RECOGNITION OF DIRECTION OF FINGER MOVEMENT FROM EEG SIGNAL USING MARKOV MODELS

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Abstract: The article describes method, process and results of single-trial EEG signal classification using Hidden Markov Models (HMM). EEG accompanying fast extension and flexion movement of right index finger is classified. The aim of our study is to verify classification possibilities of the very closely localized and similar movements. The used classification system is able to distinguish between movements. A relationship between statistic processing, results of classification and characteristic of EEG (ERS, ERD) is given.

Introduction

Our previous work [1] was concerned with the single-trial classification of right shoulder and right index finger movements from the EEG signal. The classification of right index finger fast extension and flexion (E/F) movements is more complicated, because both movements are accompanied with activation of near parts of cerebral cortex. Moreover, movements are performed on the same side of the body thus it is not possible to use EEG power difference between left and right senzorimotor area (SMA), which can help with common problem of left/right hand movements classification [2]. The application field of our research results is to improve the movement classification resolution of the existing systems in the BCI domain.

EEG Database

The data we used for our experiments were originally recorded for EEG analysis presented in [3], where a detailed description of the database can be found. Eleven subjects took part in the experiment, each of them performed ≈120 E/F movements with right index finger – see Table 1. Spacing between movements was 10-12s, persons had have closed eyes during the experiment.

EEG was recorded using 21 closely spaced silver electrodes; installation is shown in Figure 1. EEG was filtered using Laplacian operator. Only the electrodes with all neighbors were used for classification – see Figure 1. Laplacian filter was able to give accurate radial current density estimation only at these electrodes. The electrodes 5 and 10 of person 9 was removed from our experiments because they shown too much noise in the preliminary analysis.

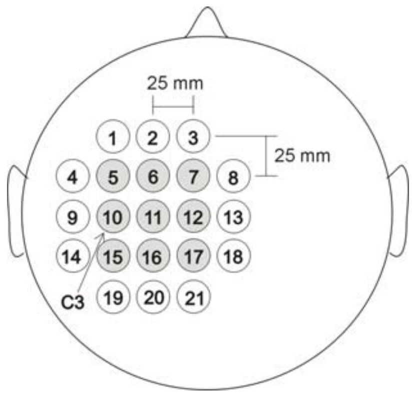

Figure 1: Placement of electrodes in experiment [3] on scalp of experimental person. The electrodes are placed over left senzomotoric cortex – contralateral to performed movements. Only shaded electrodes were used for classification.

Table 1: Number of realizations of EEG movements.

Person No.	1	2	3	4	5	6	7	8	9	10	11
No. of extension realization	73	52	41	72	99	62	74	87	44	64	84
No. of flexion realization	81	54	77	38	81	66	82	63	41	74	52

Changes in EEG accompanying movements

It is necessary to explain basic characteristics of movement EEG before the presentation of classification system function. We can see a few phenomena correlated with movement in EEG – event related potentials (ERP, time domain) and event-related desynchronization and synchronization (ERD, ERS, spectral domain). Our interest is focused to ERD and ERS.

ISSN: 1727-1983

ERD [3], [4], [9] precedes performed movement, it displays as a fall of power mainly in 8-13Hz band (μ band) in time interval <-1,5s; 0,5s> related to the time of movement. Desynchronization occurs even if the movement is not performed, it is sufficient to think about the movement. Desynchronization parameters are dependent on the character of movement. They depend for example on the speed of movement and the force that the movement exceeds. For processed movement μERD occurs always on the same frequencies, it differs between movement by power of inhibition and time span. According to [3] the flexion ERD is stronger in 8 persons, 1 person has same intensity for both extension and flexion ERD and 2 people have stronger extension ERD.

ERS [5] conversely comes after movement, displaying as a return of power to original value before the desynchronization. Moreover it displays as a rise of power mainly in 10-30Hz band (β and rarely a γ band) 1 to 3 seconds after the performed movement. ERS also carries information about the performed movement. The work [5] presents statistically important difference in βERS of extension and flexion movements. The ERS of extension movement was founded to be contralaterally stronger than ERS of flexion movement

Our aim is to show if and how can be both events used for classification of performed movement.

