Classification of Right and Left-Hand Movement Using Multi-Resolution Analysis Method

Nebi Gedik

***Abstract*—**The aim of the brain-computer interface studies on electroencephalogram (EEG) signals containing motor imagery is to extract the effective features that will provide the highest possible classification accuracy for the detection of the desired motor movement. However, achieving this goal is difficult as the most suitable frequency band and time frame vary from subject to subject. In this study, the classification success of the two-feature data obtained from raw EEG signals and the coefficients of the multi-resolution analysis method applied to the EEG signals were analyzed comparatively. The method was applied to several EEG channels (C3, Cz and C4) signals obtained from the EEG data set belonging to the publicly available BCI competition III.

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

I. Introduction

BRAIN Computer Interface (BCI) measures brain activity by providing a natural communication and control facility with the human brain, and then attempts to make the measured activities understandable to establish a direct interaction between the brain and the computer [1], [2]. EEG-based data are widely used in BCI studies than alternatives due to its non-invasive nature, low cost, and relative simplicity [3], [4]. In the literature, some of the BCI studies carried out EEG-based data containing motor imagery information. These studies focused on how to distinguish different motor imageries, and various algorithms are proposed to achieve successful results [5]-[7].

Zhang et al. [8] use the sparse Bayesian learning method of frequency bands to classify EEG signals containing motor imagery. Feature data are generated from the set of signals obtained by applying a filter bank with multiple overlapping sub-bands to raw EEG data using a common spatial model (CSP) algorithm. Sparse Bayesian learning is used to distinguish the most effective features from the feature set. Wang et al. [9] present an approach that applies time-spatial feature extraction including multivariate linear regression (MLR) to obtain distinctive steady-state visual evoked potential (SSVEP) features. MLR is applied to reduced-size EEG training data and a label matrix that is created to find the most suitable discriminating sub-areas. Zhang et al. [10] use a method based on multi-kernel extreme learning machine (MK-ELM) to classify EEG signals containing motor imagery. The effects of two different kernel functions, Gaussian, and polynomial, on the performance of ELM are investigated. MK-ELM method is created by combining these kernels with a multi-kernel learning strategy to classify the EEG motor imagery data with higher classification accuracy. Yang et al. [11] aimed to improve the classification accuracy of multi-class EEG signals and reduce the number of EEG channels needed in the BCI system based on motor imagery data. They propose a method that searches for the most appropriate time-frequency domains to extract specific features for the subject. Baali et al. [12] use a signal-dependent orthogonal transform for feature extraction called linear predictive singular value decomposition (LP-SVD). The transformation defines the mapping as left singular vectors of the LP coefficient filter impulse response matrix, and the obtaining features are presented to a logistic tree-based model classifier. Chaudhary et al. [13] present a method based on deep convolution neural networks (DCNN) to classify motor imagery EEG signals. The proposed method first converts the EEG signals to images by applying time frequency (T-F) approaches. DCNN is applied to the obtained images. The T-F approximations are short-time-Fourier transform (STFT) and continuous wavelet transform (CWT).

In this study, the classification of EEG signals containing motor imagery is performed by including the multi-resolution analysis method. The multi-resolution analysis method is wave atom transformation. The transformation is applied to selected EEG channel signals, and coefficients of transform are obtained. Two feature data are generated from these coefficients and raw EEG signals. K nearest neighborhood (k-NN) and linear discriminant analysis (LDA) methods are used as classifiers.

II. Method

The motor imagery EEG data were obtained from the BCI competition III data set IIIa. The data set includes four classes motor imagery signals. However, this study focused on the classification of right and left-hand movements. In this direction, the data containing right and left-hand motor imagery were separated from the data set and made ready for application of the method. In practice, signals of C3, C4 and Cz channels, which are often preferred in the literature [11], are processed. Butterworth filter (5-30 Hz) was applied as the first operation to the specified signals. Then, feature extraction was performed in two ways: 1- The first feature data (F1) was created by extracting the features (mean, standard deviation, and log-variance) from the filtered EEG signals. 2- The transform coefficients were obtained by applying wave atom transform to the filtered EEG signals and the second feature data (F2) were generated by subtracting (mean, standard

N. G. is with the University of Health Sciences, Institute of Hamidiye Health Sciences, Bioengineering USA, Uskudar, Turkey (e-mail: nebi.gedik@sbu.edu.tr).

deviation, and log-variance) from the coefficients. These feature data sets were presented to the k-NN and LDA classifiers separately and combining them. The flow chart of the method is as in Fig. 1.

