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Motor Imagery Classification using Wavelet-Based Features and Tensorflow

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Abstract*: *This paper proposes a methodology for making a decision on left and right motor imagery using Tensorflow and wavelet-based feature extraction. Wavelet coefficients are extracted by the Haar wavelet transforms from electroencephalogram (EEG) signals in the first step. In the second step, 60 wavelet-based features are extracted by the frequency distribution and the amount of variability in frequency distribution. In the final step, this paper classified left or right motion imagery using these 60 features as inputs to the Tensorflow. The proposed methodology shows that the performance result is 82.14% with 60 features in accuracy rate.

Keywords **: Motor Imagery, Tensorflow, Wavelet Transform, Keras.**

I. INTRODUCTION

With advances in brain science, research on brain-computer interfaces (BCIs) has also been actively conducted, enabling the understanding of human intention through electroencephalogram (EEG) signals analysis. BCI is a field for studying computer interaction with humans. It is a technology that measures EEG signals in a specific state through brain waves, extracts features, classifies them, and converts them into general control signals to control computers or devices. Artificial intelligence techniques using EEG signals have been studied to control such computers and devices [1][2][3][4][5][6]. Wavelet transform (WT) [1][2][3] is preferred and used to classify motor imagery on the left or right side by incorporating fuzzy neural networks. Fast Fourier transform (FFT) [4], Gaussian filtering [5], Laplacian filtering [6], and time-frequency based wavelet transform are used to extract the features from EEG signals.

The wavelet coefficients were extracted by the wavelet transform from the EEG signal [1]. The extracted wavelet coefficients were also used as inputs of the fuzzy support vector machine (FSVM) to make a decision on the left or right motion imagery. However, only the detail coefficients were used among the wavelet coefficients, approximation coefficients and detail coefficients [1].

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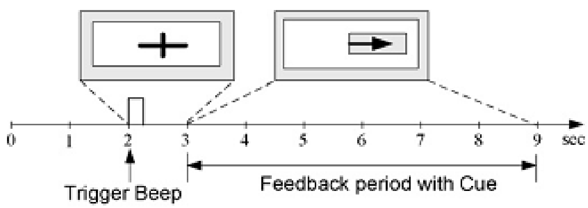
Recently, deep learning technology, which has led to an overwhelming improvement in pattern recognition performance, has brought performance improvements in various pattern recognition fields including voice recognition [7], image recognition [8], and motor imagery [9].

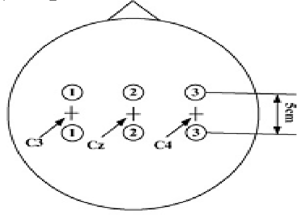
This paper also the wavelet coefficients of the EEG signal using wavelet transform. However, this paper additionally obtained the 60 features from the wavelet coefficients using the frequency distribution and the frequency variation, which are statistical methods. This paper classified left or right motor imagery using these 60 features as inputs to the Tensorflow.

II. EXPERIMENTAL DATA

Fig. 1 shows the channel setup for measuring the EEG signal of C3, Cz, and C4 and the 9-second experiment in the experiment of controlling the left or right using the EEG signal. The EEG signals used in this experiment were provided by Univ. Tech, Graz. The EEG signals are used at the 2003 BCI Competition and collected from a 25-year-old woman. The frequency of the EEG signal was 128 Hz. The EEG signals were measured seven times in 40 times, and it was composed of 280 times of data with 140 times of 9-second trains and 140 times of 9-second test. In Fig. 1 (a), the configuration of one experiment shows that the first two seconds are quiet and if subject hears a beep for the next one second, the cross is displayed on the monitor. For the next six seconds, an arrow indicating left or right appears on the monitor, which allows the subject to imagine movement. Each of the 140 training sessions consisted of 70 left or right movements.



(a) Experiment for 9 seconds



(b) Channel for EEG Signal
Fig. 1 International 10-20 Standard Electrode

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III. PREPROCESSING AND DEEP LEARNING

Recently, researches using discrete wavelet transform (DWT) have been actively conducted in signal processing for signal analysis [10][11][12][13]. In this paper, the EEG signal is generated using the Haar WT as shown in Fig. 2, and the detail coefficients and approximation coefficients of wavelet coefficients from level 1 to level 4 are generated from d1 to d4 and a1 to a4, respectively [13]. Table I shows the frequency domain of each level of the extracted wavelet coefficients. In general, the frequency range of μ waves is known to be 8 to 13 Hz and the frequency range of β waves is known to be 13 to 22 Hz [14][15]. Xu [1] used d2 and d3 corresponding to the frequency domain of μ and β waves.

