



# CORRELATION-BASED ADAPTIVE FILTERING PERFORMANCE DRIVEN BY SIGNAL DECOMPOSITION METHODS FOR EEG SIGNALS OF INDIVIDUALS WITH SEVERE MOTOR DISABILITIES

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## ABSTRACT

Electroencephalogram (EEG) signals are obtained from the surface of the scalp through a Brain-Computer Interface (BCI) and show the activity of brain regions. EEG signals are useful tools for people, especially those who have severe motor disabilities for an improved quality of life. Because of their noisy nature caused by a small movement of the head, eye blink, or even breathing, it is extremely hard to extract meaningful information from EEG signals. Thus, it is imperative to filter EEG signals without losing their essential parts. While filtering, the concept of adaptivity comes in handy because of its flexible nature to preserve important information. In this context, a novel approach that applies Wavelet Decomposition (WD), Empirical Mode Decomposition (EMD), or Variational Mode Decomposition (VMD) methods to filter EEG signals adaptively based on correlation was proposed. The performances of developed methods were calculated based on the accuracies of binary classifications of five different labels by using machine learning classifiers and compared with an Elliptic Bandpass Filter. The study shows that the proposed adaptively implemented VMD is the most useful filtering method for EEG signals, providing the best performance with 76.1% subject-wise accuracy for binary classification of word association and feet motor imagery and an average accuracy of 70.4% for all binary classifications using a Support Vector Machine (SVM) classifier. The results show that correlation is an efficient tool to adaptively implement signal decomposition methods as filters by preserving meaningful information more successfully than an Elliptic Bandpass Filter.

## 1. INTRODUCTION

Brain-Computer Interfaces are tools that provide communication between the brain and computerized systems thus enabling healthy individuals or individuals with severe disabilities to enhance their quality of life using only their thoughts. Brain-Computer Interface (BCI) systems based on Electroencephalogram (EEG) signals are the most common ones because EEG signals can be obtained through a headset that is easy to use, portable, and has fine temporal resolution and low set-up cost [1]. To control an external assistive device through a BCI system, the user should provide a series of activity patterns using an experimental paradigm. In this way, BCI-based systems can be trained and controlled by processing the EEG signals related to the activity patterns. However, the obtained EEG signals are nonlinear in nature and carry noise due to electrode impedances, electrode misplacements, eye blinks, movements, or even breathing [2]. Moreover, EEG signals related to activity patterns tend to show high variability from one healthy person to another, from one person with neurological disorders to another, or from day to day due to concentration level, resulting in poor classification accuracy and high error rates [2]. Thus, it has become imperative for the researchers in the field to filter a signal and remove artifacts in such a way as to obtain clean EEG signals without losing valuable information to enhance the accuracy of activity-related EEG classification. Many studies use traditional filters, and Wavelet Decomposition (WD), Empirical Mode Decomposition (EMD), and Variational Mode Decomposition

(VMD) methods for filtering EEG signals based on different thresholding, different adaptivity, different artifacts, etc.

Belwafi et al. tried an adaptive approach for filtering Motor Imagery EEG signals by using Common Spatial Pattern (CSP) to predict the most efficient filter parameters which are 10 to 100db Signal-to-Noise Ratio (SNR) values and 6 different filter types. They observed that the classification accuracy can be enhanced by 40% [1]. Estrada et al. applied four different threshold selection methods which are sure, heuristic sure, universal and minimax for soft and hard thresholding of continuous wavelet transform denoising and compared their results using SNR and Minimum Squared Error (MSE) parameters [3]. In another study, Alyasseri et al. used five meta-heuristic methods to predict the best Discrete Wavelet Transform (DWT) parameters for denoising EEG signals corrupted with four different noise types. They have evaluated their results using SNR, SNR improvement, MSE, Root MSE (RMSE), and Percentage Root Mean Square Difference (PRD) [4]. Suhail et al. used all the mother wavelet functions and thresholding methods to denoise EEG signals recorded during the realization of cognitive tasks and compared their results to find the most efficient pair and find that Discrete Meyer (dmey) mother wavelet with Rigrsure thresholding methods gives the best performance based on Peak SNR (PSNR), MSE, PRD, and Cross-Correlation (CC) [5]. Pise et al. compared Butterworth Low Pass Filter (LPF), Adaptive Least Mean Squares (LMS) filter, and DWT on epileptic and sleep EEG signals. It was observed that DWT gives the best performance with a 46.67 PSNR value [6]. Lahmiri et al. applied DWT to intrinsic mode functions (IMFs) of EMD and VMD and used a weighted approach with least-squares constraint to obtain clean EEG and Electrocardiography (ECG) signals by reconstructing them. The results show that VMD is the better approach with 45.8, 45.6, and 46.1 SNR values for right cortex EEG, left cortex EEG and ECG signals, respectively [7]. Gaur et al. tried a Multivariate Empirical Mode Decomposition (MEMD) subjectwise to filter Motor Imagery EEG signals. They used Riemannian geometry to classify the feature set which is made of sample covariance matrices. They obtained a 0.60 average kappa value for 9 nine subjects belonging to the BCI Competition IV-2A dataset [8]. Taran et al. applied a clustering-based VMD to EEG signals by first clustering them into homogenous groups and then decomposing them into band-limited modes. They have achieved a most successful result by obtaining an accuracy of 96% over Bern–Barcelona focal and nonfocal EEG database [9]. Dora et al. used a modified version of VMD to remove ECG artifacts from a single channel based on the information that ECG signals in an EEG signal correlate to each other. This study shows that an extra ECG channel is not necessary to remove ECG artifacts. Kaur et al. had a hybrid approach using VMD with DWT and Wavelet Packet Transform (WPT) to denoise EEG signals belonging to depression patients and evaluated their results with SNR, PSNR, and MSE values. They have used Detrended Fluctuation Analysis (DFA) to threshold IMFs obtained after VMD. VMD-WPT has given the best performance with a 22.779 PSNR value [10].

As is seen from the studies, due to many uses of EEG such as BCI applications or disease diagnosis, filtering approaches yield different results which are measured with different parameters. If the noise is known, then it is better to use SNR, PSNR, or MSE parameters, but if the noise is not known then the performance of a filtering method can be shown with a classification accuracy or kappa value, etc. Also, the adaptive nature of a filtering method can become handy for not losing valuable information because the optimal frequency range of EEG signals can change subjectwise [1]. Thus, we have proposed a novel correlation-based adaptive filtering approach for WD, EMD, and VMD methods and examined their performance results according to classification accuracy by comparing them to the results of an Elliptic Bandpass Filter between the ranges of 0.3Hz and 35Hz.

