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Flexible analytic wavelet transform in a EEG based brain computer Interface Paradigm: a study in end users with motor disabilities

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Abstract: Motor imagery electroencephalogram based brain computer interface systems can help people with disabilities to communicate with an external device and to realize rehabilitation therapies. The paper proposes flexible analytic wavelet transform (FAWT) as feature extraction method. The method was tested on a dataset that contains EEG signals acquired from subjects with motor disabilities. Classifiers linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), k nearest neighbors(kNN), Mahalanobis distance (MD) and support vector machine (SVM) were utilized to classsify the extracted features of right hand motor imagery and feet motor imagery (FEET). The best performance was given by QDA classifier with a classification rate of 97 %, sensitivity 99.65%, specificity 98.47%, kappa coefficient 0.97 and F1 score 0.98. The proposed method shows through the obtained results that can be used and easy to implement for assisting rehabitation on real time BCI systems.

Keywords: EEG; brain computer interface; motor imagery; flexible analytic wavelet transform; classifiers

1. Introduction

A Brain-Computer Interface (BCI) system enables individuals with disabilities to interact with the external environment. Communication and control commands are sent through brain signals. The ability to communicate without using conventional neuromuscular pathways brings hope to people suffering from various motor disabilities, including people with amyotrophic lateral sclerosis, spinal cord injuries, stroke and other neuromuscular diseases or injuries. Such interfaces are also particularly useful for people suffering from locked-in syndrome who are cognitively intact. Restoring communication skills to these people would significantly improve their quality of life, as well as that of their caregivers, increase independence, reduce social isolation and potentially reduce the cost of care [1].

BCIs have two major roles in rehabilitation: replacement and restauration of neurologic function. BCI systems replace lost neurologic function, enabling users to interact and control various environments and activities, including computer-based tasks, mobitity devices, neuroprosthetic devices and orthoses [2]. BCIs can be used alongside rehabilitative therapies to restore normal central nervous system function by inducing activity-dependent brain plasticity and synchronizing brain activity with actual movements and sensations [3-5].

When electrodes are applied to the scalp in order to record brain electrical activity method is known as electroencephalography (EEG). Using this method it possible to quantify and examine the electrical impulses produced by the brain. These signals provide important insights into how the brain functions, including the detection of different neurological conditions and the investigation of cognitive functions like memory, perception, and attention. Because it is safe and noninvasive, electroencephalography has become a common method for studying the electrical activity of the human brain [6].

When a limb is moved or even a single muscle is contracted changes appear in the brain. Sensorimotor rhythms (SMR) are oscillations produced in the brain's motor regions as a result of preparation for the movement or visualizing movement, sometimes referred to as motor imagery (MI). Event-related synchronization (ERS) and event-related desynchronization (ERD) are the terms used to describe the amplitude decrease or amplitude increase a specific EEG frequency band. The Alpha and Beta brain rhythms are the most important frequency ranges for motor imagery. Activity invoked by the left and right hand MI is generated from the C3 and C4 areas of the brain, respectively, whereas the foot movement imagery is originated from Cz [1].

Feature extraction methods like blind source separation, empirical mode decomposition, high-order spectral analysis have been applied in order to detect and extract relevant features from EEG signals [6].

A flexible analytic wavelet transform (FAWT) based method was tested on a dataset containing EEG signals acquired from pacients with motor disabilities in different sessions (session 1 and session 2). The purpose of this research is to test two class (right-hand motor imagery (RH) and feet motor imagery (FEET)) MI-EEG classification models for improving the classification rates.

The research paper is structured as follows: Section 1 belongs to introduction in brain computer interface related to EEG and motor imagery, in Section 2 is described the EEG dataset and the feature extraction and classification methods. The results obtained and the discussions are stated in Section 3, respectively Section 4. Section 5 belogs to the conclusions.

2. Materials and Methods

2.1. Dataset BNCI 2015-004 Motor Imagery

EEG data were collected from nine participants (seven women aged between 20 and 57, and two men aged 38 and 42) with disabilities (spinal cord injuries and stroke) over two separate days, with at least five days between sessions within a two-week period. The participants had no prior BCI training before participating at this study. They followed an experimental paradigm guided by cues and performed five distinct mental imagery tasks: mental word association (condition WORD), mental subtraction (SUB), spatial navigation (NAV), right-hand motor imagery (HAND), and feet motor imagery (FEET). Details about the participants and the number of trials with artifacts excluded from the analysis are summarized in [7].

