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Curvelet Transform Based Two Class Motor Imagery Classification

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***Abstract*—**One of the important parts of the brain-computer interface (BCI) studies is the classification of motor imagery (MI) obtained by electroencephalography (EEG). The major goal is to provide non-muscular communication and control via assistive technologies to people with severe motor disorders so that they can communicate with the outside world. In this study, an EEG signal classification approach based on multiscale and multi-resolution transform method is presented. The proposed approach is used to decompose the EEG signal containing motor image information (right- and left-hand movement imagery). The decomposition process is performed using curvelet transform which is a multiscale and multiresolution analysis method, and the transform output was evaluated as feature data. The obtained feature set is subjected to feature selection process to obtain the most effective ones using t-test methods. SVM and k-NN algorithms are assigned for classification.

***Keywords*—**Motor imagery, EEG, curvelet transform, SVM, k-NN.

I. INTRODUCTION

STARTING from the 17th week of prenatal development and emerging because of the neural activity of the brain, electrical signals represent the thinking of the mind and the state of the body. Electroencephalogram (EEG) is a fast and low-cost tool widely used in the literature that captures the electrical activities of the brain [1]. EEG signals consist of rhythmic components called brain waves, and each rhythmic component carries specific information in different frequency ranges [2], [3]. Brain-computer interface studies are carried out over these signals, and an alternative communication is tried to be established between the brain and the outside world [4]. The research aims to not only assist disabled people, but also to develop new entertainment and control ways [5].

Many studies are carried out for the classification of EEG signals. Xu et al. [6] presents a method using a deep transfer convolutional neural network based on the VGG-16 structure for the classification of EEG signals containing motor imagery. The proposed method is performed using dataset 2b from BCI competition IV. The method results are compared over the support vector machine (SVM), artificial neural network (ANN) and standard CNN methods. Mousavi et al. [7] introduce a method by blending the common spatial pattern (CSP) method, which is widely used in BCI studies, and the wavelet method. In this method, the signals are subjected to the hamming windowing process and then decomposed using wavelet packets. Two different sequences of time variables (time domain and coefficient domain series) are extracted from each packet, and these series are filtered by CSP. Right-hand (RH) and left-hand (LH) motion classification is performed using a fuzzy self-organizing feature map method. Kumar et al. [8] suggests an advanced discriminative FB-CSP method for motor image-based EEG classification. A common result is calculated over the features obtained from different frequency bands and classified after passing through a selective filter. You et al. [9] propose a new classification system for motor imagery-EEG signals based on flexible analytical wavelet transform (FAWT). The filtered motor imagery-EEG signals are first separated into their sub bands by FAWT, and time-frequency features are calculated from the sub bands. Then, principal component analysis (PCA), core principal component analysis (KPCA), locally linear placement (LLE), and Laplacian eigenmaps (LE) are used comparatively to reduce the size of the extracted features. Finally, to complete the classification of LH and RH motor imagery-EEG signals, linear discriminant analysis (LDA) is performed. On BCI competition II data set III and BCI competition III data set IIIb, the proposed approach is experimentally confirmed. For the LH and RH MI-EEG classification, Malan et al. [10] recommends a feature selection approach based on neighbor component analysis (NCA) with modified regularization parameter. The feature data is obtained using the double tree complex wavelet transform (DTCWT) and subjected to the feature selection process. It is performed classification using the SVM method. The dataset is derived from two general BCI datasets (BCI competition II data set III and BCI competition IV data set IIb).

The main purpose of this study is to extract effective features and to create a two-class MI-EG classification model. The time-frequency information in raw MI-EEG signals is captured via the curvelet transform. Calculating some features from curvelet transform coefficients, the feature set is created. The classification procedure is carried out in two ways: feeding the classifiers with individually calculated features and submitting to classifiers feature packages constructed in 10 groups after ranking the entire feature set using t-test. Classification is performed comparatively with SVM and k-NN methods.

II. MATERIALS AND METHOD

A. Data Set

The motor imagery EEG data used in this study came from BCI competition III [11]. Competitions for BCI technology are established to guarantee that diverse data analysis techniques are validated and to foster the development of BCI technology.