The paper is organized as follows: Section 2 gives detailed information about the data set used, and the adaptive filtering approaches which are WD, EMD, and VMD. Also, there are various feature extraction methods used in the study which give information about the frequency, time-frequency components, and the nonlinear nature of the signals. Finally, information about the classification method was also given in this section. In Section 3, the classification results belonging to all the filtering methods and to the reference study and other studies where the dataset was used were given in the form of true positive rates, accuracy, and standard deviation parameters. Finally, in Section 4, the paper was concluded with the evaluation of the results, positive and negative sides, and the contributions of the study.

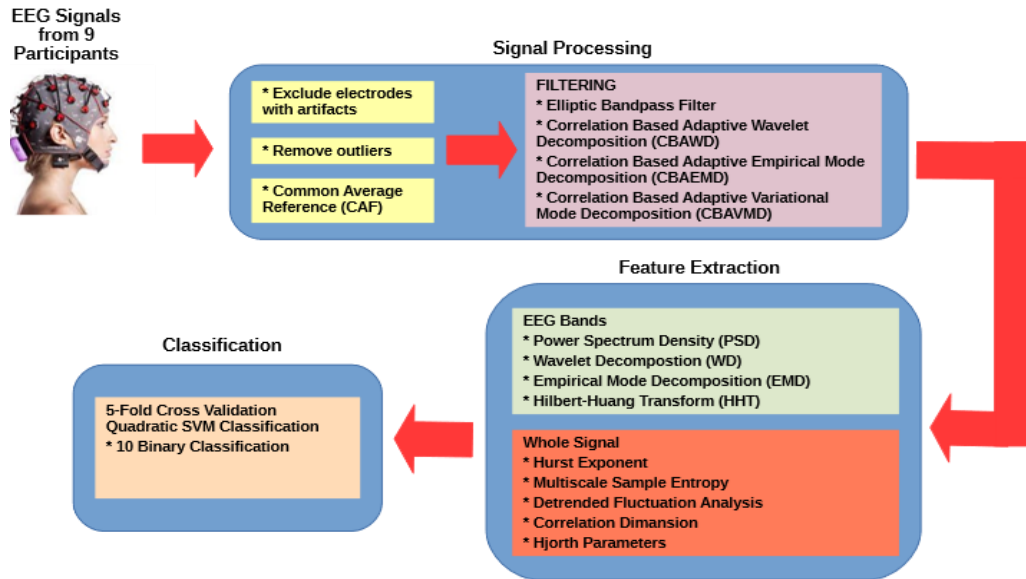


Figure 1. The flow diagram showing the steps followed in the study which consist of the used signal processing, feature extraction, and classification methods.

## 2. MATERIAL AND METHOD

In this study, the purpose was to compare the performance results of our correlation-based adaptive filtering methods with a known Elliptic Bandpass filter, which is generally used for denoising EEG signals, by using a common classification method Support Vector Machine (SVM) on binary classification. The flow diagram of the study indicating the methods used is shown in Figure 1 and explained in the following subsections.

### 2.1. Individually Adapted Imagery Dataset

The public dataset used in this study consists of EEG signals obtained from nine individuals with severe motor disabilities which are locked-in syndrome due to brainstem stroke, spinal cord injury, Massive hemorrhagic stroke in the left hemisphere, and Hemorrhagic stroke parietotemporal, right central no cranium. The demographic characteristics of the participants, which include information about their gender, age, type of injury, and the time passed after the injury, were given in [11]. EEG signals were obtained with a 256Hz sampling frequency using a g.tec GAMMASys cap which has 30 electrode channels placed according to the 10-20 system. Some of the electrode channels have artifacts and the channels with artifacts differ with all individuals. Which of the electrode channels have artifacts were mentioned in the study [11] and also, they were excluded from the analysis. In the experiments, a cue-guided paradigm was used to obtain 5 class EEG signals related to word association, mental subtraction, spatial navigation, right-hand motor imagery, and both feet motor imagery. For word association, the participants were shown letters, and they were to generate as many words as possible in Spanish starting with the given letter. For mental subtraction, the participants were to subtract a random one-digit number from randomly selected numbers between 15-30. For spatial navigation, the participants were to imagine navigation through a familiar house. For right-hand motor imagery, the participants were to imagine squeezing a ball with their right hand. For both feet motor imagery, the participants were to imagine the self-paced movement of both feet. The paradigm starts at  $t=0s$  with a cross for focusing. Then a beep sound was presented at  $t=3s$  to announce the presentation of the cue which was shown between  $t=3s$  and  $t=4.25s$ . From then on to  $t=10s$ , the participants imagine the cue-related task the experiment was finished with a beep sound and after  $t=10s$ , there is a break where the participant can move and blink for 2.5s or 3.5s. The paradigm of the experiment is shown in Figure 2. EEG signals were recorded in two sessions for all the participants. All the sessions have at least 5 days in between and are realized in two consecutive weeks. There are 8 runs in a session resulting in 40 trials for each class. In this study, we have used the second session for testing our filtering methods, because the results of the realized study [11] show that the second session has more accurate results which can mean that the participants have become more familiar with a BCI system.

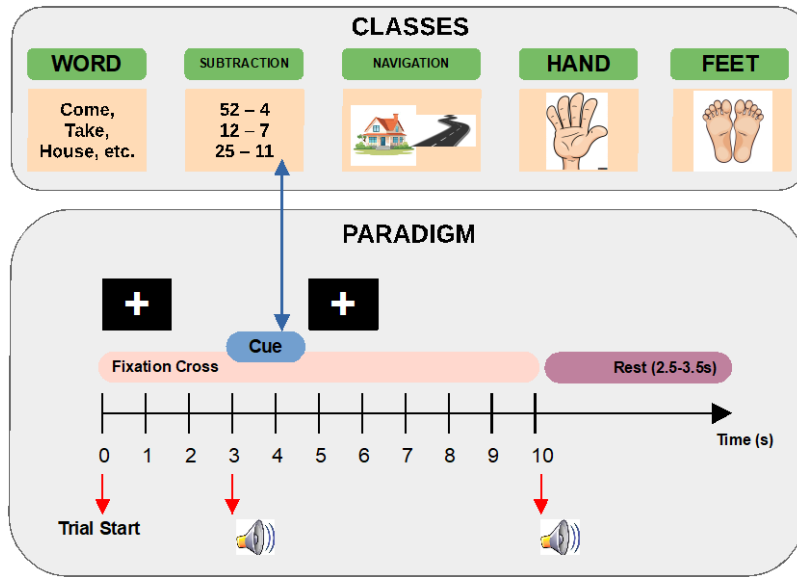


Figure 2. The experimental cue-guided paradigm of the study; fixation cross between  $t=0s$  and  $t=3s$ , cue between  $t=3s$  and  $t=4.25s$  starting with a beep, imagination of the cue between  $t=4.25s$  and  $t=10s$  and a 2.5-3.5s period for moving and blinking [11].