Participants were seated approximately 0.7 meters in front of a 17-inch monitor. Before the start of each experiment, they received instructions regarding the tasks. Each session for a participant consisted of 8 rounds, resulting in 40 trials per task per day. A single experimental trial consisted of 25 cues (5 for each mental task), which were presented in random order. Participants were asked to continuously perform the specified mental imagery task for 7 seconds.

The total duration of a single mental imagery trial was 10 seconds. The first 3 seconds were for adjustment, during which participants minimized eye movements while focusing on a fixation cross at the center of the screen. At t=3s, an auditory signal (beep) indicated the start of the experiment, and a visual cue corresponding to one of the five mental tasks appeared on the screen. The cue remained visible from t=3s to t=4.5s after which it disappeared, and the fixation cross reappeared. The trial ended at t=10s with another auditory signal. A blank screen was displayed for 2.5–3.5 seconds between trials (inter-trial interval), during which participants could move or blink freely. Each experiment began and ended with a blank screen lasting 4 seconds.

EEG signals were recorded using 30 electrodes placed on the scalp according to the international 10-20 system. Electrode positions included channels AFz, F7, F3, Fz, F4, F8, FC3, FCz, FC4, T3, C3, Cz, C4, T4, CP3, CPz, CP4, P7, P5, P3, P1, Pz, P2, P4, P6, P8, PO3, PO4, O1, and O2. Reference and ground electrodes were placed on the left and right mastoids, respectively. The g.tec GAMMAsys system with active g.LA-DYbird electrodes and two g.USBamp bio-signal amplifiers (Guger Technologies, Graz, Austria) were used for recording. Recorded EEG signals were reviewed by an expert, and trials contaminated by muscle or eye movement artifacts were excluded from further analysis. Additionally, noisy or artifact-contaminated channels were excluded across both sessions to maintain consistency in information across days.

The EEG signal was further filtered using a bandpass filter of 0.5–100 Hz (with a 50 Hz notch filter) and sampled at a rate of 256 Hz.

2.2. FAWT applied to EEG signals

Wavelet Transform (WT) is considered as one of the powerful statistical tools used for non-stationary signals [8].

Various WT approaches including discrete wavelet transform (DWT), dual-tree complex wavelet transform (DTCWT), tunable-Q wavelet transform (TQWT) have been applied for MI-EEG classification.

The flexible analytic wavelet transform (FAWT) presents significant advantages in the analysis of oscillatory signals, particularly for biomedical signals like electroencephalogram (EEG). In FAWT, the quality-factor (QF), dilation factor and redundancy parameters can be modified flexibly. It also allows users to analyse EEG signals with adjustable parameters p, q, r, s and β. The p and q are the up and down sampling factor for lowpass channel respectively, r and s are the up and down samplingfactor for high pass channel respectively. β is a positive constant that weighs the QF [9].

The original EEG signal is decomposed into Jth level using iterative filter bank. Each level comprises of two high-pass filters (the two high pass filters manages the positive and negative frequencies respectively) and one low-pass filter. The low-pass filter [10]can be defined as:

$$H(\omega) = \begin{cases} \sqrt{pq}, |\omega| < \omega_p \\ \sqrt{pq}\theta\left[(w - w_p)/(w_s - w_p)\right], w_p \le w \le w_s \\ \sqrt{pq}\theta\left[(\pi - w + w_p)/(w_s - w_p)\right], -w_s \le w \le -w_p \\ 0, |w| > w_s \end{cases} \tag{1}$$

The high-pas filter is defined[10] as:

$$G(w) = \begin{cases} \sqrt{2rs\theta}[(\pi - w - w_0)/(w_1 - w_0)], \omega_0 \le w \le w_1 \\ \sqrt{2rs}, w_1 < w < w_2 \\ \sqrt{2rs\theta}[(w - w_2)/(w_3 - w_2)], w_2 \le w \le w_3 \\ 0, w \in [0, w_0) \cup (w_3, 2\pi] \end{cases} \tag{2}$$

The parameters from equations (1) and (2) are expressed as:

$$w_p = \frac{\left((1-\beta)\pi + \varepsilon\right)}{p}, w_s = \frac{\pi}{q}, w_0 = \frac{\left((1-\beta)\pi + \varepsilon\right)}{r}, w_1 = \frac{(p\pi)}{(qr)}, w_2 = \frac{(\pi - \varepsilon)}{r}, w_3 = \\ = \frac{(\pi + \varepsilon)}{r}, \varepsilon \le \frac{\pi(p - q + \beta q)}{(p+q)}, \theta(x) = \\ = \frac{[2 - \cos(w)]^{\frac{1}{2}}[1 + \cos(w)]}{2}, (w \in [0, \pi])$$

2.3. Feature Extraction and Classification

In this research were implemented different types of classification methods: linear classifiers, linear Bayesian classifiers and nearest neighbor classifiers in order to improve the classification rates.

