Classification of Hand Movement in EEG using ERD/ERS and Multilayer Perceptron

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Abstract: Continuous EEG activity in the measured subjects includes different patterns depending on what activity the subject performed. ERD and ERS are examples of such patterns related to movement, for example of a hand, finger or foot. This article deals with the detection of motion based on the ERD/ERS patterns. By linking ERD/ERS, feature vectors which are later classified by neural network are created. The resulting neural network consists of one input and one output layer and two hidden layers. The first hidden layer contains 3,000 neurons and the second one 1,500 neurons. A training set of feature vectors is used for the training of this neural network and the back-propagation algorithm is used for the subsequent adjustment of the weights. With this setting and training, the neural network is able to classify motion in an EEG record with an average accuracy of 79.92%.

1 INTRODUCTION

Since the beginning of time humanity has been plagued by many diseases and medical conditions. One of those medical conditions is a stroke, which can be caused, for example, by high blood pressure. People who have survived a stroke may be permanently partially paralyzed and therefore have limited limb mobility. This paper seeks to help these patients, specifically ones with limited hand mobility.

Electroencephalography is commonly used as a recording technique for non-invasive BCI (Brain-computer interface) systems. BCI provides a connection between a human and an external device or application using neurophysiolohical signals. BCI systems can be divided into two types, invasive and non-invasive. Invasive BCI is directly implanted in brain tissue, while non-invasive BCI uses electrophysiological records.(Birbaumer and Cohen, 2007)

BCI technology can increase the effectiveness of rehabilitation and thus improve muscle control for stroke patients and other patients with limited mobility. This can be done by detecting ERD/ERS in the brain activity and supply the patient's impaired muscle control, e. g. send trigger fig. 1.

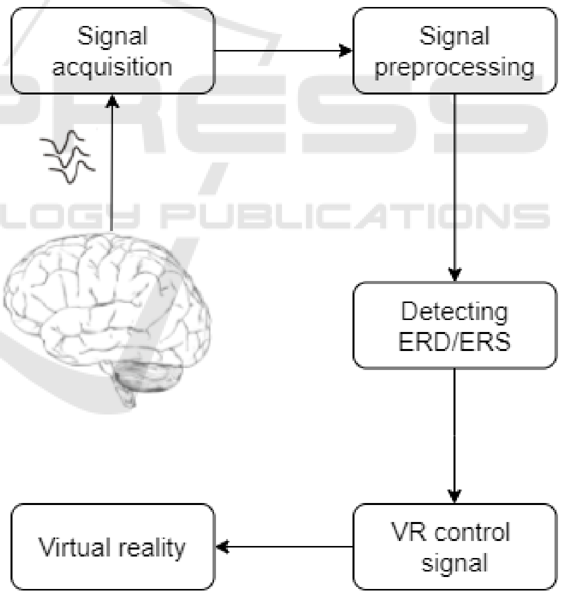

Figure 1: BCI system that is capable of detecting ERD/ERS from spontaneous imaginary movements. The intended movement will be induced by electrical stimulation.

Artifical neural network (ANN) was used for classification of the movement. Accuracy of the ERD/ERS pattern classification by this neural network was aproximately 80% in our case. After a minor modification (converting the classifier to online mode) it is possible to link the classifier to virtual reality (VR) kit. The affected patient will just put on a VR kit, with a book loaded, in which the patient will be able to browse at will only by thinking of hand movement.

For data processing and neural network classification, the Python programming language with MNE and Keras tools was used.

The structure of this article is as following. Chap-

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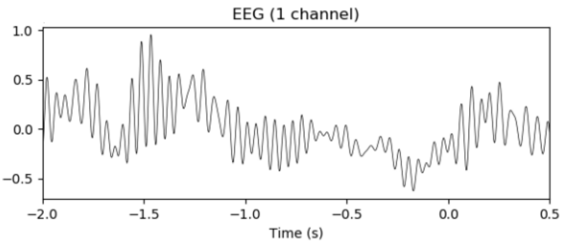

Figure 2: This chart shows filtered, squared, averaged and normalized epochs (54 epochs found). The X-axis indicates the time that is defined from -2.5 to 0.5. The Y-axis indicates the power of signal.