## 2.2. EEG Signal Processing

Firstly, we have realized all our applications using MATLAB R2019b software. We have used the signals between  $t=5s$  and  $t=10s$  where there is the imagination of a given task. This choice was motivated by common MI paradigms in which effective imagery is sustained after the initial onset, as well as by the desire to reduce computational load without sacrificing discriminative information. The minimum and maximum 3% of the signals' amplitude were accepted as outliers and removed from the signals. Finally, for SNR optimization, the Common Average Reference (CAR) method was applied to all the signals belonging to all the channels without artifacts. After preprocessing the signals, we have tried different filtering methods before feature extraction and compared the filtering performances based on the binary classification results.

EEG signal is a very complicated signal, thus, a signal perceived as noisy may contain meaningful information so filtering the signal without losing information is challenging. The adaptivity concept provides a filtering method to be more flexible thus, preserving different frequencies depending on the individuals. The resulting sub-signals after decomposition are all parts of the main signal so they all correlate to the main signal. Due to this feature, we have decided to use correlation as an adaptivity criterion. On the other hand, because the meaningful information in EEG signals comes from five EEG bands, which are delta, theta, alpha, beta, and gamma, we have applied a 20th order Elliptic Bandpass zero-phase filtering with 0.3Hz and 35Hz cut-off frequencies and have compared its results with our proposed adaptive filtering methods, which are named Correlation Based Adaptive Wavelet Decomposition (CBAWD), Correlation Based Adaptive Empirical Mode Decomposition (CBAEMD) and Correlation Based Adaptive Variational Mode Decomposition (CBAVMD) filtering explained in the following subsections.

### 2.2.1. Correlation Based Adaptive Wavelet Decomposition (CBAWD)

DWT is a time-frequency analysis method that decomposes a signal into its approximation and detail coefficients by using low-pass and high-pass filters. With each level of decomposition, the approximation coefficient also decomposes into its approximation and detail coefficients, and so on [12]. The detail coefficients represent high-frequency components and approximation coefficients represent low-frequency components. The denoising of a signal can be realized by reconstruction of the coefficients after applying thresholding or higher-level detail coefficients can be subtracted from the original signal to get rid of the redundant information. In this study, we have applied wavelet decomposition as an adaptive filter for not losing meaningful information in EEG signals. We have

decomposed the signals into 9-level approximation and detail coefficients using Biorthogonal 3.9 mother wavelet function which has the optimum denoising result for removing Electrooculography (EOG) signals according to the study [4]. After the decomposition, the correlations of the approximation and detail coefficients to the original signal were calculated. If the correlation value is negative, there is a negative relation. On the other hand, if it is positive, it is an indication of a positive relation. Thus, the correlation values were used as effect coefficients, so they were normalized by scaling them based on the median value of their absolute deviations (MAD) to increase the differences between the correlations or to eliminate its negative effect if the sign of the correlation is negative. For adaptivity, the new values were multiplied by the relevant coefficients to obtain new approximation and detail coefficients. The sum of the new coefficients composes the filtered signal.

### **2.2.2. Correlation Based Adaptive Empirical Mode Decomposition (CBAEMD)**

EMD is an analysis method for non-linear and non-stationary signals [13]. EMD works directly in temporal space rather than frequency space on the assumption that a signal has many oscillating components with different frequencies superimposed on one another [13-15]. EMD can decompose a signal  $k$  times recursively without previous knowledge of the signal, and there is not a huge loss in meaningful information because the decomposition is realized with high-resolution [15]. The oscillating components are named Intrinsic Mode Functions (IMF) and they are amplitude-modulated-frequency-modulated (AM-FM) signals  $u_k$  where the phase  $\phi_k(t)$  is a non-decreasing function, and the amplitude or the envelope  $A_k(t)$  is a positive signed function [14]. The change in instantaneous frequency  $\omega_k(t) = \phi'_k(t)$  and the amplitude is much slower than the phase, so if the time interval is sufficiently long then the IMF is a pure harmonic signal [14].

$$u_k = A_k(t) \cos(\phi_k(t)) \quad (1)$$

The oscillating components must satisfy the following conditions to be counted as IMFs; The number of extreme values and zeros-crossings must either be equal to each other or differ from one another at most by one, and the mean value of the enveloping signals, which are called local maxima or local minima, must be equal to zero at any time for a signal [16].

We have used a 5-level EMD with spline interpolation for our correlation-based adaptive filter. The researchers revealed that splines as interpolation methods for the definition of enveloping signals are preferred because linear or polynomial interpolations increase the number of sifting iterations which causes the over-decomposition of signals [17].

After the decomposition, the correlations of the resulting 5 IMFs to the original signal were calculated. As with CBAWD, the correlation values were normalized by scaling them based on the median value of their absolute deviations to increase the distinctions between them and to relieve them from their negative sign if so. Also, the new IMFs are generated by multiplying the normalized correlations with the old IMFs. The sum of the new IMFs results in the filtered signal, where the filtering method is called CBAEMD.

### **2.2.3. Correlation Based Adaptive Variational Mode Decomposition (CBAVMD)**

EMD is a recursive process that is heavily dependent on the interpolation method and a stopping criterion for the sifting process and there is a lack of mathematical theory to realize these processes, so to overcome these points a new approach VMD was developed [18]. Like EMD, VMD also decomposes a signal into its  $K$  IMFs which are concentrated around their respective instantaneous frequencies [13]. A detailed explanation of VMD can be looked into from [14]. As a short explanation, for the  $k$ th level mode function, VMD establishes the analytical signal by applying Hilbert-Huang Transform (HHT) and thus, calculating the unilateral Hilbert spectrum of the mode function [15]. The time-frequency representation of a signal with HHT is the more natural and meaningful form of a signal because it does not contain artificial oscillations [16]. The Hilbert Spectrum of the IMF is shifted to the baseband based on the principle of displacement of Fourier Transform. Then, the sum of spectral widths of the IMFs should be minimized, which is estimated through the H1 Gaussian smoothness, and is also an optimization problem as follows [15];

$$\min_{\{u_k\}, \{\omega_k\}} \left\{ \sum_{k=1}^K \left\| \partial_t \left[ \left( \delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 \right\}$$

$$s. t. \sum_{k=1}^K u_k = f$$
(2)

As in EMD,  $u_k$  is the mode function,  $\omega_k$  is the instantaneous central frequency,  $K$  is the total mode number, and the constraint function is the sum of the modes which equals the original signal  $f$ .

The optimization problem can be converted into an unconstrained problem by introducing a penalty parameter  $\alpha$  and Lagrangian multiplier  $\lambda$ , thus VMD can iteratively solve the unconstrained optimization problem which is as follows [15];

$$L(\{u_k\}, \{\omega_k\}, \lambda) = \alpha \sum_{k=1}^K \left\| \partial_t \left[ \left( \delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right\|_2^2 + \left\| f(t) - \sum_{k=1}^K u_k(t) \right\|_2^2$$

$$+ \lambda(t), f(t) - \sum_{k=1}^K u_k(t)$$
(3)

In this study, we have applied VMD as a filter to obtain 9 IMFs whose correlations were calculated with the original signal. As in the other adaptive filters, to increase the distinctions among each other and to relieve them from their negative sign, if so, we have normalized the correlation values by scaling them based on the median value of their absolute deviations. MAD-based normalization was employed for all methods to stabilize the weighting process, reduce sensitivity to extreme correlation values, and ensure consistent scaling across subjects and components. The sum of the new IMFs, which were obtained by the dot product of the normalized correlation vector and the previous IMF vector, constructs the filtered signal, thus naming the resulting filtering level method as CBAVMD. The generalized adaptive filtering algorithm of the decomposition methods is given in Figure 3, along with its pseudocode, to gain a clear understanding.