Linear discriminant analysis (LDA) projects the data into a new space by minimizing the spread within a class and maximizing the spread between classes. The linear classifier assumes that the data distribution is normal and the covariance matrix is equal for both classes (RH/FEET) [8].

The quadratic discriminant analysis (QDA) has been successfully applied in BCI paradigms based on motor imagery and for implementation, Bayes' rule is used to determine the probability of events and objects belonging to a certain group.

Nearest neighbor classifiers are nonlinear discriminant classifiers. They are based on assigning a feature vector to a class based on its nearest neighbor. This neighbor can be a feature vector from the training set as in the case of the "k nearest neighbors"(kNN) classifier or a prototype class as in the case of the Mahalanobis distance (MD) [11].

The Mahalanobis distance [11] is simple and robust and presents a prototype for each mental task calculated as the average of that class (RH or FEET in our research) using the data from the training period. The classifier's decision for the current sample from the testing set is the class with the closest prototype calculated based on the Mahalanobis distance.

The support vector machine (SVM) algorithm is based on decision planes that defines certain boundaries. A decision plane is a plane that separates a set of objects from different classes. With a suitable nonlinear mapping, data from different classes can be separated by a hyperplane. SVM searches the hyperplane using support vectors (the training sets) and the separation area (defined by the support vectors) [8].

The data were classified using LDA, QDA, MD, kNN and SVM classifiers. A tenfold cross-validation procedure was used to determine the performance of the classifiers.

The classification rate is the ratio between the number of correctly classified samples and the total number of samples:

$$Classification\ rate = \frac{TP+TN}{TP+TN+FP+FN} * 100 \quad (3)$$

Sensitivity or recall is defined as the ratio between the number of correctly detected samples and the actual number of samples that meet the selection criterion.

$$Sensitivity = \frac{TP}{TP+FN} * 100 \quad (4)$$

Specificity represents the ratio between the number of correctly detected negative samples and the actual number of samples that do not meet the selection criterion.

$$Specificity = \frac{TN}{TN+FP} * 100 \quad (5)$$

Precision is the proportion of positive class predictions that actually belong to the class in question.

$$Precision = \frac{TP}{TP+FP} * 100 \quad (6)$$

The F1 score combines precision and recall to represent a model's total classwise accuracy [12].

$$F1\ score = \frac{2*TP}{2*TP+FP+FN} \quad (7)$$

Cohen's Kappa coefficient examines for the assessment of agreement beyond chance, considering both the observed agreement and the expected agreement by chance [13].

$$Kappa = \frac{2*(TP*TP-FN*FP)}{(TN+FN)*(FN+TP)+(FP+TP)*(TN+FP)} \quad (8)$$

The confusion matrix is defined by [14]:

- true positive (TP) represents the number of instances that have been correctly predicted as positive from the positive class;
- true negative (TN) is defined as the number of instances that have been correctly predicted as negative from the negative class;
- false positive (FP) is the number of instances that have been incorrectly predicted as positive from the negative class;
- false negative (FN) is the number of instances that have been incorrectly predicted as negative from the positive class.

Totaling up TP,FP, FN and TN the model will provide the total number of predictions and the confusion matrix.

In Figure 1 is presented the flow sheet for the FAWT based method, the feature selection, feature extraction and classification.