ter 3 describes what ERD/ERS is and how it can be calculated. This chapter also describes the creation of feature vectors from the obtained ERD/ERS. Chapter 4 describes in detail the scenario used in the measurement, the course of the measurement and the hardware used for the measurement. The chapter 5 describes the structure of the artificial neural network and it's configuration in detail. Obtained results are also discused here. Conclusions and future work are mentioned in the last chapter 6

2 STATE OF THE ART

The idea of BCI was originally proposed by Jaques Vidal in (Vidal, 1973) where he proved that signals recorded from brain activity could be used to effectively represent a user's intent.

The author of (Sepulveda, 7 05) used features produced by Motor Imagery to control a robot arm. Features such as the band power in specific frequency bands (alpha: 8-12Hz and beta: 13-30Hz) were mapped into right and left limb movements. In addition, they used similar features with Motor Imagery, which are the ERD/ERS comparing the signal's energy in specific frequency bands with respect to the mentally relaxed state. It was shown in (Mohamed, 2011) that the combination of ERD/ERS and Movement-Related Cortical Potentials improves EEG classification as this offers an independent and complimentary information.

A single trial right/left hand movement classification is reported in (Kim et al., 2003). The authors analyzed both executed and imagined hand movement EEG signals and created a feature vector consisting of the ERD/ERS patterns of the mu and beta rhythms and the coefficients of the autoregressive model. Artificial Neural Networks is applied to two kinds of testing datasets and an average recognition rate of 93% is achieved.(H. et al., 2013)

Linear Discriminant Analysis was used to classify ERD/ERS patterns associated with Motor Imagery. (Pfurtscheller et al., 2000) used brain oscillations (ERS) to control an electrical driven hand orthosis (open or close) for restoring the hand grasp function. The subjects imagined left versus right hand movement, left and right hand versus no specific imagination, and both feet versus right hand, and chieved an average classification accuracy of approximately 65%, 75% and 95%, respectively.

3 EVENT-RELATED DESYNCHRONIZATION AND EVENT-RELATED SYNCHRONIZATION

Certain events can block or desynchronize the ongoing alpha activity (Pfurtscheller and da Silva, 1999). These types of changes are time-locked to the event but not phase-locked, and thus cannot be extracted by a simple linear method, but may be detected by a frequency analysis or a Fourier Transform (Pfurtscheller, 1977). This means that these events may be either decreases or increases of power in given frequency bands.

The first case is called Event-related desynchronization (or ERD) and the second one is called Event-related synchronization (ERS). Of course both ERD and ERS phenomena are not only found on EEG recordings but also on MEG recordings (Pfurtscheller, 2001). ERD/ERS phenomena can be viewed as generated by changes in one ore more parameters that control oscillations in neuronal networks.

One of the basic features of ERD/ERS measurements is that the EEG/MEG power within identified frequency bands is displayed relative to the power of the same EEG/MEG derivations recorded during the stimulation or resting phases a few second before the event occurs (Krause et al., 2008) (in our case movement with left or right hand). Because event-related changes in ongoing EEG/MEG need time to develop and to recover, especially when alpha band rhythms are involved, the interval between two consecutive events should last at least 10 seconds.

3.1 Computing ERD/ERS

There are multiple ways to calculate ERD/ERS from EEG data. I chose one of the simpler methods described below.

To calculate ERD/ERS it is necessary to filter the input EEG data. Because ERD is located at frequencies from 8 Hz to 12 Hz and ERS at frequencies from