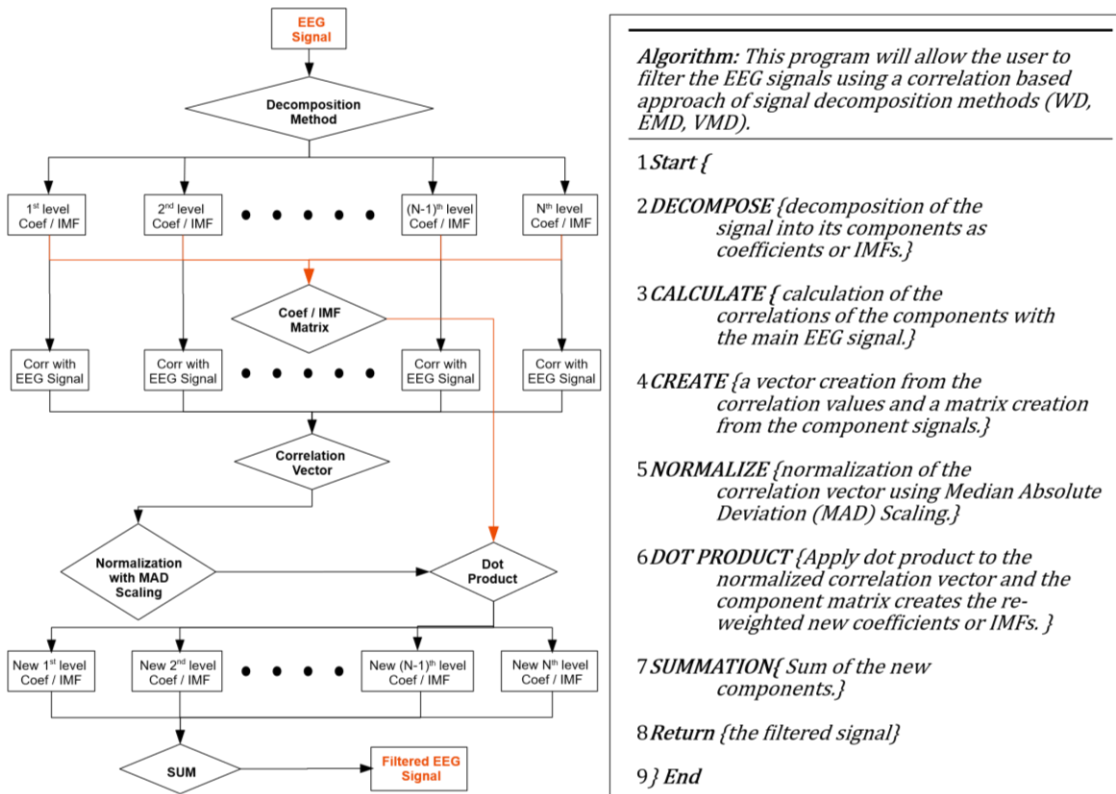


Figure 3. The generalized adaptive filtering algorithm of the signal decomposition methods and its pseudocode.

In this study, we have applied VMD as a filter to obtain 9 IMFs whose correlations were calculated with the original signal. As in the other adaptive filters, to increase the distinctions among each other and to relieve them from their negative sign, if so, we have normalized the correlation values by scaling them based on the median value of their absolute deviations. MAD-based normalization was employed for all methods to stabilize the weighting process, reduce sensitivity to extreme correlation values, and ensure consistent scaling across subjects and components. The sum of the new IMFs, which were obtained by the dot product of the normalized correlation vector and the previous IMF vector, constructs the filtered signal, thus naming the resulting filtering method as CBAVMD. The generalized adaptive filtering algorithm of the decomposition methods is given in Figure 3, along with its pseudocode, to gain a clear understanding.

### 2.3. Feature Extraction

Before feature extraction, we normalized the signals filtered by four different filtering methods between the ranges of [0 1]. Also, each participant exhibited different sets of problematic or noisy electrodes, which had to be removed prior to feature extraction. As a result, the final number of available EEG channels and extracted features varied across subjects. We calculated statistical features based on frequency and time-frequency methods. 5 EEG bands (delta, theta, alpha, beta, and gamma) of the signal were obtained by using 5 Elliptic Bandpass filters with cut-off frequencies related to the EEG bands. Then, statistical measures which are mean, standard deviation, skewness, kurtosis, and Shannon entropy values were calculated for Welch Power Spectrum Density (PSD), 9th level db4 (which is more commonly used in EEG feature extraction) Wavelet Transform coefficients, 5 IMFs of EMD, and Hilbert Spectrum belonging to all the EEG band signals obtained from all the electrode channels without artifacts.

After obtaining these frequency and time-frequency features, we have also obtained some non-linear features which can accurately express the non-linear nature of EEG signals. Entropy-based methods are one type of method that can give some ideas about the non-linearity of a signal. The first such method is Approximate Entropy (ApEn) which calculates the irregularity of a signal with a pattern length and a tolerance value [19]. This method's drawback is that ApEn requires a substantial amount of data and is not relatively consistent [19]. Sample Entropy (SampEn) can resolve these issues because it does not depend on the pattern length [19, 20]. Multiscale Entropy (MSE) was developed to analyze the irregularity of a signal over different time scales because increasing entropy does not always indicate meaningful irregularity [19]. Thus, it clears up ambiguity between uncorrelated randomness and meaningful irregularity [19]. In this study, we have calculated the mean value of the MSE of the filtered signals for  $m=2$ ,  $r=0.15$ , and time scale=20 ( $m$ : embedding dimension of the vector to be formed,  $r$ : tolerance).

Another non-linear method is Hurst Exponent (HE) which can estimate the long-range dependency of a time-series signal, based on chaos theory because time-series have a decaying dependency with increasing long-range time intervals [19, 21]. If the HE is equal to 0.5, it indicates uncorrelated randomness in a signal. If HE is between the range of 0 and 0.5, the signal is anti-correlated. If HE is between 0.5 and 1, then the signal has a long-range correlation with  $1/f$  power spectrum characteristics [19]. We have calculated three Hurst estimates of the signal which are the Discrete Second Derivative Estimator (DSOD), Wavelet version of DSOD, and Wavelet details regression estimator. The detailed explanations of these estimates can be found in [22, 23].