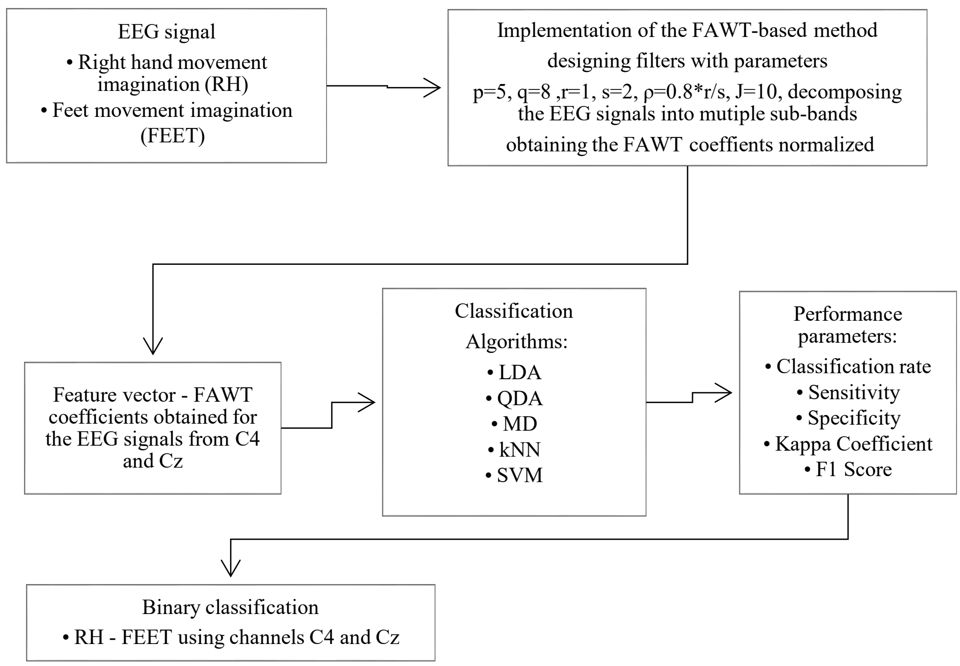

Figure 1. The flow diagram of the FAWT based method

3. Results

The proposed framework was implemented in Matlab 2021b. The EEG signals corresponding to right hand motor imagery (RH) and feet motor imagery (FEET) from channels C3, CP3, P3, PZ, CZ, P4, CP4 and C4 were extracted according to session 1 and session 2.

For the implementation of the FAWT-based method were used the following parameters: $p = 5, q = 8, r = 1, s = 2, \rho = 0.8\, r/s, J = 10$. By applying the designed filters, EEG signal was divided in sub-bands, the coefficients of the FAWT transform for the 8 channels were obtained and after that they were normalized.

Only the EEG signals corresponding to channels C4 and Cz were used for feature vector because of their location in the motor area [15].

The data were classified using LDA, QDA, MD, kNN and SVM classifiers. A tenfold cross-validation procedure was used to determine the performance of the classifiers.

First are presented the results obtained after testing the proposed method on signals acquired in session 1 and after that for session 2.

In Figure 2, Figure 3 and Figure 4 are displayed the classification rates (%), sensitivities (%) and specificities (%) obtained with classifiers LDA, QDA, MD, kNN and

SVM for RH-FEET, session 1. The highest classification rates above 90% were achieved with classifiers LDA and QDA. Sensitivities were in the range 55% - 100% and specificities in the range 78% - 98%.

