Classification of Sensorimotor Rhythms Based on Multi-layer Perceptron Neural Networks

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Abstract — **Sensorimotor rhythms are represented by mu rhythm with 8-12Hz frequency band and beta rhythm with the 12-30Hz frequency range. The movement or preparation of the movement is typically accompanied by a decrease of the mu and beta rhythms, especially in the contralateral area of the movement, which is a piece of very important knowledge for the implementation of a brain computer interface. The EEG signal was recorded using 8 active electrodes placed in the motor areas of the scalp. Features extraction was performed by decomposing the original signal in subcomponents signal with the frequency band in the interest range using multiresolution wavelet analysis based Daubechies wavelets. Multi-layer perceptron neural networks (MLP-NN) method is utilized for the classification of the features. This classifier performs well, 95.45% was the maximum classification rate for the subjects involved in the study. The superiority of the classifier MLP-NN was sustained also by The Friedman Two-way Analysis of Variance (ANOVA) by Ranks Test.**

Keywords—sensorimotor rhythms, wavelet, neural networks, multi-layer perceptron, brain computer interface

I. INTRODUCTION

Sensorimotor rhythms (SMR) are oscillations recorded in brain activity in the somatosensory and motor areas. Brain oscillations are usually classified according to the specific frequency (delta: <4 Hz, theta: 4-7 Hz, alpha: 8-12 Hz, beta: 12-30 Hz, gamma:> 30 Hz). The activity of the alpha rhythm recorded in the sensorimotor areas is also called mu rhythm. For awake people, the sensory cortical areas and the primary motor areas usually produce on the electroencephalographic (EEG) recording, activities with the frequency of 8-12 Hz, only if they are not engaged in the processing of sensory stimuli or in producing motor responses [1]. Some studies [2, 3] have also shown that the mu rhythm activity comprises a variety of rhythms of 8-12 Hz, distinct from each other by location, frequency and/or relationship to sensory inputs or competing for motor outputs. These mu rhythms are usually associated with beta rhythms of 18-26 Hz. While some beta rhythms are harmonic of the mu rhythms, some are separable from them by topography and/or temporal localization and thus are independent EEG features [4]. Several factors suggest that mu and/or beta rhythms may be signals - features for EEG-based communication. These are associated with those cortical areas most directly related to the normal motor output channels of the brain. The movement or preparation of the movement is typically accompanied by a decrease of the mu and beta rhythms, especially in the contralateral area of the movement. This decrease is known as event-related desynchronization (ERD) [5]. On the contrary, the increase of the amplitude of the mu and beta rhythms, called event-related synchronization (ERS), occurs after the movement, during relaxation. Besides, and particularly relevant for use in Brain Computer Interface (BCI) domain they also occur in imagining movement [6], [6]. Thus, they can be the basis of a BCI.

BCI is a communication system in which messages or commands sent to the outside world by an individual do not pass through the normal pathways (consisting of peripheral nerves and muscles) [7]. For example, at a BCI based on EEG signals, messages are encoded in EEG activity. To decode the messages from the brain, advanced signal processing methods are necessary. In this paper, are proposed the wavelet multiresolution method for the feature extraction and the multi-layer perceptron neural networks for classification purpose.

II. DATABASE AND METHODS

A. Data recordings

A presentation of the database and the methods used in this paper are sketched in Fig.1. The first step in this research was the signal acquisition. In this paper are used recordings of 32 volunteer subjects that performed motor imagery of both hands tasks (flexion and reflection of the fingers of the right respectively left hand). The EEG signals were recorded using a g.tec (g.MOBIlab+) [8] portable biosignal acquisition and analysis system and the BCI2000 software. The electrodes placement is showed in Fig. 1, and the channels CP3, CP4, P3, C3, Pz, C4, P4 and Cz, were strategically chosen to cover largely the sensorimotor areas. The training paradigm consists of recording the EEG signals while the stimulus is presented to the subjects indicating the tasks that they must fulfill (movement/motor imagery of right/left hand or relaxation). In the testing paradigm subjects try to control a target on a monitor only by movement/motor imagery of a chosen hand and relaxation. The training and the testing paradigms are very detailed described in the paper [9].