Detrended Fluctuation Analysis (DFA) is another method that also calculates the long-range correlation of a signal with the scaling exponent  $\alpha$  [19]. If  $\alpha=0.5$ , there is uncorrelated randomness in the signal. If  $\alpha<0.5$ , the signal is anti-correlated. If  $0.5<\alpha<1$ , then the signal has a long-range correlation. If  $\alpha=1$ , there is the presence of noise similar to the  $1/f$  power spectrum. If  $\alpha>1$  and approaches 1.5, it is the indication of a Brownian noise, which is the integration of white noise [19]. We have calculated 3 different  $\alpha$  values for polynomial orders of 2, 3, and 4 with a window size changing from 50 to 500 with an increase of 20.

Correlation Dimension (CD) is a fractal dimensionality measure that describes the chaotic nature of a signal by calculating the minimum number of variables the system processes [19, 21]. If the system is chaotic then the value of CD is a non-integer value much larger than 1 [19].

The last non-linear features we have used in this study are Hjorth parameters which are Activity (HA), Mobility (HM), and Complexity (HC) developed in the time-domain [21]. HA is the representation of a signal power which is the variance of the signal [24]. HM is the mean frequency of the power spectrum [21]. HC is the representation of the change in frequency which measures the similarity of a signal to a pure sine wave [21, 24]. Table 1 shows all the features used in this study with their domains.

Table 1. Features used in this study based on their domain.

Feature Type		Features	
Delta, Theta, Alpha, Beta, Gamma Bands	Frequency	Welch Power Spectrum Density	Mean Standard Deviation Skewness Kurtosis Shannon Entropy
	Time-Frequency	9th Level db4 Wavelet Coefficients	
		5 IMFs of EMD	
		5 IMFs of Hilbert Spectrum	
Whole Signal & All Frequencies	Nonlinear	Approximate Entropy (ApEn)	
		Sample Entropy (SampEn)	
		Multiscale Entropy (MSE)	
		Hurst Exponent (HE)	Discrete Second Derivative Estimator (DSOD)
			Wavelet version of DSOD
			Wavelet Details Regression Estimator
		Detrended Fluctuation Analysis (DFA)	
		Correlation Dimension (CD)	
		Hjorth parameters	Activity (HA)
			Mobility (HM)
Complexity (HC)			

## 2.4. Classification

Filtering performance was evaluated within subjects by classifying data in its simplest form, without feature selection or hyperparameter optimization and averaging the results. We have realized the classifications of all five classes as pairs and this procedure is named binary classification. Support Vector Machine (SVM) which can derive a boundary function to classify data in a multi-dimensional space by minimizing the errors and maximizing the margin between the classes was used in this study [25]. The SVM used in this study has a quadratic polynomial kernel function. It is the same for all the binary combinations of the classes because the main purpose of the study was to compare all correlation-based adaptive filtering methods based on classification accuracies. We have used the Classification Learner application in MATLAB and the SVM classifier used in the study has given the best performances generally throughout all the classifications. Also, we have applied 5-fold cross-validation to subject-wise classification to avoid the overfitting problem. Data of each subject was split into 80% training and 20% testing. The 80% training partition was then evaluated using 5-fold cross-validation to optimize the model and prevent overfitting. The held-out 20% was used exclusively for final testing.

After performing all primary classifications using Support Vector Machines (SVM), we further evaluated the effectiveness of the proposed filtering methods by testing them with additional machine learning classifiers. These comparative analyses were conducted specifically for the hand and feet classes, as the majority of motor imagery EEG studies in literature predominantly focus on these two motor tasks.

## 3. RESULTS AND DISCUSSION

After obtaining all the features from the signals belonging to the electrode channels without artifacts for all the participants and before applying the SVM classifier to all the data, we normalized all the feature

spaces belonging to all binary classification pairs using robust z-score normalization which have a median value of 0, and a median absolute deviation value of 1.

For comparison, we have obtained classification results after filtering the signals using the four filtering methods mentioned before and evaluated them based on accuracy, recall, precision, and F1-Score values. Table 2 shows the binary classification results of the signals denoised by the Elliptic Bandpass filter. According to the average results of nine participants, the least accurate classification belongs to the classification pair of right-hand and both-feet motor imagery with 0.52 accuracy and 0.54 F1-Score. On the other hand, the most accurate classification pair is word association and right-hand motor imagery with 0.72 accuracy and 0.72 F1-Score.

Table 3 shows the binary classification results belonging to the signals that were denoised by the Correlation Based Adaptive Wavelet Decomposition (CBAWD) filter. According to the average results of nine participants, the least accurate classification belongs to the classification pair of right-hand and feet motor imagery with 0.56 accuracy and 0.55 F1-Score. On the other hand, the most accurate classification belongs to word association and right-hand motor imagery pair and word association and both feet pair with 0.75 accuracy and 0.75 F1-Score.

Table 2. Averaged binary classification results of signals belonging to all the participants after Elliptic Bandpass Filtering (1: Word Association, 2: Mental Subtraction, 3: Spatial Navigation, 4: Right-Hand Motor Imagery, 5: Both Feet Motor Imagery)

Classification	Accuracy	Recall	Precision	F1-Score
1 vs 2	0.63	0.65	0.62	0.63
1 vs 3	0.67	0.69	0.67	0.68
1 vs 4	0.72	0.73	0.71	0.72
1 vs 5	0.70	0.70	0.69	0.70
2 vs 3	0.66	0.67	0.66	0.66
2 vs 4	0.67	0.68	0.66	0.67
2 vs 5	0.67	0.66	0.68	0.67
3 vs 4	0.69	0.70	0.68	0.69
3 vs 5	0.67	0.69	0.67	0.68
4 vs 5	0.52	0.56	0.52	0.54

Table 3. Averaged binary classification results of signals belonging to all the participants after Correlation Based Adaptive Wavelet Decomposition (CBAWD) Filtering (1: Word Association, 2: Mental Subtraction, 3: Spatial Navigation, 4: Right-Hand Motor Imagery, 5: Both Feet Motor Imagery)

Classification	Accuracy	Recall	Precision	F1-Score
1 vs 2	0.66	0.64	0.66	0.65
1 vs 3	0.73	0.73	0.72	0.73
1 vs 4	0.75	0.74	0.76	0.75
1 vs 5	0.75	0.73	0.76	0.75
2 vs 3	0.67	0.68	0.68	0.68
2 vs 4	0.71	0.71	0.70	0.71
2 vs 5	0.73	0.72	0.73	0.72
3 vs 4	0.69	0.68	0.69	0.69
3 vs 5	0.71	0.71	0.71	0.71
4 vs 5	0.56	0.55	0.56	0.55

Table 4 shows the binary classification results belonging to the signals which were denoised by the Correlation Based Adaptive Empirical Mode Decomposition (CBAEMD) filter According to the average results of nine participants, the least accurate classification belongs to the classification pair of

right-hand and feet motor imagery with 0.55 accuracy and 0.55 F1-Score. On the other hand, the most accurate classification pair is word association and right-hand motor imagery with 0.75 accuracy and 0.75 F1-Score.