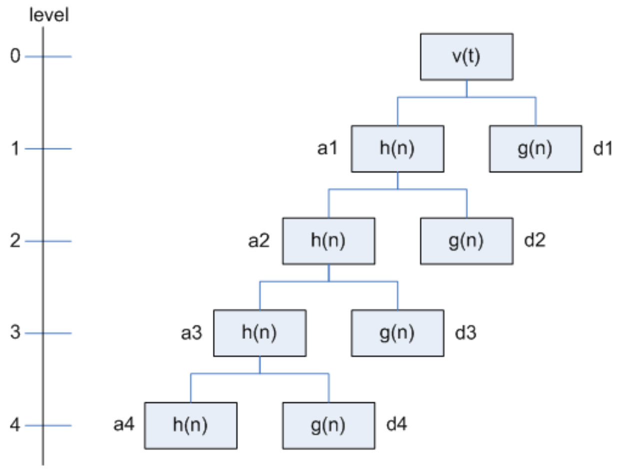

Fig. 2 Discrete wavelet transform with scale level 4

TABLE I Frequency Ranges for Each Scale Level After Wavelet Transform

Scale level	Frequency range (Hz)
D2	16~32
D3	8~16
D4	4~8
A2	0~16
A3	0~8
A4	0~34

Table II describes the features to be used in this paper to extract features from the collected EEG signals for subjects to experiment with imagination of movement. Features 1, 4, and 5 describe the feature extraction method used by Tzanetakis [16]. Xu's papers compared in this paper used features 1 and 4 [1]. Features 1, 2, and 3 described in Table II represent frequency distributions for EEG signals. In addition, features 4 and 5 represent the frequency variation.

In Xu's paper, which is compared in this paper, feature 1 and feature 4 were extracted using only d2 and d3 in Fig. 2 in C3 and C4 channels. In this paper, a total of 15 features were generated from each of the five features described in Table II using d2, d3, and d4 in the C3 channel. Fifteen features were generated in the same way on the C4 channel. Also, 15 features on each of a2, a3, and a4 were generated in the C3 and C4 channels. 60 features were finally extracted as initial features.

TABLE II Feature Description

Feature	Feature description
1	Average of the absolute values of all coefficients in each scale level
2	Median of all coefficients in each scale level
3	Average of squared all coefficients in each scale level
4	Standard deviation of all coefficients in each scale level
5	Absolute ratio of the mean of all coefficients in the scale level between adjacent scale levels

The deep learning framework of this paper uses a deep neural network library called Tensorflow and Keras. Deep learning is defined as a set of machine learning technologies that attempts a high level of abstraction and multi-layers through a combination of several nonlinear transformations. Deep in deep learning means multi-layers of neural networks, and each layer has several hidden units. This paper used the fully connected neural network (FCNN) that is comprised of 4 dense layers and 2 dropouts to avoid overfitting. The FCNN has loss function (binary_crossentropy), optimizer (rmsprop), and activation (relu and sigmoid) and that the batch size is 1 and the epoch is set to 5 times for learning.

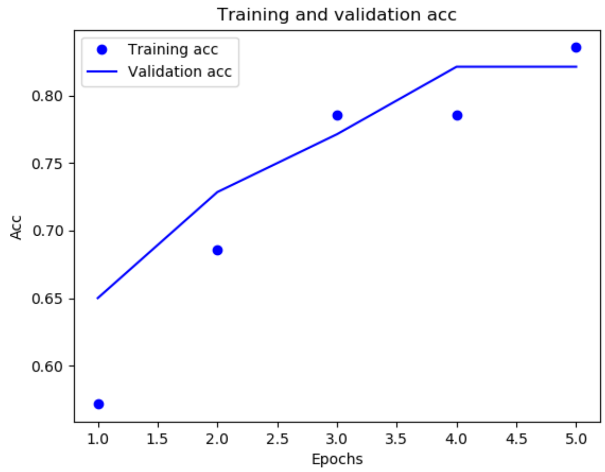

Fig. 3 The accuracy graph of training and validation (acc : accuracy)

IV. EXPERIMENTAL RESULTS

In this paper, Xu used Univ. To make a decision on left or right motor imagery from EEG signals. The EEG signals used in the 2003 BCI Competition provided by of Tech, Graz was used [1]. Xu experimented with FSVM and four wavelet transforms Symlet (sym2), Daubechies (db4), Biorthogonal (Bior3.1), and Coiflet (coif3). The results are described in Table III. Xu's experiment showed the highest accuracy when using Daubechies wavelet transform. Fig. 3 shows that the accuracy result of the validation is 82.14%.

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TABLE III comparison of tensorflow and Xu [1]

Classifier	Wavelet transforms	Accuracy (%)
FSVM	Sym2	80.00%
	Bior3.1	77.86%
	Db4	80.71%
	Coif3	80.00%
Tensorflow	Haar	82.14%

V. CONCLUSION

This paper proposes a methodology for making a decision on left and right motor imagery using a Tensorflow and wavelet-based feature extraction. The Haar WT is used to extract wavelet-based features as inputs of Tensorflow. The wavelet-based features are used as inputs of the fully connected neural network supported by Tensorflow. This paper classified left or right motion imagery using 60 wavelet-based features as inputs to the Tensorflow. The proposed methodology shows that the performance result is 82.14% with 60 features in accuracy rate.

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