B. Features extraction

EEG signals contain an unknown mix of components that represents brain processes. That is why it is very important to find reliable signal processing tools to extract features of BCI system signals. In my research [10] the feature extraction method with the best results was multiresolution wavelet analysis, so in this paper is applied using the Daubechies wavelet. Most suitable for highlighting the desynchronization of sensorimotor rhythms were found to be Daubechies2.

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This method consists in the decomposition of the signal into multiple levels using low-pass and high-pass filtering. The original EEG signal (0-128Hz) is initially decomposed into high (64-128Hz) and low (0-64Hz) frequency bands which embody detail and approximation of the input signal in level one. Then low frequency at the first level approximation is further divided into high (32-64Hz) and low (0-32Hz) frequency bands which represent detail and approximation at level two. Similar way low frequency bands will be decomposed at each level till level four. The detail of level 3 (16-32 Hz) and level 4 (8-16 Hz) became the signals subcomponents of most interest to us.

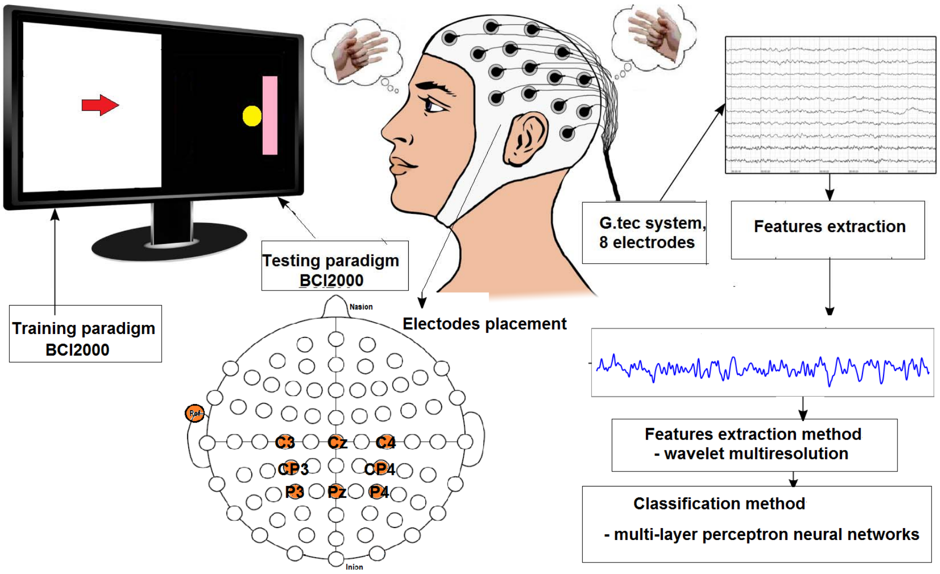

Fig. 1. The research steps. Signal acquisition is performed with 8 electrodes placed on the scalp according to the 10-20 international system which is found in both sides of the sensorimotor area of the brain. The signal is recorded in both situations (training and testing) then it`s processed. For the feature extraction it was used wavelet multiresolution analysis and for the classification multi-layer perceptron neural network method