Parameterization and Classification

FFT parameterization was selected as follows the first experiments [1]. The vector of parameters consisted of 35 samples – spectral lines amplitudes (5-40 Hz, time resolution 200ms, spectral resolution 1Hz, f_{sample}=256 Hz). Frequency band 1-35Hz was used for classification originally; better classification score was archived but according to used method of data recording the classification was influenced by long-term changes in EEG and low-frequency artifacts. In opposite to that the classification in 5-40Hz band works more with β/μ band. That is why we used frequency band 5-40Hz finally.

The classification system [6] used in our study is the same, which was used in our work [1]. Due to a small number of EEG movement realizations (signal is hard to obtain) the data were 16 times randomly divided into two disjunctive sets for training and testing in 1:1 ratio, then classified and results were statistically processed (mean and std. deviation computed). This approach suppressed influence of selection concrete training and testing sets on the classification score.

Classifying HMM models had left-to-right, no skips architecture [8] with 4 emitting states corresponding to four significant phases of movement-related EEG (silence, desynchronization, synchronization, silence [1] – see Figure 2). Every model state used 35 spectral lines – 35 vectors of mean and variance.

A separate model was used for every person and type of movement. In contrast to speech recognition it is not possible to generalize the trained model to more than one person. EEG represents brain activity of experimental person and so it is in some way individual. Model trained for one person is not able to classify EEG of another experimental person satisfyingly.

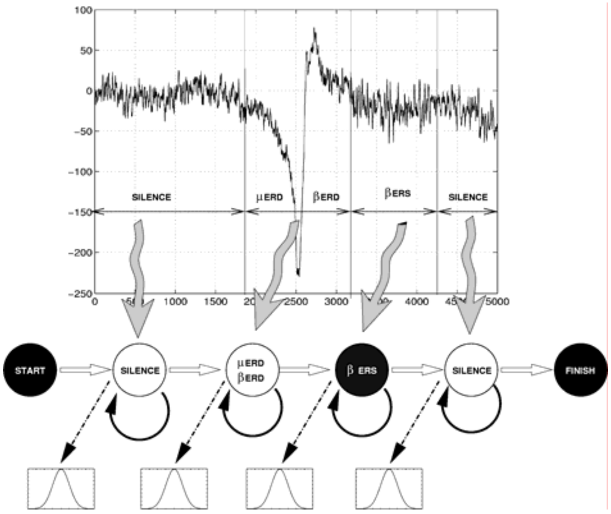

Figure 2: Architecture of used model and correspondence with EEG. On top we can see the time progress of the EEG movement realization; on bottom HMM modelling the EEG realization spectrum.

Reasons for using the HMM architecture:

- Physiological compatibility: The selected 4-state architecture matches the physiological process, it is even possible to segment the EEG with the help of the Hidden Markov model classifier.
- Ease of the interpretation: It is quite simple to interpret the contents of the trained model. This is a big advantage compared to e.g. some kinds of neural networks, where the implementation of the trained system is not so straightforward. That can be used for statistic analysis of EEG or for deeper understanding of classification.
- Ability to model the EEG: We are able to generate synthetic realizations of the EEG for tests of various algorithms.

Statistic analysis

Our next aim was to prove that the classification system truly recognizes components bounded with movement and not for example systematic noise related with used recording method. If this type of interference would be founded, the appropriate combination of person-electrode is discarded from further experiments.

Spectral processing was applied on recorded EEG extension and flexion movement signals. Spectrograms were computed by Fourier transform; short-time magnitude spectrum time development was captured by 1sec long advancing windows (frequency resolution 1 Hz), with 0,2sec overlay (time resolution 200 ms). The data is divided into 10sec long epochs with the movement onset in the 5th second (time instant 5.00 sec). Presented spectrograms were created by averaging across all realization of each person and electrode. Color scale is the same in each spectrogram is same for both movements so the figures are mutually comparable. Acquired spectrograms and the classification results diametrically differed between persons, smaller differences were observed among electrodes of the same person.