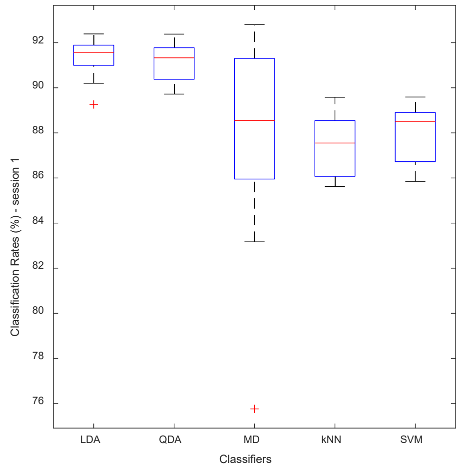

Figure 2. Classification Rates (%) obtained for RH-FEET- session 1

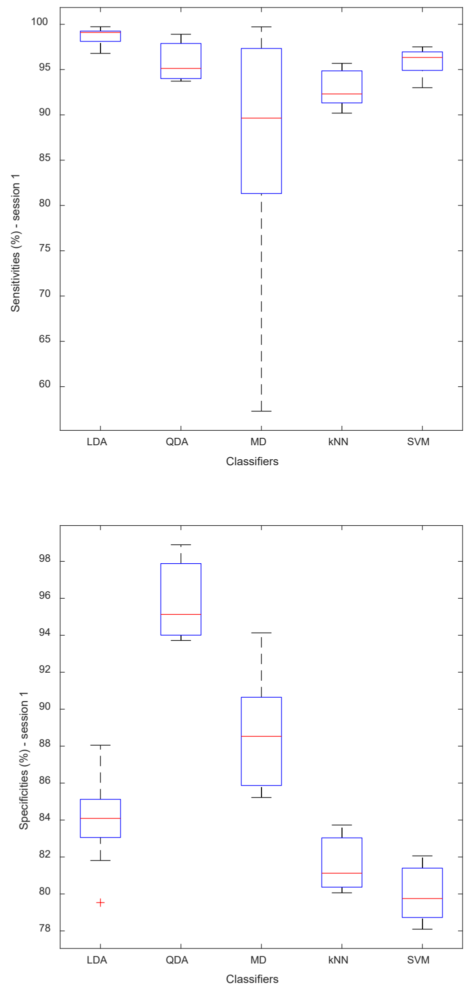

Figure 3. Sensitivities (%) and Specificities (%) attained for RH-FEET- session 1

Kappa Coefficient and F1 score evaluated the performances of the classifiers for session 1 (Figure 5).

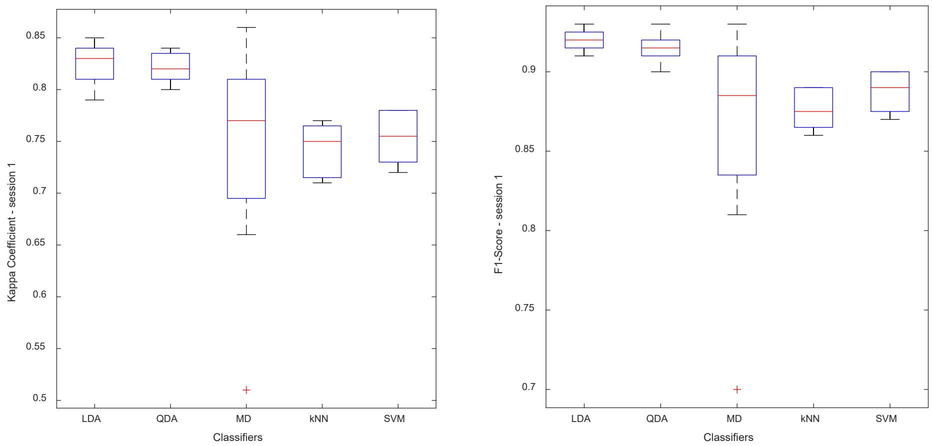

Figure 4 Performances of the classifiers based on Kappa Coefficient and F1 score – session 1

The classification rates (%), sensitivities (%) and specificities (%) attained for RH-FEET in session 2 using LDA, QDA, MD, kNN and SVM are shown in Figure 5 and Figure 6. In Figure 7 are shown the results obtained after applying Kappa Coefficient and F1 score in session 2.

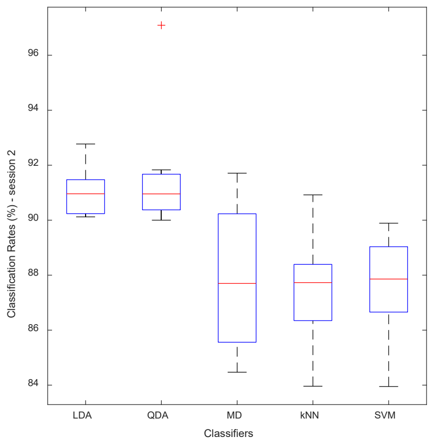

Figure 5. Classification rates (%) achieved for RH-FEET- session 2

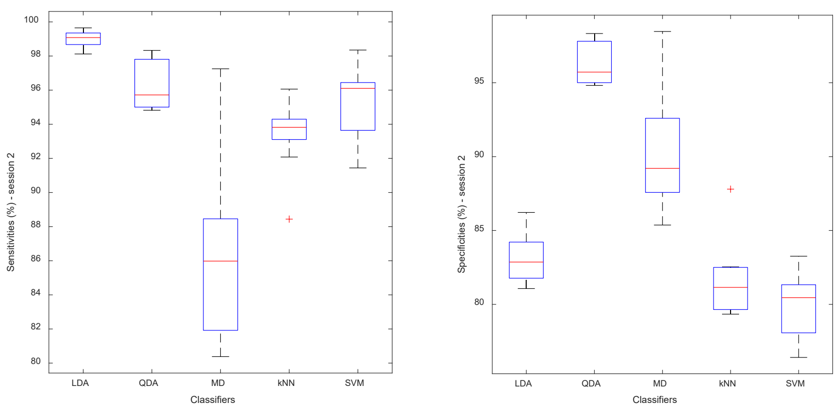

Figure 6. Sensitivities (%) and specificities (%) attained for RH-FEET- session 2