*Table 4. Averaged binary classification results of signals belonging to all the participants after Correlation Based Adaptive Empirical Mode Decomposition (CBAEMD) Filtering (1: Word Association, 2: Mental Subtraction, 3: Spatial Navigation, 4: Right-Hand Motor Imagery, 5: Both Feet Motor Imagery)*

Classification	Accuracy	Recall	Precision	F1-Score
1 vs 2	0.60	0.58	0.60	0.59
1 vs 3	0.70	0.71	0.70	0.70
1 vs 4	0.75	0.74	0.75	0.75
1 vs 5	0.74	0.73	0.75	0.74
2 vs 3	0.65	0.64	0.65	0.65
2 vs 4	0.68	0.69	0.67	0.68
2 vs 5	0.68	0.69	0.68	0.68
3 vs 4	0.70	0.70	0.70	0.70
3 vs 5	0.69	0.69	0.68	0.69
4 vs 5	0.55	0.55	0.55	0.55

Table 5 shows the binary classification results belonging to the signals that were denoised by the Correlation Based Adaptive Variational Mode Decomposition (CBAVMD) filter. According to the average results of nine participants, the least accurate classification belongs to the classification pair of right-hand and feet motor imagery with 0.58 accuracy and 0.58 F1-Score. On the other hand, the most accurate classification pair is word association and both feet motor imagery with 0.76 accuracy and 0.76 F1-Score. It is seen from the results that the most successful average results of the binary classifications belong to the CBAVMD filtering method.

Table 6 shows the binary classification results belonging to the original study realized on the EEG signal dataset. The filtering of the signals was done by designing an 8Hz-30Hz Bandpass Filter with Common Spatial Pattern (CSP) algorithm, but the classification was realized by using Fisher's Linear Discriminant Analysis (LDA) [11]. According to the average results of nine participants, the least accurate classification belongs to the classification pair of right-hand and feet motor imagery with 0,65 accuracy and 0.65 F1-Score. On the other hand, the most accurate classification pair is mental subtraction and both feet motor imagery with 0.78 accuracy and 0.78 F1-Score.

*Table 5. Averaged binary classification results of signals belonging to all the participants after Correlation Based Adaptive Variational Mode Decomposition (CBAVMD) Filtering (1: Word Association, 2: Mental Subtraction, 3: Spatial Navigation, 4: Right-Hand Motor Imagery, 5: Both Feet Motor Imagery)*

Classification	Accuracy	Recall	Precision	F1-Score
1 vs 2	0.66	0.67	0.65	0.66
1 vs 3	0.74	0.75	0.74	0.74
1 vs 4	0.75	0.77	0.74	0.76
1 vs 5	0.76	0.75	0.77	0.76
2 vs 3	0.71	0.73	0.70	0.71
2 vs 4	0.71	0.73	0.70	0.72
2 vs 5	0.73	0.73	0.73	0.73
3 vs 4	0.70	0.73	0.69	0.71
3 vs 5	0.71	0.73	0.70	0.72
4 vs 5	0.58	0.58	0.58	0.58

Table 6. Averaged binary classification results of signals belonging to the original study of the dataset filtered by CSP based Bandpass Filter (1: Word Association, 2: Mental Subtraction, 3: Spatial Navigation, 4: Right-Hand Motor Imagery, 5: Both Feet Motor Imagery)

Classification	Accuracy	Recall	Precision	F1-Score
1 vs 2	0.69	0.68	0.70	0.69
1 vs 3	0.67	0.68	0.67	0.67
1 vs 4	0.77	0.77	0.78	0.77
1 vs 5	0.76	0.76	0.76	0.76
2 vs 3	0.70	0.71	0.70	0.71
2 vs 4	0.76	0.77	0.75	0.76
2 vs 5	0.78	0.80	0.77	0.78
3 vs 4	0.72	0.72	0.72	0.72
3 vs 5	0.70	0.71	0.70	0.71
4 vs 5	0.65	0.64	0.66	0.65

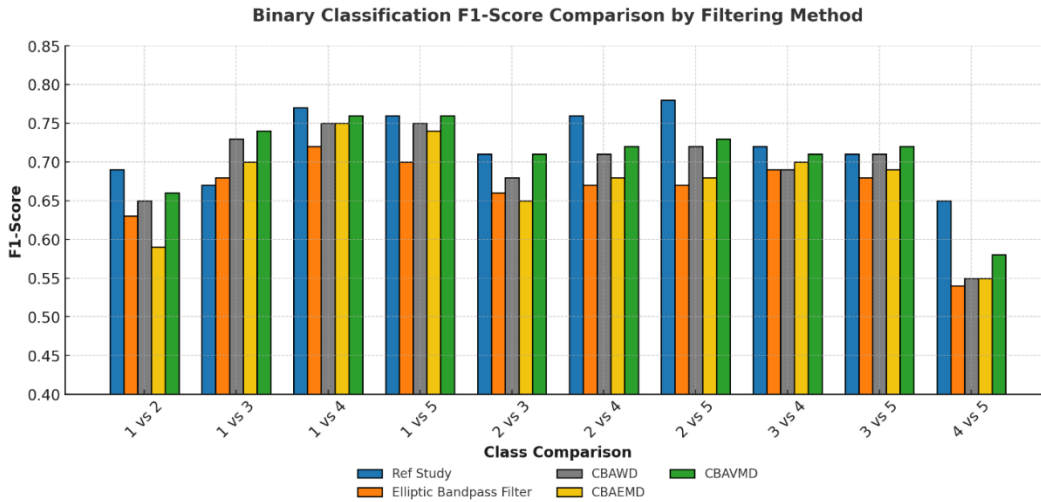


Figure 4. F1-score results of the proposed filtering methods, the Elliptic bandpass filter and the reference study.

As a summary, Figure 4 presents the F1-score values of binary classifications obtained from all the proposed filtering methods, the Elliptic bandpass filter, and the reference study. CBAVMD filtering method surpassed the success of the reference study while classifying word and navigation classes. For other binary classifications CBAVMD generally came close to reference study. VMD (Variational Mode Decomposition) can be said to provide high performance in EEG classifications because it produces IMF-like modes that are robust to noise, have good separation into bands, and are stable.

Table 7 presents the average classification accuracies obtained across all subjects for the hand versus feet motor imagery tasks using different filtering methods in combination with multiple machine learning classifiers. The results indicate that the CBAVMD filtering approach consistently achieved the highest or near-highest accuracy across most classifiers, reaching an average of 0.53 with the Decision Tree and Trilayered Neural Network, and 0.58 with the Quadratic SVM. This performance demonstrates the strong discriminative capability of VMD for separating motor imagery-related EEG components. The CBAEMD approach also performed relatively well, particularly with the Quadratic SVM (0.55), whereas the CBAWD showed modest accuracy levels across classifiers. In contrast, the traditional elliptic filter yielded the lowest overall accuracy, especially with the Decision Tree (0.50), suggesting that conventional bandpass filtering is less effective for isolating task-specific EEG features in this binary classification scenario. Overall, these findings demonstrate that adaptive decomposition-based filtering methods, particularly VMD, provide a clear advantage in enhancing classifier performance for hand-foot motor imagery discrimination.