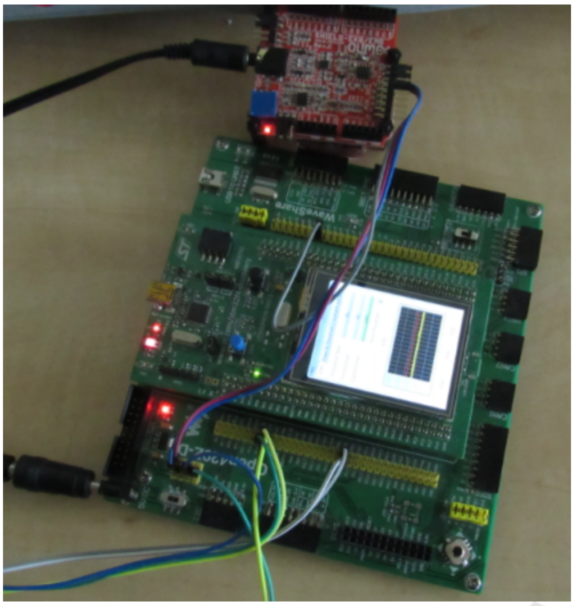

Figure 3: Microcontroller board STM324F429I-DISCO and EKG/EMG shield from company Olimex.

14 Hz to 22 Hz, the coresponding bandpass filters are applied to input data. Afterwards, the filtered data are squared and coresponding epochs are found in this data. The epochs are locked to synchronization marks saved in EED. Each mark determines the beginning of moving activity of the measured subject. The epochs starts 2.5s before synchronization mark and the ends 0.5s after synchronization mark. It is important to choose the correct EEG channel in which the data for ERD/ERS calculation will be used. For right/left hand movement the EEG channels C3/C4 was used. In the next step the epoched data for channel are averaged and ERD is evaluated by following expression 1. (Formaggio et al., 2013)

$$ERD_i(\%) = \frac{Act_i - R}{R} 100 \qquad (1)$$

Act represents the averaged epochs and R can be calculated using eq. 2.

$$R = \frac{1}{k+1} \sum_{i=r_0}^{k+r_0} Act_i \qquad (2)$$

According to the equation we can say that R is averaging of values in the interval $[r_0, r_0 + k]$, which r_0 is approximately two seconds before the event and $r_0 + k$ is approximately 0.5 seconds after the event.

The result of this procedure for ERD can be seen in the fig. 2 (MACHIDA and TANAKA, 2018)

3.2 Creating Feature Vectors

ERD / ERS can be imagined as two vectors containing just as many items as the given epoch contains milliseconds. The easiest way to prepare EEG data for classification is to create a vector with a size of the sum of the ERD (2501 samples) and ERS (2501 samples) vector sizes. After creating the vector the ERD vector is saved into it and the ERS vector is placed behind ERD vector. This is a relatively simple way of create feature vectors from the ERD and ERS, which can then be used in most classifiers. This feature vector contains exactly 5002 items.

When ERD / ERS was calculated from the stimulation phase, the number 1 was placed at the end of the feature vectors. When ERD / ERS was calculated from the resting phase, the number 0 was placed at the end of the feature vectors.

4 MEASURING EEG

The whole EEG scenarion for measurement consists of 4 cycles, each cycle containing a resting and stimulating phase. At the start of each cycle, the subject is in the resting phase for one minute, where he must sit completely at rest withnout any movement. This includes reducing blinking to a minimum if his eyes are open. After the resting phase, the subject enters a stimulation phase that lasts 2 minutes, where the subject moves wrist movement with left or right hand. In the stimulation phase, the subject performs the given task after a five second interval. The subject is notified of the phase change by a green LED placed in front of the subject. When the LED is on, the subject is in the stimulation phase and performs the task. When the LED is off, the subject is in the resting phase. The phases are then alternated this way and each of them is repeated three times. This means that each cycle lasts exactly 9 minutes.

As mentioned above, the whole measurement consists of 4 cycles. The cycles differ from each other by the task performed by the subject in the stimulation phase, optionally combined with alternating open or closed eyes. List of the cycles:

1. Movement with left hand with open eyes.
2. Movement with left hand with close eyes.
3. Movement with right hand with open eyes.
4. Movement with right hand with close eyes.

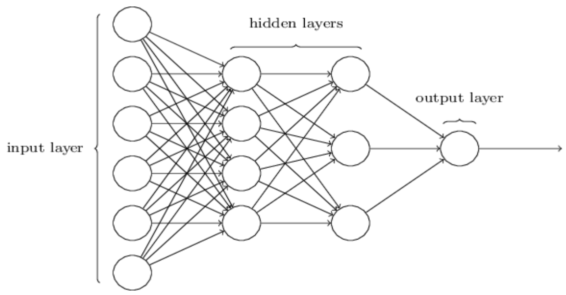

Figure 4: Structure of a multilayer binary perceptron that contains one input and output layer and two hidden layers.