Our analysis of EEG differed from the detailed analysis introduced in work [3] by method of processing the spectrum. While work [3] analyzed EEG with the standard medical process and with respect to physiology of its genesis, we wanted to see EEG in the way the classification system used it. That allowed us to evaluate its correct function. We used approach known from data mining – we let the classification system to learn and found the electrodes where the types of movement can be easily differentiated and than we found out if the founded differences were really relate to movement EEG.

Result of statistical processing

We divided the differences in EEG to two parts - differences between experimental subjects and differences between electrodes to underline the interpersonal variability and influence of localization of brain centers.

Differences between experimental subjects

The electrode 11, C_1 was selected as an example – ERS [5] can be founded on it and it shows interesting results.

We can see easily visible synchronization in Figure 3 following the performed movement. Here it is evidently larger for extension movement in opposite to Figure 4 where the difference is not so distinctive. This corresponds with better archived classification score with person 2.

On the other hand we can see noticeable fall of power (desynchronization) on spectral lines ≈ 11-12Hz, see Fig. 5. Unluckily the ERD magnitude is the same for both extension and flexion movement and thus unsuitable for the classification between the movements. The synchronization is also neither strong enough nor different between movements – this is the same for all electrodes of person 1.

Similar difference as in Figure 3 can be seen in Figure 4, conversely the synchronization is expressively large for flexion movement. In an opposite to both any significant differences between movements cannot be found in Figure 6 in both ERD and ERS.

We can see how big are differences between each experimental person's EEG signal by simple comparison of the 4 presented spectrograms. In so doing we showed only a small part from the whole EEG database.

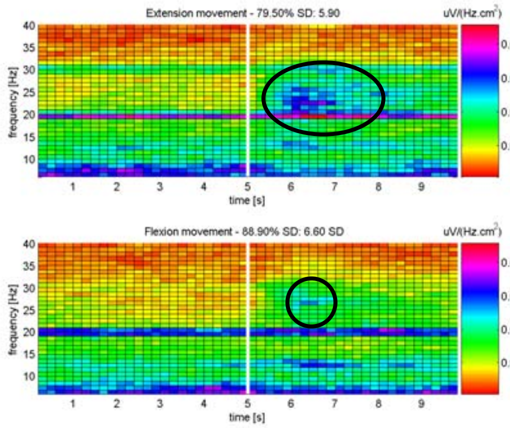

Figure 3: Estimation of the EEG short time magnitude spectrum time development; EEG accompanying both movements – person 2, electrode 11 – C_1. We can see ERS in β band. The event is marked with the black circle. Compare the differences in power of ERS between the movements. The time instant of the performed movement is marked with thin white line in the middle of the picture.

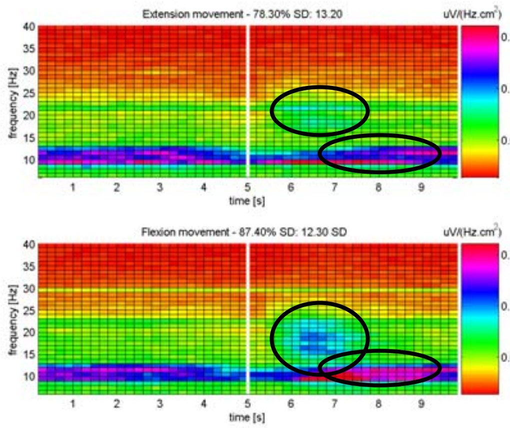

Figure 4: Person 10, electrode 11 – C_1: We can see clearly βERS and even μERS in EEG short time spectra time development. Both are marked with circles. The power of ERS depends on the type of movement. The classification system works on this electrode satisfyingly thanks to ERS.

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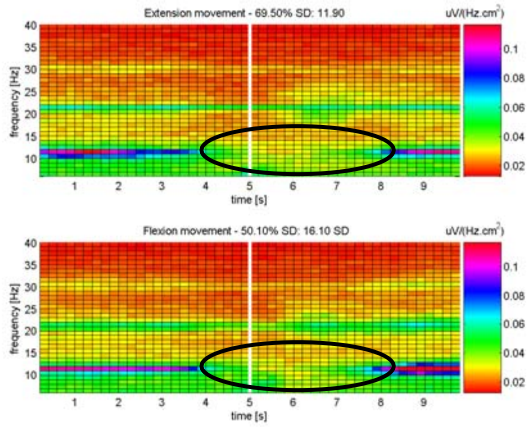

Figure 5: Person 1, electrode 11 – C_1: Manifestation of ERS cannot be seen in spectrum, but we can see noticeable μERD – marked with circles on the picture. ERD achieves the same parameters for both types of movement.