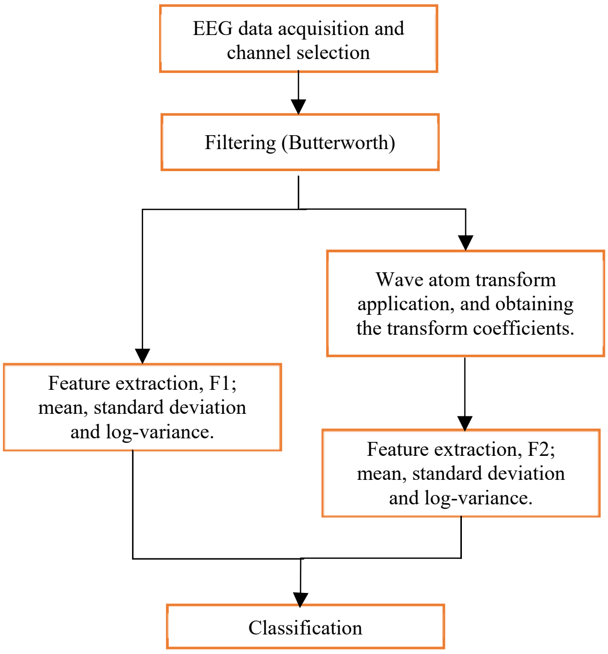

Fig. 1 Flow chart of the method

A. Wave Atom Transform

Wave atom transform [14] is a non-adaptive structure of compact backed wave packets. j scaled real-valued 1-D wave atom function is expressed as:

$$\psi^{j}_{m,n}(x) = \psi^{j}_{m}(x - 2^{-j}n) = 2^{j/2}\psi^{0}_{m}(2^{j}x - n) \quad (1)$$

where j controls the resolution scale, while the location in the frequency and time domain is controlled by m and n. F^{-1} is the inverse Fourier transform. The symmetrical double pump main wave atom function is defined as:

$$\hat{\psi}^{0}_{m}(\omega) = e^{-j\omega/2}\left[e^{j\alpha_m} g\left(\varepsilon_m\left(\omega - \pi(m+1/2)\right)\right) + e^{-j\alpha_m} g\left(\varepsilon_{m+1}\left(\omega + \pi(m+1/2)\right)\right)\right] \quad (2)$$

where $\alpha_m = \pi/2\,(m + 1/2)$, $\varepsilon_m = (-1)^m$, g is the real valued C^∞ pump function with compact support in the 2π interval [14]. On the condition of (3), an orthonormal basis is created in $L^2(\mathbb{R})$ and uniform tiling is provided in the frequency axis.

$$\sum_m \left|\hat{\psi}^{0}_{m}(\omega)\right|^2 = 1 \quad (3)$$

B. Data Set

Motor imagery EEG data were taken from BCI competition III [15]. BCI competitions are held to ensure the validation of various data analysis techniques and to encourage the development of BCI technology. In each competition, various 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 laboratories in BCI technology. These records consist of two parts: the labeled data partition (the "training set") and the unlabeled data partition (the "test set"). The proposed method was evaluated using the data set IIIa, which includes four classes motor imagery data in the BCI competition III. It includes right hand, left hand, foot and tongue information from three subjects. Also, it consists of 60 channels and 60 trials for each class [16]. The recording of EEG signals was performed with a 64-channel EEG amplifier, using the left mastoid for reference and the right mastoid as the ground. Channel positions are shown in Fig. 2.

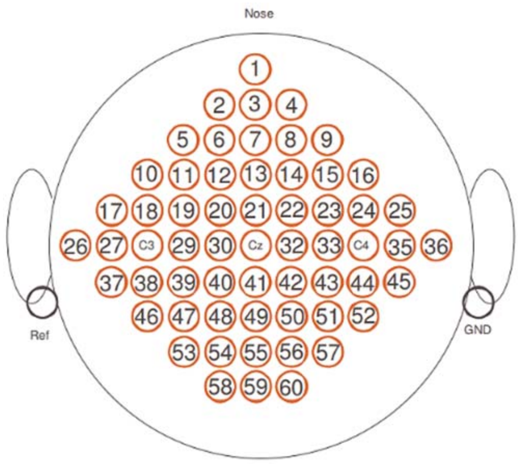

Fig. 2 Channel positions for EEG recording of data set IIIa [16]

The subject performed imagery right hand, left hand, foot and tongue movements according to the randomly presented signals while sitting in a comfortable chair. The processing time sequence for each recording is shown in Fig. 3.