Table 7. The average accuracies of hand vs feet classifications performed by different machine learning classifiers to compare the performances of the proposed filtering methods.

Avg Acc for Hand vs Feet	Decision Tree	Quadratic SVM	Kernel Naive Bayes	Medium KNN	Trilayered Neural Network
Elliptic Bandpass	0.50	0.52	0.52	0.53	0.53
CBAWD	0.51	0.56	0.51	0.52	0.52
CBAEMD	0.52	0.55	0.53	0.54	0.55
CBAVMD	0.53	0.58	0.51	0.54	0.53

To see the results clearly and as a whole, we have put together a table with the obtained average accuracies belonging to all the binary classifications by using all the filtering methods and also the results of the reference study and the other studies that used the same dataset. Table 8 shows all the average accuracies resulting from all the binary classifications and the accuracies of other studies realized on the same dataset. Also, for a clearer comparison, Figure 5 shows the average accuracies and their standard deviations of the binary classifications belonging to our methods and the other studies, which used the same dataset, in a column chart.

The results show that Elliptic Bandpass, CBAWD, and CBAEMD filtering yield the best classification with word association and right-hand motor imagery class pair. On the other hand, CBAVMD yields the best classification with word association and both feet motor imagery pair. The original study, where CSP-based Bandpass filtering was applied to the signals, yields the best classification with mental subtraction and both feet motor imagery pair. Among the adaptive filtering methods that we developed, CBAVMD has the best classification result with 0.71 average accuracy of all binary classification whereas a traditional filtering method of Elliptic Bandpass results in a 0.66 accuracy rate.

Table 8. The average accuracies of all the binary classifications obtained from all the proposed filtering methods, to compare with the results of the reference study of the dataset, and other studies on the same dataset. (1: Word Association, 2: Mental Subtraction, 3: Spatial Navigation, 4: Right-Hand Motor Imagery, 5: Both Feet Motor Imagery. Acc: Accuracy (%). Std: Standard Deviation. Green: Optimal Results, Red: Non-Optimal Results)

Filtering Method	Time Segments	Average Accuracies of All Participants										Average Acc For All Classifications	Std of Average Acc
		1-2	1-3	1-4	1-5	2-3	2-4	2-5	3-4	3-5	4-5		
Elliptic Bandpass with SVM	5s-10s	62.8	67.4	71.7	69.7	66.2	66.6	67.2	68.8	67.3	52.5	66.2	5.3
CBAWD	5s-10s	65.5	72.5	75.1	75.0	67.8	67.5	72.6	69.9	71.2	56.0	69.3	5.7
CBAEMD	5s-10s	59.7	70.1	74.6	73.9	65.2	67.4	68.3	70.0	68.5	54.9	67.3	6.1
CBAVMD	5s-10s	65.6	73.9	75.1	76.1	70.6	71.2	72.9	70.1	71.0	57.8	70.4	5.3
CSP Bandpass [11]	0s-10s	69.8	66.8	77.4	76.1	70.4	75.9	77.9	71.8	70.4	65.3	72.2	4.4
WPT [26]	3s-4.25s	80.0	80.1	73.8	78.6	79.0	73.6	78.3	73.9	80.8	77.9	77.6	2.8
RCSP [27]	4s-7s	-	-	-	-	-	-	73.0	-	-	-	-	-
Riemannian Geometry with SVM [28]	4.25s-10s	-	-	-	-	-	-	72.0	-	-	-	-	-
LR with SVM [29]	4s-7s	-	-	-	-	-	-	-	-	-	54.0	-	-
FUCONE with DR [30]	-	-	-	-	-	-	-	75.8	-	-	-	-	-

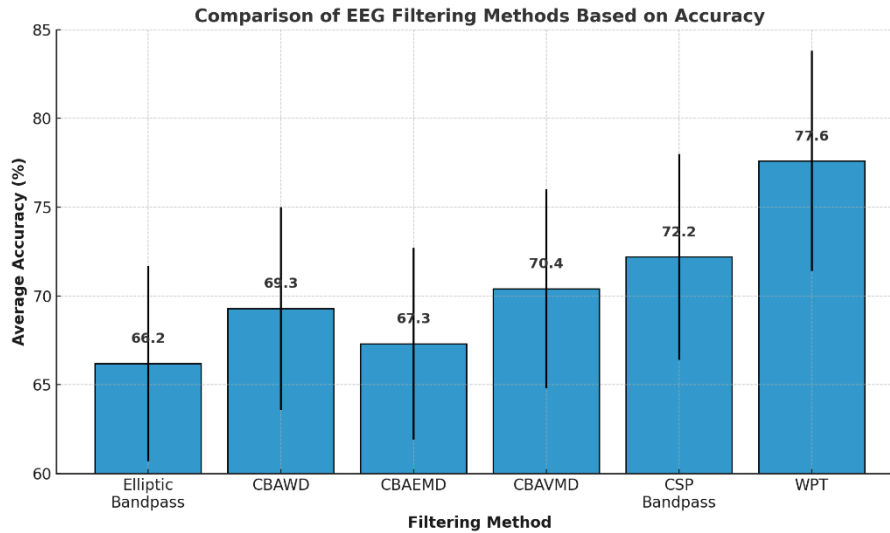


Figure 5. Comparison of the proposed methods with other studies based on average accuracies and standard deviations of binary classifications.

On the other hand, the original study has the best classification average accuracy of 72.2%. However, the preprocessing and feature extraction procedures, time segments, and binary class pairs differ for all the studies. For example, unlike the original study, we have not eliminated any of the frequency components of the signals, just changed their influences by adaptively changing their coefficients with the used methods. Also, the traditional Elliptic Bandpass filter was designed to pass the frequency components belonging to the 0.3Hz and 35Hz band, unlike the original study where the filter was designed to pass the frequency components between 8Hz and 30 Hz. The features used in the original study were not mentioned so we cannot make a comparison in this regard. Also, the classifiers used in the studies differ from each other, because we have used an SVM classifier with a quadratic kernel function, but Fisher's LDA was used in the original study of the dataset. So, the difference in the results from our study and the reference study can be explained due to these different filtering, feature, and classifier conditions. Another aspect that differs our study from the original study of the dataset and the other studies is the limits and the lengths of the time segments. We have used a time segment that only consists of the imagination of the cue instead of the full segment of the paradigm which the reference study used [11], or the cue segment where there is a visual triggering [26]. So, the differences in the classification performance can also change based on these distinct time segments. Our work itself with the same conditions for all methods can prove that the correlation-based adaptive filtering of WD, EMD, and VMD can achieve better classification results than Elliptic Bandpass filtering which was designed to consider all the wavebands of an EEG signal. Some of the other studies that used the same dataset only classified two classes: [27], [28], [29] classified mental subtraction with both feet motor imagery, and [29] classified right-hand and both feet motor imagery.