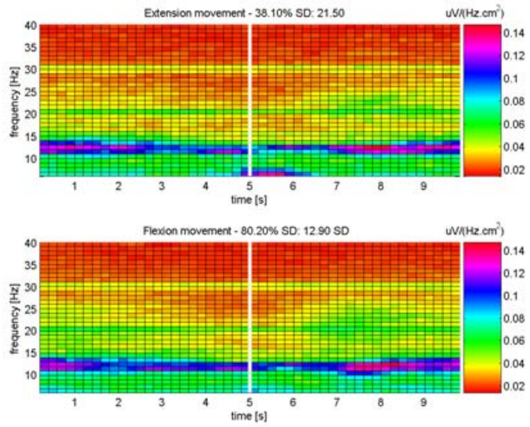

Figure 6: Person 3, electrode 11 – C_1: We cannot see nearly any manifestation of ERD or ERS in spectrum. That is in accordance with bad differentiation of both movements using the EEG recorded from this electrode.

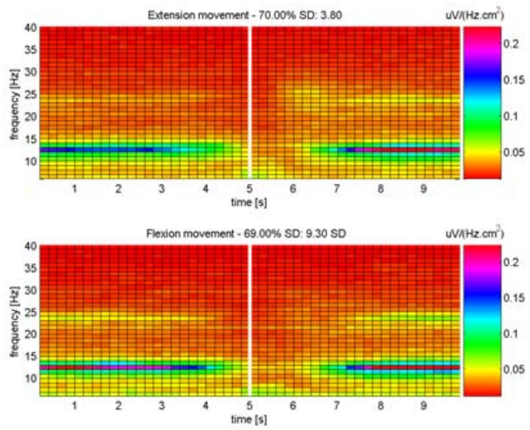

Figure 7: Person 8, electrode 15 – C_{3p}: We cannot see ERS in spectrum, only μERD. ERD is approximately the same in both movements.

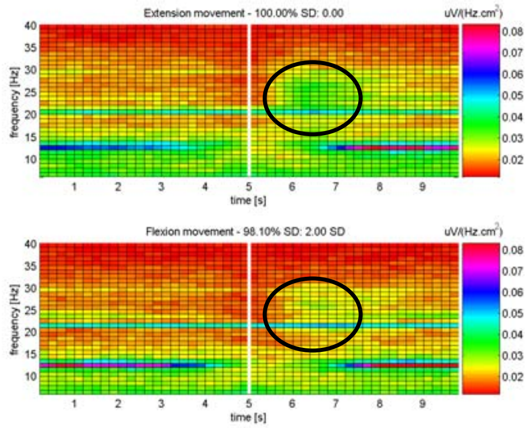

Figure 8: Person 8, electrode 11 – C_1: EEG spectrum on this electrode again shows μERD about the time of movement – here it is stronger for extension movement. βERS is also observed, also stronger for extension movement.

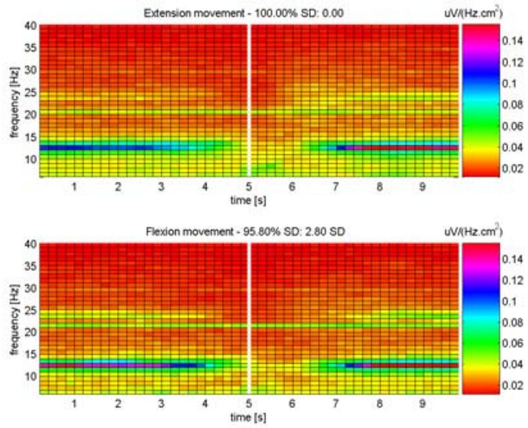

Figure 9 Person 8, electrode 10 – C_3: Excellent classification score can be achieved using this electrode EEG, yet spectrogram does not show large differences.