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Various data sets are made available to everyone on the Internet throughout each competition, and each data set is a record of brain signals prepared in experienced and leading BCI facilities. The labeled data partition (the "training set") and the unlabeled data partition make up these records (the "test set"). The suggested method was tested using data set IIIa from the BCI competition III, which contains four classes of motor imagery data. It contains information on the right hand, left hand, foot, and tongue from three different participants. In addition, each class has 60 channels and 60 trials [12]. EEG signals were recorded with a 64-channel EEG amplifier, with the left mastoid serving as the reference and the right mastoid serving as the ground. Fig. 1 depicts the channel placements.

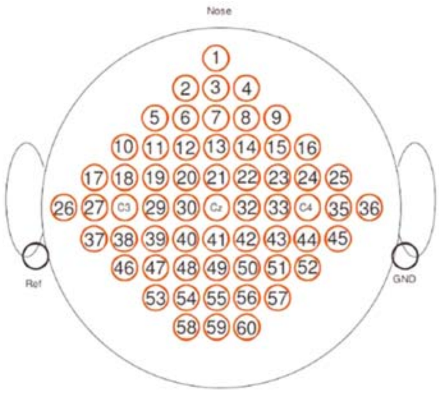

Fig. 1 Channel positions for EEG recording of data set IIIa [12]

While sitting in a comfortable chair, the individual conducted imagined right hand, left hand, foot, and tongue motions in response to the randomly provided signals. Fig. 2 depicts the processing time progression for each recording.

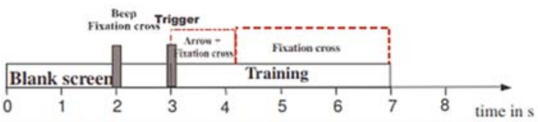

Fig. 2 Time sequence of processing for each recording step [12]

The first two seconds of each experiment in Fig. 3 are silent. A warning sound signals the start of the trial after 2 seconds, and a cross "+" displays on the screen. Then, for 1 second, an arrow pointing up, down, left, and right emerges at the 3rd second. Meanwhile, until the arrow departs from the screen (t = 7s), the participant is instructed to visualize a left hand, right hand, tongue, or foot movement in the direction of the arrow.

B. Curvelet Transform

The curvelet transform was introduced by Candès and Donoho in 1999 [13] as the first version and in 2006 [14] as the second version. The two most important features of the transform are: they represent curves inexorably and with very few coefficients and remain as coherent waveforms under the influence of the wave equation in a smooth medium. The curvelet transform contains elements with a very high degree of directional specificity. For a given function f, the curvelet transformation can be defined by an inner product as:

$$C(j,l,k) = \langle f, \phi(j,l,k) \rangle = \int f(x)\phi_{j,l,k}\, dx \tag{1}$$

where $\phi(j,l,k)$ denotes the curvilinear basis function and j,l,k denotes the scale, direction (orientation) and position parameter, respectively. The discrete curvelet transformation is defined as:

$$C^D\ (j,l,k) = \sum_{0\le x1,y1<n} f[x_1,y_1]\, \phi^D_{j,l,k}\, [x_1,y_1] \tag{2}$$

where $\phi^D_{j,l,k}\ [x_1,y_1]$ denotes the discrete curvelet waveform.

C. Method

The motor imagery EEG dataset, which is used in this study, was obtained from the BCI competition III dataset IIIa. The dataset contains four classes of motor imagery signals (LH, RH, foot, and tongue) from three subjects. However, this study focused on two classes of classification, which includes classification of RH and LH movements. For this reason, as the first operation, the EEG data containing the RH and LH motor imagery were separated from the data set, and a new data set was created. From this new data set containing 60 channel signal information, the data set for three channels (C3, C4 and Cz), which is also preferred in the literature [15], [16], is separated and the application method validation is carried out with this data. The four-frequency band information of the signal recordings from the C3, C4 and Cz electrodes are separated, and curvelet transform is applied to the signals of each frequency range. Then, the feature data is created by calculating the mean (AVG), standard deviation (STD), entropy (ENT) and log variance (LVAR) over the transformation coefficients. Following this step, classification is carried out in two ways; 1) by presenting each computed feature data to the classifiers separately, 2) by performing feature selection on the calculated feature data set based on the t-test statistic and presenting the ranked features to the classifiers for ten ranges of values. The classification process is performed using SVM and k-NN (k value starts with 3 and takes 30 different values) algorithms, comparatively. The flow chart of the method is shown in Fig. 3.

