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Wave Atom Transform Based Two Class Motor Imagery Classification

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***Abstract*—**Electroencephalography (EEG) investigations of the brain computer interfaces are based on the electrical signals resulting from neural activities in the brain. In this paper, it is offered a method for classifying motor imagery EEG signals. The suggested method classifies EEG signals into two classes using the wave atom transform, and the transform coefficients are assessed, creating the feature set. Classification is done with SVM and k-NN algorithms with and without feature selection. For feature selection t-test approaches are utilized. A test of the approach is performed on the BCI competition III dataset IIIa.

***Keywords*—**Motor imagery, EEG, wave atom transform, SVM, k-NN, t-test.

I. Introduction

EEG signals originating from different brain locations are used in the development of brain computer interface (BCI) systems to generate command signals to control external devices, and EEG signals are classified according to the corresponding mental activity. Some of these classifications include processes in which organ movements such as right-left hand, right-left foot, which are defined as motor imageries, are investigated [1]. The main operations in research on signals are machine learning methods such as feature extraction and classification [2]-[4]. Much of the research on the classification of motor imagery EEG signals focuses on proposing new methods.

Hsu et al. [5] propose using time-series prediction based on the adaptive neuro-fuzzy inference system (ANFIS). The ANFIS time-series prediction is combined with multiresolution fractal feature vectors (MFFVs) for feature extraction in motor imagery classification. Finally, classification is performed using a simple linear classifier known as linear discriminant analysis (LDA). Jin et al. [6] utilize Pearson's correlation coefficient to manually choose the channel with the most connected information, then extracted usable features using the regularized common spatial pattern (RCSP) and a support vector machine (SVM) as a classifier. In order to classify ERPs, Zhang et al. [7] use a spatial-temporal discriminant analysis (STDA) for brain-computer interface system. By cooperatively creating two projection matrices from geographical and temporal dimensions, the STDA approach tries to optimize discriminant information between target and nontarget classes. The proposed STDA approach is tested using dataset II from the BCI Competition III and data from their own investigations. Sun et al. [8] employ the following method: data is denoised using the wavelet algorithm, and channels corresponding to the supplementary motor area are chosen. The data is then split into alpha and beta frequency components. In this stage, the welch power spectral density (WPSD) of various beats is determined and identified using SVM. Ma et al. [9] offer a processing method that reduces the impact of individual differences on classification. The discrete wavelet transform is used to compute the energy in each sub-band to find the best frequency band. For feature extraction and classification, a convolutional neural network based on power spectral density and a visual geometric group network is used. The method is demonstrated in a test of the BCI competition IV dataset IIa. Pattnaik et al. [10] used the discrete wavelet transform (DWT) to extract characteristics from EEG motor activity, and then used an artificial neural network (ANN) to categorize the signal to distinguish between left- and right-hand imagery movements. Two sets of feature vectors from beta rhythm are fed into the feed-forward neural network classifier. Three feature vectors, such as mean, standard deviation, and peak power, are discovered to be employed as inputs.

The current research proposes a method for classifying motor imagery EEG signals using feature extraction based on multi-scale analysis. The wave-atom transform is used to distinguished EEG data into sub bands, and feature vectors (F1 and F2) are calculated across the transform coefficients to generate feature data. By lowering the size of the feature data obtained through the transformation, feature selection is conducted to boost the distinguishability of the features and improve classification performance. t-test algorithms are the favored strategies at this stage. SVM and k-NN algorithms are used to compare the classification of left- and right-hand motor imagery EEG data.

II. Material and Method

A. Dataset

The motor imagery EEG data provided BCI competition III [11] are used in this investigation. Competitions for BCI technology are held to ensure that various data analysis methodologies are evaluated and to promote BCI technology development. Throughout each tournament, different data sets are made available to everyone on the internet, and each data set is a record of brain signals prepared in experienced and leading BCI facilities. These records are made up of the labeled data partition (the "training set") and the unlabeled data partition (the "test set"). It includes data from three separate

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volunteers on the right hand, left hand, foot, and tongue. There are also 60 channels and 60 trials in each class [12]. A 64-channel EEG amplifier is used to record EEG signals, with the left mastoid serving as the reference and the right mastoid serving as the ground. The channel placements are shown in Figure 1.