4.1 Measurement Process

To this day twelve healthy people were measured (men of age 21-26 and women of age 18-23).

Before starting the measurement, it was explained to each subject how the whole measurement will be done and before each cycle it was specified how the cycle will be done. Meanwhile the nurse attached an EEG cap on the subject's head, fitted with Ag / AgCl electrodes according to a 10-20 system. Afterwards, she attached 2 electrodes to the subject's hand and one ground electrode below the elbow, because the distance to the bone is smallest there. Lastly a reference electrode of EEG cap was attached to the earlobe.

After finishing the preparation, the subject was placed in a dark sound-proof chamber to avoid disturbance by the surroudings during measurement. Before closing the chamber all electrodes were checked if their resistance is less than 5KΩ. This check was followed by a quick reminder of what the subject sould do in the stimulation phase. After that, the measurement of the first cycle began. After each cycle, the chamber door was opened and it was explained to the subject what to do in the next cycle.

The EEG data were recorded by the BrainAmp DC amplifier with BrainVision recorder software. For EMG recording, synchronization pulses generation and driving stimulation scenario the microcontroller STM324F429I-DISCO board with EKG/EMG shield of Olimex company were used. Fig. 3.

5 CLASSIFICATION RESULTS

To classify the created feature vectors, I chose an artificial neural network programmed in Python using the Keras module.

Training and classification data are loaded from files into arrays that represent the input layer.

The entire artificial neural network is made up of the Sequential model, which is essentially a linear stack of layers. This can be imagined as a layer list, where each additional item in the list represents an additional layer. After extensive testing a multilayer perceptron was used, with one input layer, one output layer and two hidden layers. The threshold used was Keras default (0.5). This is a binary neural network, which means that the output layer has only one neuron.

A sigmoidal activation function is used in all the hidden layers and in the output layer, defined by the Eq. 3. Binary Cross-Entropy is used as a loss function.

$$f_s(u) = \frac{1}{1+e^{-u}} \tag{3}$$

Next a back-propagation training algorithm is used, with the number of iterations set to 100.

The biggest problem was to determine the optimal number of neurons in hidden layers. The artificial neural network was started a hundred times with each setting and the results averaged. Testing has shown that the best possible number of neurons for the first hidden layer is 3 000 and 1 500 for the second hidden layer. The accuracy of the classifier with this setting ranged between 75.00 % - 85.42 %, where the average value of all measured results is 79.92 %. This accuracy interval is determined by random setting of weights when training artificial neural network. The numbers of neurons and the resulting accuracy can be seen in tab. 1

The resulting simplified network architecture can be seen in Fig. 4.

Table 1: Adjusted parameters of artificial neural network and their minimum, maximum and average accuracy. If the number of neurons in the second layer is 0, it means that the network had only one hidden layer.

Number of neurons in hidden layers		Min. acc.	Max. acc.	Average acc.
1. layer	2. layer			
250	0	64.58%	83.33%	76.23%
500	0	70.83%	83.33%	77.35%
50	25	68.75%	85.42%	76.42%
100	50	68.75%	85.42%	77.42%
200	100	68.75%	87.50%	77,77%
500	250	70.83%	83.33%	77.35%
1 000	500	68.75%	85.42%	79.23%
2 500	1 250	75.00%	85.42%	79.90%
3 000	1 500	75.00%	85.42%	79.92%

6 CONCLUSIONS AND FUTURE WORK

The suggested ANN has proven to be suitable for classification of movement in EEG data. As mentioned in the introduction, after a minor modification it is possible to link the classifier to VR kit. The affected patient will just put on a VR kit, with a book loaded, in which the patient will be able to browse at will only by thinking of hand movement.

Taking into account of the results of the other works published in Chapter 2, we plan to do in the future:

- Modification of ANN architecture and use of Deep learning to improve the results of classification.
- Complementing the scenario with the possibility of measuring and detecting imagiantion of movement.
- Connection with VR kit.

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