suitable to be applied for the hybrid BCI system fusion. Though the proposed fusion approach has improved the accuracy, it has some limitations as well, such as EEG-fNIRS must have the same dimensions (channels and recorded instances) to be processed using the MSVD algorithm. Finally, it is noticeable that in system-based fusion any outlier, noises or the presence of bad channels can deteriorate the performance of the system.

CHAPTER 7

CONCLUSION

In this study, the hybrid EEG-fNIRS configuration for motor task classification is proposed. The primary goal of this work is to reduce the computational cost while not compromising the classification accuracy. In order to realize such a hybrid system, for the first system it is proposed to utilize the correlation coefficient for the selection of most optimized channels. To validate the effectiveness of the proposed approach, data from eight different subjects are gathered for multiple trials. As is evident from the results, the hybrid system significantly reduces the computational burden while achieving the classification accuracy with high reliability comparable to the existing literature.

The classification accuracy of 52.49±4% achieved by the EEG using statistical features was quite low. It might be due to the reason that the subjects involved in the experiments were exposed to the motor imagery task for the first time. In order to improve the performance for motor imagery tasks, it is suggested by [31] that all the subjects need to be trained for 1-4 hours with visual feedback informing the subject whether his/her imagery strategy is correctly classified. Secondly, as EEG suffers from low spatial resolution, it directly affects the overall performance of the hybrid system. To improve the classification accuracy, spectral analysis using last layer of DWT approximation coefficient is used as the main feature for EEG system. The classification performance of CCA feature-based fusion approach demonstrated a significant improvement compared to the performance of EEG-fNIRS concatenating approach. On the other hand, system-based fusion achieved an improvement in the classification accuracy using last layer approximation coefficient of DWT as the main feature and classified through KNN-Tree classifiers. System-based fusion using MSVD achieved an improvement in the classification. As to the future work, the focus is on the validation of the results and the investigation of the performance of the entire system using online data. Furthermore, different feature set and fusion approaches will be explored to further improve the performance of the hybrid BCI.

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