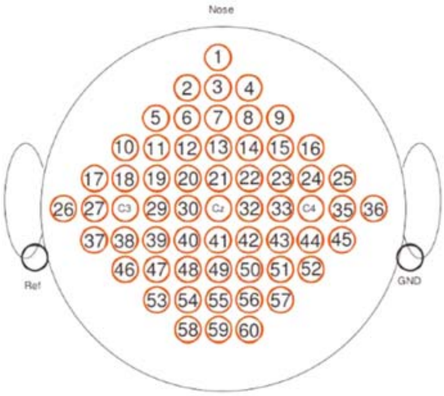

Fig. 1 Channel locations for BCI competition III Data Set IIIa [12]

While creating the dataset, it is carried out experiment consists of several runs (at least 6) with 40 trials each. After the trial starts, the first two seconds are quiet; then, at t=2s, an acoustic stimulus indicates the start of the trial, and a cross "+" is displayed; then, from t=3s, an arrow to the left, right, up, or down is displayed for 1s; at the same time, the subject is asked to imagine a left hand, right hand, tongue, or foot movement, until the cross disappears at t=7s [12]. It is depicted in Figure 2.

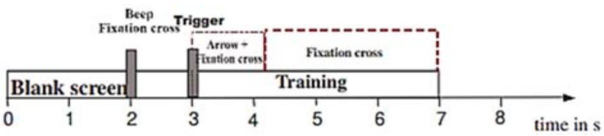

Fig. 2 Timeline for the paradigm [12]

B. Wave Atom Transform

Demanet presented the Wave Atom Transform [13] in 2007 as a non-adaptive structure of compact backed wave packets. The transformation, which follows the parabolic scaling law, can be thought as a 2D wavelet packet variation. Wave atom transforms have two key characteristics. The first is the ability to adapt to arbitrary patterns in local directions. The capacity to sparsely express anisotropic patterns aligned with the axes is the second. Compared to other wave packets, wave atoms provide more precise frequency localization.

Wave atoms are made up of the tensor products of 1D wave packets. Wave packets in one dimension can be represented as $\psi^{j}_{m,n}(x)$ for $j, m \geq 0$. To create two-dimensional wave atoms $\varphi_{\mu}(x_1, x_2)$, ortho-normal basis functions is used with subscript $\mu = (j, m, n)$. The basis function is formed as

$$\varphi^{+}_{\mu}(x_1, x_2) = \psi^{j}_{m_1}(x_1 - 2^{-j}n_1)\psi^{j}_{m_2}(x_2 - 2^{-j}n_2) \quad (1)$$

From the "Hilbert-transformed" wavelet packets, a dual orthonormal basis can be defined as

$$\varphi^{-}_{\mu}(x_1, x_2) = H\psi^{j}_{m_1}(x_1 - 2^{-j}n_1)H\psi^{j}_{m_2}(x_2 - 2^{-j}n_2) \quad (2)$$

Finally, the ortho-normal basis is combined to generate the wave atom tight frame [13].

$$\varphi^{1}_{\mu} = \frac{\varphi^{+}_{\mu}+\varphi^{-}_{\mu}}{2}, \varphi^{2}_{\mu} = \frac{\varphi^{+}_{\mu}-\varphi^{-}_{\mu}}{2} \quad (3)$$

C. Proposed Method

The motor imagery EEG dataset used in this study came from the BCI competition III dataset IIIa. The data set has four types of motor imagery signals (right hand (rh), left hand (lh), foot, and tongue) contributed by three people. This study, however, concentrated on classification of rh and lh movements. So, the first operation is to remove the EEG data from the data set, comprising the rh and lh motor imagery, and a new data set is created. This new data set containing 60 channel signal information was used to build another data set for three channels (C3, C4, and Cz), which is also preferred in the literature [14], [15], and method validation is carried out with this data. As the last step in dataset editing, the signal recordings from the C3, C4, and Cz electrodes are divided into two frequency bands, and the wave atom transform is applied to the data in each frequency range. The feature data is then created by calculating mean (mn), standard deviation (sd), entropy (en), median (md), maximum value (mx), kurtosis (kr), skewness (sk), and log-variance (lv) from the transformation coefficients. Classification is performed in three ways: 1) by submitting each generated feature vector (F1 and F2) to the classifiers separately for each frequency band, 2) by combining each generated feature vector (F1+F2), 3) by performing feature selection on the whole feature dataset using the t-test statistic and presenting the ranked features to the classifiers for ten ranges of values. SVM and k-NN (k-value starts with 3 and accepts 30 different values) algorithms are used in the classification process, respectively. The method's flow chart is depicted in Figure 3.