C. *Classification*

Starting from the remarkable performances and capabilities that the human being manifests in different areas of activity, in particular from the performances of the human brain, different theoretical, technical and applicative fields have tried and still try to achieve similar performances by “copying” different systems and functions of the human body. The artificial neuron models represent the behavior of a real neuron. Thus, connections between neurons, called synaptic weights, are used to store information. After local processing of the input signal according to the information stored in the synaptic weights (its multiplication with the stored information values), there is a global integration of the obtained results - a process similar to the one that takes place in the cell body of a real biological neuron. If the obtained overall response exceeds a certain threshold, the information is transmitted further. Artificial neural networks are artificial structures which try to copy how the human brain works and they are made up of several processing elements or artificial neurons grouped into layers, each layer having a variable number of elements. Most generally, each neuron can receive information from other neurons and/or even from itself [11]. Initially, neural networks were used for simple classification problems, but due to the increase in computing power, now there are stronger architectures that can solve more complex problems. One of these is called the feed-forward neural network. A constructive feature of these is the possibility to identify sets of elementary neurons grouped in layers, which offer similarities of connection. We identified an input layer, an output layer, and all the others are called hidden layers. The input layer is formed by several neurons equal to the number of features of the data in the set. The values contained in neurons are equal to the characteristics of the samples. The hidden layers are linked to the input layer, or the previously hidden layer (if any). The output layer is linked to the last (or only) hidden layer. The number of neurons in the output layer is equal to the number of classes. The output is a function of the weighted sum of the inputs [12]. Mathematically we can express this as:

$$y = f\left(\sum_{i=1}^{N} w_i x_i - w_0\right) = f\left(\sum_{i=0}^{N} w_i x_i\right) = f(z) \qquad (1)$$

, where y is the output term, x_i is the i-th of N inputs and w_i its associated weight.

The procedure steps of applying multi-layer perceptron neural networks (MLP-NN) in MATLAB are: i) the structure of the network is defined, using *newff* function, selecting the inputs and set de hidden layer at 10, ii) the training parameters are defined (detail coefficients of level 3 and 4, of the training set for channels C3, CP3 and P3 for the right hand movement/motor imagery and channels C4, CP4 and P4 for the left hand movement/motor imagery), iii) run the training algorithm, iv) simulate the output of the neural network with the measured input data. The result is compared with the measured outputs, v) final validation is carried out with the testing data (for each C3, CP3 and P3 channel for the right hand movement/motor imagery and each C4, CP4 and P4 channels for the left hand movement/motor imagery).

D. *Statistical Analysis*

The Friedman Two-way Analysis of Variance (ANOVA) by Ranks Test was performed using Statistical Package for the Social Sciences (SPSS) on the maximum rates of classification obtained whit MLP-NN proposed classifier and the percentages of success obtained after the testing paradigm by BCI2000 software. The null hypothesis is that the distribution of classifications for LDA and MLP-NN (on channels C3 respectively C4, CP3 respectively CP4 and P3 respectively P4) are the same. The significance level was chosen 0.05.

III. RESULTS

The classification was performed on the C3, CP3 and P3 channels corresponding to the movement/motor imagery of the right hand and C4, CP4 and P4 channels for the movement/motor imagery of the left hand. Using the Daubechies2 (db2) wavelet, the signal is decomposed in the signal subcomponents with patterns of interest. Db2 was found to be a suitable wavelet for highlighting the desynchronization of sensorimotor rhythms. The features matrix is constructed from the detailed coefficient of the fourth level with an 8-16 Hz frequency band corresponding to the features range 85-137 and the detailed coefficient of third level decomposition with a 16-32 Hz frequency band with features from 1 to 84 in the matrix. This features matrix is created for the training and also the test signals. Classification is performed between two classes: the relaxation and the movement / imagined movement of one hand. In the results tables, are also presented the classification accuracy obtained with BCI2000 software based on the LDA classifier (the standard classifier offered by the software package). Those percentages of classification are displayed at the end of the testing paradigm. This classifier has a low accuracy, which is why throughout my research I used different methods to improve it, [13, 14], so for this paper was tested MLP-NN classifier.

To present the results of the classifier used in this study, there have been completed Table I and Table II for the subjects that performed movement/motor imagery tasks of the right hand (13 subjects) or the left hand (19 subjects) versus relaxation, during testing paradigm. For all classifiers methods the results were depicted for C3, CP3 and P3, respectively C4, CP4 and P4 channels.