For a more extensive comparison with the other studies in literature, we have put together Table 9 presenting the accuracy results of similar types of classifications where the majority of the studies were based on right hand vs foot and used different datasets and filtering methods. The majority of the studies have given better accuracy but the datasets that were used consisted of EEG signals of healthy subjects while ours consisted of subjects with motor disabilities which is obvious with a %57.8 accuracy of right-hand vs both feet motor imagery classification. The other study [29] where the same dataset was used was less successful than ours with a %54.0 accuracy. Although the reference study [11] and the study using the WPT method [26] yields more successful results, the time segments used were different from ours.

Table 9. The comparison of classification accuracy results is based on a similar type of classification in literature using other datasets and filtering methods.

Author	Dataset	Participating Subjects	Classification Type	Filtering Method	Acc
Lotte et al. [31]	BCI Competition III-IVa	5 healthy subjects	Right Hand vs Foot	RCSP	73.6
Zhang et al. [32]	BCI Competition III-IVa	5 healthy subjects	Right Hand vs Foot	Z-score tested LDA	79.7
Alomari et al. [33]	PhysioNet EEG Dataset	109 healthy subjects	Fist vs Foot	0.5-50Hz Bandpass Filter	89.1
Kevric et al. [34]	BCI Competition III-IVa	5 healthy subjects	Right Hand vs Foot	MSPCA	94.5
Abdi-Sargezeh et al. [35]	BCI Competition IV-Dataset 1	7 healthy subjects	Right Hand, Left Hand, Foot (2 out of 3 classes)	AWCCR	72.5
Krishnan et al. [36]	Their Own Dataset	50 healthy subjects	Right Hand vs Foot	EEGNet with STFT	72.6
				EEGNet with STFT + VMD	85.7
Velasco et al. [37]	Their Own Dataset	20 healthy subjects	Fist vs Toe	DWT	95.0
Kardam et al. [38]	BNCI Horizon 2022 Dataset	10 healthy subjects	Right Hand vs Foot	DFT + RF	66.8
Fu et al. [39]	Their Own Dataset	8 healthy subjects	Right Hand vs Left Hand	CSP + LDA	85.4
Gu and Hua [40]	BCI Competition IIb	9 healthy subjects	Right Hand vs Left Hand	ELM + LCD + CSP	78.3
Scherer et al. [11]	Individually Adapted Imagery Dataset	9 subjects with motor disabilities	Right Hand vs Foot	CSP Bandpass	65.3
Türk et al. [26]	Individually Adapted Imagery Dataset	9 subjects with motor disabilities	Right Hand vs Foot	WPT	77.9
Samiee et al. [29]	Individually Adapted Imagery Dataset	9 subjects with motor disabilities	Right Hand vs Foot	LR with SVM	54.0
Our Study	Individually Adapted Imagery Dataset	9 subjects with motor disabilities	Right Hand vs Foot	CBAVMD	57.8

#### 4. CONCLUSION AND SUGGESTIONS

In conclusion, the purpose of this study was to provide a new adaptive approach that is based on correlation for filtering EEG signals. In line with our purpose, we have compared the classification performance results of the proposed correlation-based adaptive filtering of WD, EMD, and VMD methods, and traditional Elliptic Bandpass Filter on EEG signals which were individually adapted for subjects with severe motor disabilities. A traditional Elliptic Bandpass Filter deals with specified frequency components which are between 0.3Hz and 35Hz while adaptive filtering methods do not eliminate specific frequency components but change their effectiveness based on different criteria. In this study, we have decided the adaptivity of the used methods to be based on the correlations of the obtained signals with their sub-signals after decompositions. The results show that our methods CBAWD, CBAEMD, and CBAVMD yield more successful results for binary classification with average accuracies of 69.3%, 67.3%, and 70.4%, respectively than the Elliptic Bandpass Filter which has 66.2% average accuracy. As it is seen, CBAVMD is the most efficient method to filter EEG signals. On the other hand, the reference study, where the dataset was initially used, has an average accuracy of 72.2% but unlike our study, the cut-off frequencies were 8Hz and 30Hz and the classifier used was LDA. Also, the length of the time segments used in our study and the other studies differ from each other, causing the resulting differences in the filtering performances. Thus, it can be summarized that with the same preprocessing, feature extraction, classification methods, and time segments, CBAVMD gives us optimally clean EEG signals without losing meaningful information. It can be clearly stated that correlation-based adaptivity is effective for EEG filtering, even if the noise is unknown. Also, the methods can give better results overall if they are applied to EEG signals belonging to healthy individuals.

This study has several limitations that should be acknowledged. First, although classification performance is reported using mean accuracy and standard deviation across subjects, no inferential statistical tests (e.g., Friedman or repeated-measures ANOVA) were conducted to assess the statistical significance of differences between filtering methods. The evaluation was intentionally restricted to classification outcomes, as the underlying noise structure of EEG signals is unknown and subject-specific, making direct statistical comparison of filtering effects nontrivial.

For future studies, the performances of the given adaptive filtering methods can be tested on different EEG signals obtained from subjects who are healthy or have different neurological health problems. Also, the paradigms of the experiments can be different while recording EEG signals to show how the filtering effects change. Finally, classification with deep learning algorithms can also show the performances of these filtering methods from another perspective.

### **Conflict of Interest Statement**

There is no conflict of interest between the authors.

### **Statement of Research and Publication Ethics**

The authors declare that this study complies with Research and Publication Ethics.

### **Artificial Intelligence (AI) Contribution Statement**

This manuscript was entirely written, edited, analyzed, and prepared without the assistance of any artificial intelligence (AI) tools. All content, including text, data analysis, and figures, was solely generated by the authors.

### **Contributions of the Authors**

The adaptive filtering methods were developed and applied by E. Kaya. Feature extraction was performed by İ. Saritaş. All authors contributed to the analysis, conceptualization, and writing of the manuscript.

### **Data Availability**

The “Individual Imagery” dataset available from the BNCI-Horizon 2020 project homepage (<http://bnci-horizon-2020.eu/database/data-sets>) was used in this study. Also, the reference of the dataset is “R. Schere, J. Faller, E. V.C. Friedrich, E. Opisso, U. Costa, A. Kübler, G. R. Müller-Putz, 2015. Individually adapted imagery improves brain-computer interface performance in end-users with disability, PloS one, 10(5), e0123727. <https://doi.org/10.1371/journal.pone.0123727>”.

### **Code Availability**

Codes of adaptive filtering methods are not available.

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