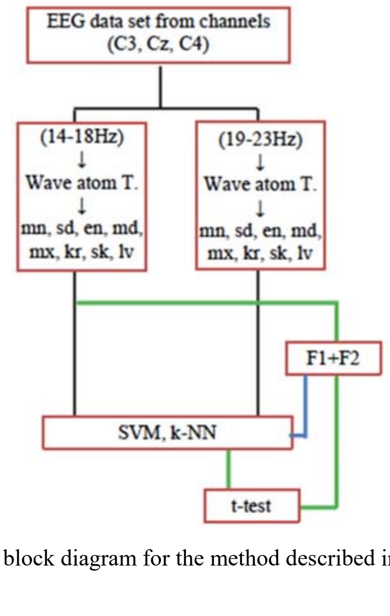

Fig. 3 The block diagram for the method described in this paper

III. Findings

After the selected channel signals are transferred to the frequency bands using the wave atom transform, the mn, sd, en, md, mx, kr, sk and lv values are calculated over the transform coefficients, and the feature matrix is generated. The classification procedure is divided into three steps. Table I shows the classification results from the first two phases for each subject. The third phase classification results of the feature data categorized by the t-test method are given in Table II. In the table, there are classification results of ten feature clusters determined by t-test for each subject.

TABLE I
THE CLASSIFICATION RESULTS FROM THE FIRST TWO PHASES FOR EACH SUBJECT

Feature set	Subject	SVM	k-NN	k
F1	Subject 1	56,67	54,44	9
	Subject 2	55	58,33	3
	Subject 3	61,67	58,33	27
F2	Subject 1	58,89	57,78	5
	Subject 2	63,33	66,67	17
	Subject 3	60	58,33	13
F1+F2	Subject 1	58,89	54,44	3
	Subject 2	66,67	68,33	9
	Subject 3	60	61,67	19

Considering the three classification approaches, the best classification performance belongs to the SVM classifier with the feature data of subject three categorized by the t-test method. F1 feature data has lower classification accuracy when assessed individually. Classification success rates improve in both classifiers when F1 and F2 feature data are merged. In both classifiers, the best classification results are obtained from the data of subject 2 if an evaluation is conducted per-subject. When the t-test method is used, a similar issue occurs. The t-test improves classification success rates for the three subjects, with data from subjects 2 yielding the best result. Figure 4 and 5 depicts the changes in classification over subjects using the t-test approach for SVM and k-NN classifiers, respectively.

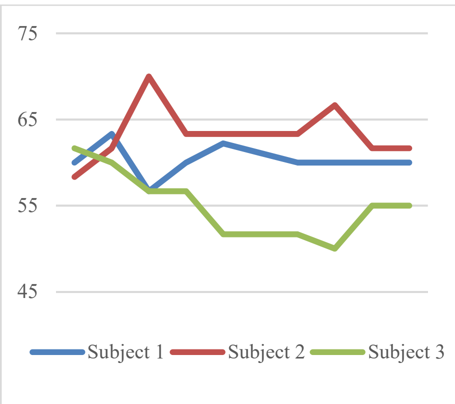

Fig. 4 The changes in classification over subjects using the t-test approach for SVM

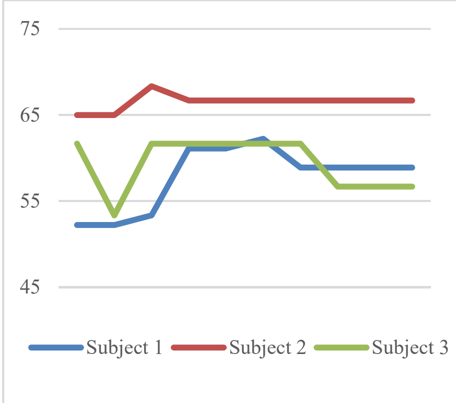

Fig. 5 The changes in classification over subjects using the t-test approach for k-NN

TABLE II
THE RESULTS OF THIRD PHASE CLASSIFICATION VIA THE FEATURE DATA CATEGORIZED BY THE T-TEST METHOD

	SVM	k-NN	k
Subject 1	60	52,22	3
	63,33	52,22	3
	56,67	53,33	5
	60	61,11	17
	62,22	61,11	17
	61,11	62,22	11
	60	58,89	5
	60	58,89	5
	60	58,89	5
	60	58,89	5
Subject 2	58,33	65	15
	61,67	65	15
	70	68,33	23
	63,33	66,67	33
	63,33	66,67	33
	63,33	66,67	33
	63,33	66,67	33
	66,67	66,67	33
	61,67	66,67	33
	61,67	66,67	33
Subject 3	61,67	61,67	21
	60	53,33	3
	56,67	61,67	39
	56,67	61,67	39
	51,67	61,67	39
	51,67	61,67	39
	51,67	61,67	39
	50	56,67	11
	55	56,67	11
	55	56,67	11

IV. Conclusion

In this study, an alternative method is presented to investigate the success of wave atom transform in the classification of motor imagery EEG signals containing right- and left-hand movement information. The three-channel EEG data is split into two frequency bands, and the signals are decomposed using the wave atom transform. The feature data sets are formed by using the transformation coefficients and evaluating them with two different classifiers. Overall, three classification phases are used, with the combination of t-test and SVM employing features from subject 2 yielding the best results.

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