TABLE I. RESULTS OF CLASSIFICATION FOR MOVEMENT / MOTOR IMAGERY OF THE RIGHT HAND

Subject	BCI2000 (%)	Classification with MLP-NN (%)					
		C3	Features Range	CP3	Features range	P3	Features range
1	54	86.36	14-33	**95.45**	11-102	86.36	56-70
2	77	81.81	43-109	90.9	42-107	86.36	41-107
3	36	90.9	48-96	86.36	44-104	86.36	66-104
4	77	90.9	16-22	**95.45**	41-98	90.9	64-106
5	45	**95.45**	14-27	90.9	50-84	90.9	60-120
6	81	90.9	10-13	86.36	24-76	86.36	8-39
7	72	86.36	98-108	86.36	60-83	86.36	10-73
8	81	90.9	53-58	**95.45**	14-19	90.9	54-106
9	50	86.36	16-29, 87-109	90.9	91-129	90.9	16-36
10	63	90.9	60-81	86.36	127-136	90.9	88-108
11	67	90.9	86-93	86.36	16-19	81.81	37-41
12	68	86.36	20-87	86.36	34-113	86.36	19-81, 85-110
13	90	81.81	35-58	90.9	50-73	86.36	22-80
Mean	66.23	88.45		89.85		87.75	

It can be seen from Table I that the maximum level of classification of 95.45% for motor imagery of the right hand was obtained for four subjects. The best classification rates were obtained for the CP3 channel. MLP-NN performed better than BCI2000 classifier for all channels and almost all subjects, except subject 13 for C3 and P3 channels. The minimum classification rate obtained is 81.81% in only two cases. The means of classification rates are 89.85% for CP3, 88.45% for C3 and 87.75% for P3. The maximum classification rate was obtained for a very wide range of features and these ranges are also different for the same subject for the three channels. For the first subject, for example, we have obtained the maximum accuracy, 86.36%, on channel C3 and P3 for the features range 14-33 respectively 56-70 (corresponding to the beta rhythm), but the accuracy of 95.45%, on channel CP3, was obtained for a wider range of features 11-102 (including both mu and beta rhythms). The second subject had discriminated both sensorimotor rhythms and we obtained the maximum accuracy on very close features ranges (43-109 on C3, 42-107 on CP3 and 41 - 107 on P3) for the three channels. If we look very carefully at the features ranges we observe that most subjects discriminated better the beta rhythm, due to the best classification rates obtained in the intervals of the features 1-84 and also we have subjects that discriminated both rhythms.

TABLE II. RESULTS OF CLASSIFICATION FOR MOVEMENT / MOTOR IMAGERY OF THE LEFT HAND

Subject	BCI2000 (%)	Classification with MLP-NN (%)					
		C4	Features range	CP4	Features range	P4	Features range
14	54	90.9	118-124	86.36	41-74	90.9	102-108
15	63	86.36	119-120	86.36	13-108, 44-54	86.36	44-54
16	86	81.81	18-19, 75-115	86.36	22-29	86.36	11-32, 83-92
17	59	90.9	18-36	86.36	48-77	86.36	96-137
18	63	86.36	20-60, 38-63	90.9	85-134	90.9	69-131
19	36	86.36	25-62	86.36	50-73	86.36	21-30, 82-97
20	40	86.36	28-30	**95.45**	17-21	90.9	23-47
21	55	86.36	8-42	86.36	34-60	86.36	13-22, 54-67
22	68	86.36	51-128	90.9	9-62, 41-114	86.36	60-116
23	63	86.36	97-106	86.36	65-67	86.36	25-38
24	86	86.36	35-40, 49-100	81.81	28-33, 129, 133	86.36	14-16, 129-133
25	77	86.36	35-36, 67-123	86.36	10-20, 15-128	90.9	91-92
26	81	86.36	16-34, 28-81	86.36	9-19, 86-123	**95.45**	33-109
27	72	86.36	17-42, 18-41	81.81	11-35, 58-107	86.36	24-59, 86-92
28	45	86.36	13-57, 109-110	86.36	15-76, 17-68	90.9	103-124
29	86	90.9	29-42, 94-127	86.36	13-81, 79-116	90.9	100-124
30	77	90.9	21-73	86.36	15-136	90.9	120-126
31	77	86.36	14-18	86.36	29-135	90.9	110-134
32	68	90.9	34-46	**95.45**	53-124	90.9	93-100
Mean	66.1	87.31		87.31		88.98	