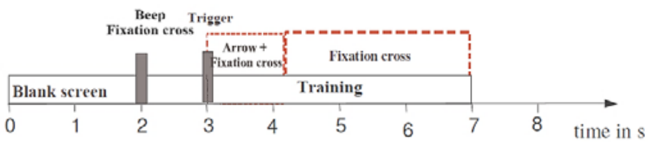

Fig. 3 Processing time sequence for each recording stage

In Fig. 3, on each trial, the first 2s are quiet. At 2s, a warning beep is emitted indicating the start of the trial, and a cross "+" appears on the screen. Then, at the 3rd second, an arrow showing up, down, left, and right direction appears for 1s. Meanwhile, the subject is asked to imagine a left hand, right hand, tongue, or foot movement, respectively, in the direction of the arrow until the arrow disappears from the screen (t = 7s).

III. Findings

After filtering the EEG signals of the selected channels, feature extraction was performed in two ways. The first one, F1, involves the computation of mean, standard deviation, and log-variance features from directly filtered signals. The second one, F2, wave atom transform was applied to filtered data, and coefficients of transform were obtained. Then, mean, standard deviation and log-variance features were calculated using these coefficients. Classification success rates were determined by presenting these two feature sets to classifiers separately and by combining them. The results are given in Table I.

TABLE I
CLASSIFICATION RESULTS (ACCURACY)

Feature set	Subject	Classifiers		
		k-NN	k-value	LDA
F1	Subjects 1	54,44	29	50
	Subjects 2	56,67	11	51,67
	Subjects 3	60	13	58,33
F2	Subjects 1	62,22	15	51,11
	Subjects 2	63,33	13	53,33
	Subjects 3	68,33	3	55
F1+F2	Subjects 1	55,56	5	51,11
	Subjects 2	51,67	31	50
	Subjects 3	60	13	45

The most successful results in the classification process were obtained from the features obtained from wave atom transform using k-NN classifier. For the k value of the classifier, 30 different values starting from 3 were used, and the highest classification accuracy was evaluated. These classification results are shown in Fig. 4.

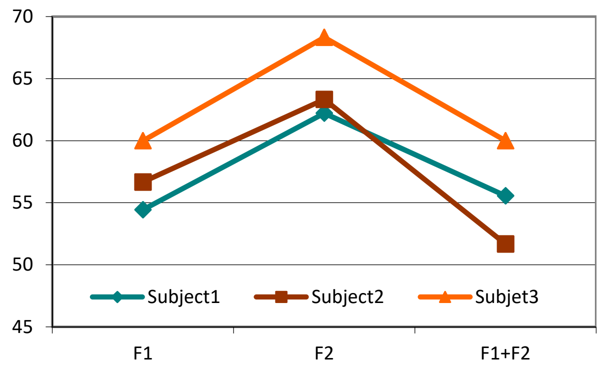

Fig. 4 Accuracy values of k-NN classification, based on feature set and subject

Considering all subjects, the best average classification result was 57.03 with k-NN classifier for features obtained directly from EEG signals (F1), while it was 64.62 wit k-NN classifier for features derived from wave atom transform (F2). When both feature data were combined (F1 + F2), the best average classification result was 55.74 with k-NN classifier for all subjects. The most successful classification results were derived from the features obtained from the EEG signals of subject 3. A comparative representation of the classifiers based on average classification results of all subjects is shown in Fig. 5.

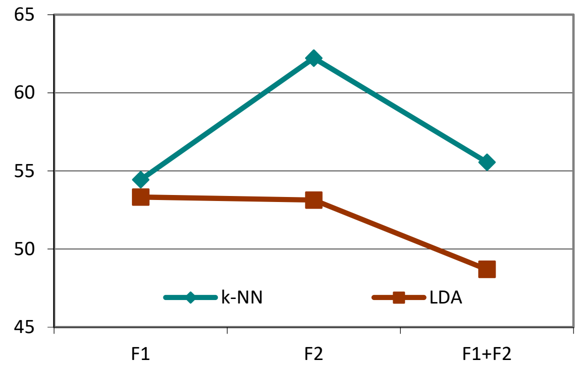

Fig. 5 Average classification results of all subjects for k-NN and LDA

IV. CONCLUSION

The aim of the study was to classify the motor imagery EEG signals containing right- and left-hand movements. Two different feature data were created, and the classification success of these features was evaluated comparatively using two different classifiers. The feature data were generated from the EEG signals and the wave atom transform applied to the EEG signals. It was concluded that the feature data obtained from wave atom transform give more successful results in classification. In addition, it was observed that the method gave more successful results in distinguishing right- and left-hand movements with the data of subject 3.