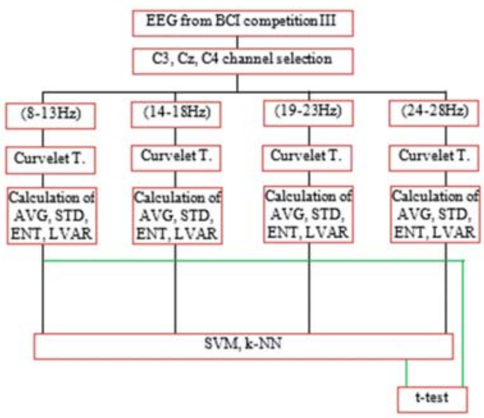

Fig. 3 The block scheme for the method presented in this paper

III. Findings

After the selected channel signals are raced to the frequency bands, curvelet transform is applied and the AVG, STD, ENT and LVAR values are calculated over the transform coefficients and the feature matrix is created. Classification was carried out in two stages. Classification for each feature value calculated from the transformation coefficients was performed on each subject, Table I. By applying the t-test to all feature data, the ranked features were classified over each subject for ten value ranges, Table II.

TABLE I
Classification Results for Each Calculated Feature Separately

		SVM	k-NN	k
Subject 1	AVG	51,11	57,77	7
	STD	75,55	67,77	33
	ENT	74,44	73,33	9
	LVAR	**77,78**	75,55	3
Subject 2	AVG	55	56,67	3
	STD	60	53,33	11
	ENT	50	60	7
	LVAR	65	60	11
Subject 3	AVG	50	63,33	3
	STD	71,67	63,33	7
	ENT	65	68,33	27
	LVAR	73,33	66,67	25

According to two different classification processes, one of the most successful results is obtained with curvelet+LVAR and SVM by using the data of subject 1 in the classification made separately for each calculated feature data. Considering all three subjects and both classifiers, it is seen that the curvelet+LVAR feature data has the most successful results. The other most successful result was obtained with the feature set of subject 1 and the SVM classifier in the classification stage obtained by applying the t-test.

IV. Conclusion

In this study, an alternative method is presented to classify motor imagery EEG signals containing right- and left-hand movement information and the success of curvelet transformation is investigated. EEG data was divided into four different frequency bands and distinguished by applying curvelet transform. The feature data was created over the transformation coefficients and evaluated comparatively by using two different classifiers. The classification success of individual features was examined, and it was observed that the curvelet+LVAR data gave the most successful results. The most successful results in both the t-test ranking and the separate feature classification processes were obtained with the data set of subject 1.

TABLE II
Classification Results Over the T-Test of All Features

	SVM	k-NN	k
Subject 1	71,11	66,66	3
	74,44	67,77	33
	74,44	68,88	33
	75,55	64,44	33
	75,56	68,88	15
	76,67	67,77	15
	67,78	75,55	19
	65,56	70	11
	72,22	70	15
	73,33	72,22	11
Subject 2	60	58,33	11
	61,66	58,33	21
	61,67	58,33	25
	60	60	39
	61,67	60	29
	61,66	56,66	35
	56,67	58,33	5
	60	56,66	5
	60	56,66	15
	55	56,66	11
Subject 3	66,67	63,33	31
	65	63,33	35
	70	66,66	7
	65	70	17
	63,33	66,67	11
	58,33	56,66	15
	55	56,67	11
	51,66	53,33	39
	51,66	53,33	39
	55	51,66	13

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