Results of classification with MLP-NN for movement/motor imagery of the left hand are presented in Table II. The maximum level of classification of 95.45% for motor imagery of the left hand, was obtained for two subjects on the CP4 channel and one subject on the P4 channel. This classifier performs better than BCI2000 based LDA classifier for all subjects. The minimum obtained classification rate is also 81.81% in only three cases. The average classification rates for the movement and motor imagery of the left hand are 87.31% for C4, 87.31 for CP4 and 88.98 for the P4 channel. The maximum classification rate was obtained for a very wide range of features and these ranges are also different for the same subject for all three channels. Approximately 20% of the subjects discriminated better only the mu rhythm (features range 85-137), 30% only beta rhythm (features range 1-84) and 50% of subject discriminated both mu and beta rhythms.

The Friedman Two-way ANOVA by Ranks Test demonstrates that the LDA classifier used by BCI2000 has a lower performance than the MPL-NN obtaining the mean rank of 1.12. The p-value was 0,000 and the null hypothesis was rejected which means the distribution of the two classifiers is not the same.

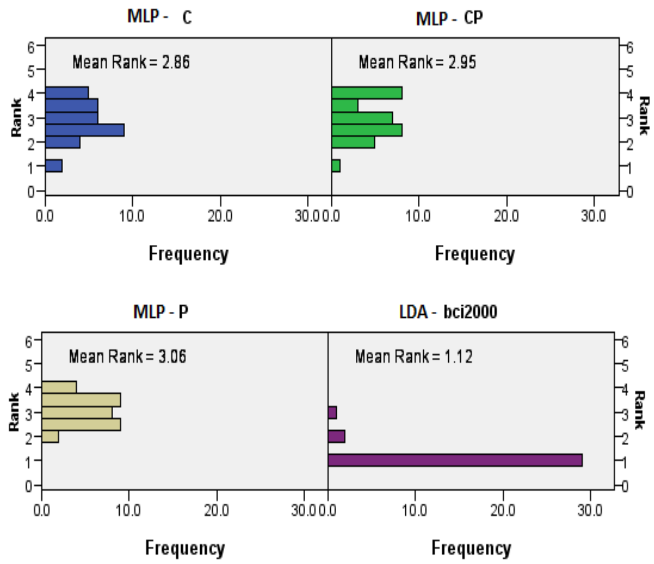

Fig. 2. Related-samples Friedman`s Two-Way Analysis of Variance by Ranks

IV. Conclusions

The maximum classification rate obtained with the proposed method is 95.45%. This accuracy was obtained for three subjects on the CP3 channel and one subject on the C3 channel for movement/motor imagery of the right hand. For the movement/motor imagery of the left hand, Table II of classification results, it can be seen the maximum rate of 95.45% on the CP4 channel for two subjects and P4 for one subject. In the first table the maximum averaged classification, 89.85%, was obtained on the CP3 channel while in the second table the maximum average is 88.98% on the P4 channel. The MLP-NN classifier performs better than the classifier proposed by BCI2000 and this affirmation was sustained also by The Friedman Two-way ANOVA by Ranks Test. This maximum classification rate of 95% was obtained also with other classifiers used in previous researches, but when we analyze the means obtained for each channel this MLP-NN classifier performs better than all others. So, the classification based on k-nearest neighbor's method was obtain 82.5% on C3, 81.9% on CP3 and 82.6 on C3, 82.05 on C4, 83.8 on CP4 and 83% on P4 [14]. The classification results obtained with the proposed Linear Discriminant Analysis were 78.9% on C3, 78.68% on CP3, 78% on P3 and for the left hand 78.82 on C4, 79.05% on CP4 and 79.52 on P4. The classifier based on the Support Vector Machine had the averaged classification results of 79.71% on C3 and 79% on C4 channels [9].