REFERENCES

[1] C. Guger, B.Z. Allison, and G. Edlinger, *Brain-Computer Interface Research: A State-of-the-Art Summary 2*, Springer, New York, NY, USA, 2014.
[2] A. Vallabhaneni, T. Wang, and B. He, “Brain-computer interface,” In Neural engineering, 2005, pp.85-121.
[3] A. Constantin, and A. Danyluk, A Brain-Computer Interface for the Classification of Motor Imagery. Bachelor thesis, Williams College, USA, 2007.
[4] E.A. Curran, and M.J. Stokes, “Learning to control brain activity: A review of the production and control of EEG components for driving brain–computer interface (BCI) systems,” Brain and cognition, vol. 51(3), pp. 326-336, 2003.
[5] Y. Wang, Z. Zhang, Y. Li, X. Gao, S. Gao, and F. Yang, “BCI competition 2003-data set IV: an algorithm based on CSSD and FDA for classifying single-trial EEG,” IEEE Transactions on Biomedical Engineering, vol. 51(6), pp. 1081-1086, 2004.
[6] H. Ramoser, J. Muller-Gerking, and G. Pfurtscheller, “Optimal spatial filtering of single trial EEG during imagined hand movement,” IEEE transactions on rehabilitation engineering, vol. 8(4), pp. 441-446. 2000.
[7] D. Garrett, D.A. Peterson, C.W. Anderson, and M.H. Thaut, “Comparison of linear, nonlinear, and feature selection methods for EEG signal classification,” IEEE Transactions on neural systems and rehabilitation engineering, vol. 11(2), pp. 141-144, 2003.
[8] Y. Zhang, Y. Wang, J. Jin, and X. Wang, “Sparse Bayesian learning for obtaining sparsity of EEG frequency bands-based feature vectors in motor imagery classification,” International journal of neural systems, vol. 27(02), pp. 1650032, 2017.
[9] H. Wang, Y. Zhang, N.R. Waytowich, D.J. Krusienski, G. Zhou, J. Jin, ... and A. Cichocki, “Discriminative feature extraction via multivariate linear regression for SSVEP-based BCI”. IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 24(5), pp. 532-541, 2016.
[10] Y. Zhang, Y. Wang, G. Zhou, J. Jin, B. Wang, X. Wang, and A. Cichocki, “Multi-kernel extreme learning machine for EEG classification in brain-computer interfaces,” Expert Systems with Applications, vol. 96, pp. 302-310, 2018.
[11] Y. Yang, S. Chevallier, J. Wiart, and I. Bloch, “Subject-specific time-

frequency selection for multi-class motor imagery-based BCIs using few Laplacian EEG channels," Biomedical Signal Processing and Control, vol. 38, pp. 302-311, 2017.

[12] H. Baali, A. Khorshidtalab, M. Mesbah, and M.J. Salami, "A transform-based feature extraction approach for motor imagery tasks classification," IEEE journal of translational engineering in health and medicine, vol. 3, pp. 1-8. 2015.

[13] S. Chaudhary, S. Taran, V. Bajaj, and A. Sengur, "Convolutional neural network-based approach towards motor imagery tasks EEG signals classification," IEEE Sensors Journal, vol. 19(12), pp. 4494-4500, 2019.

[14] L. Demanet, and L. Ying, "Wave atoms and sparsity of oscillatory patterns," Applied and Computational Harmonic Analysis, vol. 23(3), pp. 368-387, 2007.

[15] BCI competition III, http://www.bbci.de/competition/iii/ (last accessed 30.10.2020).

[16] BCI competition III dataset IIIa, http://www.bbci.de/competition/iii/desc_IIIa.pdf (last accessed 30.10.2020).

Nebi Gedik received his B.S. degree in Electrical and Electronics Engineering from Firat University in 2001, his PhD degrees in Electrical and Electronics Engineering from Karadeniz Technical University in 2013, and his MSc degree in 2005 from Atatürk University. He is now an Associate Professor at University of Health Science. His research interest includes medical image and signal processing, pattern recognition and machine learning.