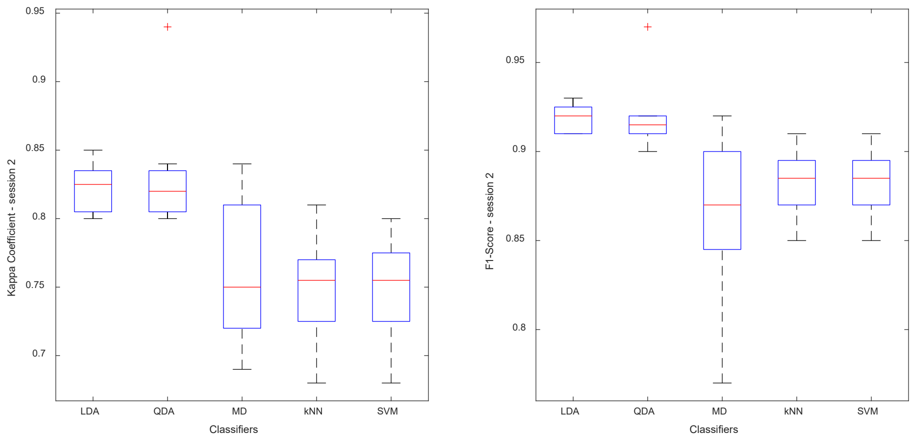

Figure 7. Performances of the classifiers based on Kappa Coefficient and F1 score – session 2

Table 1 summarizes some works where the dataset was used, feature extraction methods and classification methods.

Table 1. Works that used the dataset BNCI 2015-004 Motor Imagery

Work	Classes	Method	Number of channels	Classifier
[16]	5	quadratic time-frequency distribution	30	deep belief network-driven isolation forest
[17]	5	metoda meta-transfer-learning	30	symmetric positive define matrices and convolutional neural networks
[18]	5	entropy	8	neural network entropy algorithm and Friedman test

5. Discussion

The purpose of this research was to achieve improved classification rates for right hand motor imagery and feet motor imagery by using different types of classifiers. the values of the FAWT parameters were chosen from articles and adjusted for the current dataset. In most or the articles Jth level of decomposing in sub-bands was below 10. Parameter J=10 was chosen because of data dimensions. Only the information contained in EEG signlas from channels C4 (corresponding to right hand motor area) and Cz (corresponding to feet motor area) were further utilized. The EEG signals from session 1 and session 2 were examined.

According to Figure 2 classification rates obtained in session 1 were above 90% for classifiers LDA and QDA and above 88% for classifiers MD, kNN and SVM. Two outliners were identified for classifier LDA – value 89% and for classifier MD – value 75%. Overall the classification rates were in the range 80% - 93%. The highest sensitivities were achieved with LDA classifier, while the highest specificities were obtained for QDA classifier. Kappa coefficient was in the range 0.5 – 0.85 and F1 score was in the range 0.7 – 0.9 (session 1).

In session 2, classification rates were higher than 90% for classifiers LDA and QDA and classification rates above 86% were attained with MD, kNN and SVM (Figure 6). Sensitivities and specificities had values higher than 78%. The highest values for Kappa coefficient and F1 score were obtained for classifiers LDA and QDA in session 2.

The EEG data were collected from nine participants with disabilities with no prior BCI training and each participant completed two sessions on separate days, spaced at least five days apart. Although participants had no BCI training, the classification rates for all sessions were in the range 86% - 90%. Subject J obtained a classification rate of 97.09% in session 2 for classifier QDA (the outliner from Figure 5).

The results obtained in session 2 were 1 - 2% higher that the results achieved in session 1.

6. Conclusions

The research investigates the usefulness of FAWT-based features for classifying RH and FEET motor imagery tasks based on EEG signals achieved from patients with motor disabilities. In order to obtain improved classification accuracies multiple classifiers (LDA, QDA, MD, kNN and SVM) were tested.

The classification rates obtained for all classifiers and all the subjects were above 80%.

FAWT based method is simple to implement with few computational requirements and could be a potential tool for MI based BCI real time paradigms.

Future work include verifying the FAWT based method on larger datasets with more subjects and applying a multi-class classifier for classifying imagery tasks like: right hand motor imagery, left hand motor imagery, feet motor imagery and tongue motor imagery.

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