The variability of the features ranges for which the maximum results of the classifications were obtained demonstrates once again the chaotic and nonlinear characteristics of the EEG signals. Also, we can see that approximatively 10% of the subjects discriminated better only the mu rhythm, 20% only beta rhythm and 50% of subjects discriminated both mu and beta rhythms.

In conclusion, this method of classification based on neural networks performs better than BCI2000 software for all the subjects. Also, this classifier performs better than all classification methods used in previous research.

References

[1] H. Gastaut, "Electrocorticographic study of the reactivity of rolandic rhythm", Rev Neurol (Paris), 1952, pp. 176-182.

[2] G.E Chatrian., "The mu rhythm. In: Re´mond A, editor. Handbook of electroencephalography and clinical neurophysiology: the EEG of the waking adult", Amsterdam: *Elsevier,* 1976, pp. 46–69.

[3] H. Yuan and He B, "Brain-computer interfaces using sensorimotor rhythms: current state and future perspectives." IEEE transactions on bio-medical engineering vol. 61,5, 2014, pp. 1425-1435.

[4] A. Minkyu, C. J. Sung, "Performance variation in motor imagery brain–computer interface: A brief review", Journal of Neuroscience Methods, Volume 243, 2015, Pages 103-110, ISSN 0165-0270.

[5] [Pfu1] G. Pfurtscheller, C. Neuper, D. Flotzinger and M. Pregenzer "EEG-based discrimination between imagination of right and left hand movement", Electroencephalogr. Clin. Neurophysiol, 1997, 103, pp. 642–51.

[6] D. J. McFarland, L. A Miner, T. M.Vaughan and J. R. Wolpaw,. "Mu and beta rhythm topographies during motor imagery and actual movements", Brain topography, 2000, 12(3), pp. 177-186.

[7] J. J. Shih, D. J. Krusienski and J. R. Wolpaw,. (2012, March). "Brain-computer interfaces in medicine", 2012, Mayo Clinic Proceedings, Elsevier, Vol. 87, No. 3, pp. 268-279.

[8] Guger Thechnologies Web site http://www.gtec.at/. Accessed September 5, 2019

[9] R Toderean, I. Chiuchisan, "Application of Support Vector Machine for the classification of sensorimotor rhythms in Brain Computer Interface", 2017, E-Health and Bioengineering Conference (EHB)

[10] R. Aldea, "Multiresolution wavelet analysis and Hurst estimation used for highlighting sensorimotor rhythms", bulipi-eee.tuiasi.ro, 2013, Vol. LIX (LXIII), pp. 63-71.

[11] H. D. Beale, H. B. Demuth and M. T. Hagan, "Neural network design", 1996, Pws, Boston.

[12] G. V. Sridhar and P. M. Rao, "A Neural Network Approach for EEG classification in BCI", 2012, International Journal of Computer Science and Telecommunications, 3(10),pp. 44-48.

[13] R. Aldea, M. Fira and Lazăr A., "Classifications of motor imagery tasks using k-nearest neighbors", 2014, In 12th Symposium on Neural Network Applications in Electrical Engineering (NEUREL), IEEE, pp. 115-120.

[14] R. Aldea and M. Fira, "Classifications of motor imagery tasks in brain computer interface using linear discriminant analysis", 2014, International Journal of Advanced Research in Artificial Intelligence, 3(7), pp. 5-9.