Differences between electrodes

The differences between EEG electrodes of one person are documented on subject 8, because her EEG can be successfully classified – see Table 2 below.
Synchronization following performed movement can be clearly see in Figure 8 (electrode 11) which demonstrate the rise of power (here in frequency range 20-30Hz) in opposite to Figure 7 (electrode 15) where this rise of power is nearly not noticeable – this is with accordance with the lower classification score. Compare with Figure 9 (electrode 10), where so large difference between movements cannot be seen from statistical processing, yet the excellent classification score is achieved. Further analysis is needed in this case.

Placement of the brain center is responsible to extension and flexion movement can be estimated from the statistical processing, even better than from classification results, which are more dependent on the differences between each movement. Here we can conclude that the responsible brain center is placed near to electrode 11 (C_1).

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Result of Classification

The classification score for each experimental subject and type of movement is shown in Table 2.

Table 2: The classification results – mean and uncertainty on 67.7% level of significance (1×σ).

Person No.	Electrode No. (10/20 position)	classification score Ext. [%]	classification score F. [%]
1	6 (FC_1)	66.3 ± 3.8	55.4 ± 3.5
2	10 (C_3)	93.3 ± 1.0	91.6 ± 1.5
3	6 (FC_1)	69.8 ± 3.4	82.4 ± 1.9
4	5 (FC_3)	94.6 ± 0.7	90.9 ± 1.8
5	6 (FC_1)	78.1 ± 2.5	85.0 ± 2.8
6	11 (C_1)	67.7 ± 2.9	72.7 ± 3.0
7	6 (FC_1)	91.7 ± 1.2	68.5 ± 1.6
8	11 (C_1)	100.0 ± 0.0	98.1 ± 0.6
9	5 (FC_3)	99.7 ± 0.3	84.4 ± 2.0
10	6 (FC_1)	76.2 ± 3.4	86.1 ± 2.2
11	5 (FC_3)	95.4 ± 1.3	80.0 ± 2.8

With the help of contingency tables – see [7] – we have further analyzed classification score and determinate the credibility of results.
The probability of null hypothesis H0: “Result of classification does not depend on really performed movement.” was estimated using chi square test. The analysis is executed on α=99.5 % confidence level. The following chi square distribution quantils were determined:

Person 01, p=0.36056
Person 02, p=1.00000 – rejecting H0
Person 03, p=0.99828 – rejecting H0
Person 04, p=0.99998 – rejecting H0
Person 05, p=0.99794 – rejecting H0
Person 06, p=0.76514
Person 07, p=1.00000 – rejecting H0
Person 08, p=1.00000 – rejecting H0
Person 09, p=1.00000 – rejecting H0
Person 10, p=0.99888 – rejecting H0
Person 11, p=1.00000 – rejecting H0

It can be concluded that classification system truly recognizes extension and flexion movement for persons 2,3,4,5,7,8,9,10,11. For remaining two persons the results are uncertain. Person 6 - 67.7 and 72.7% successfully recognized movements with respect to the numbers of available realizations (62 and 66) gives poor results. Person 1 archives the worst classification score – only 66.3% a 55.4% for both movements. We can see the large EEG variability between persons in the classification result.

Relation Between Our Results And Other Published Works

Works [3] and [5] analysed ERD and ERS accompanying movements in detail. Our analyses shown these results:

1. ERD can be easily seen in the area of electrodes C_1 and C_3 – electrodes 10 and 11 in our experiment. Moreover, [3] states that there are significant differences between both types of movements in the EEG pre- and post-movement epochs.
2. ERS can be founded more frontally (direction to forehead) related to ERD. Work [5] stated that ERS reaches its maximal scalp amplitude on 2.5 cm frontally from electrode C_3 and 5-7.5 cm to the left from electrode C_z. Electrodes 5 and 6 are placed in this area in our experiment.

Presented conclusions are in compliance with the result of our classification. When we look at the best classification results we can divide them into two categories:

1. Persons, for which the best classification score is achieved on electrodes 5 and 6 – here the system probably based the classification on ERS.
2. Persons, for which the best classification score is achieved on electrodes 10 and 11 – classification based on the differences in ERD between movements.

Conclusion and next steps

We successfully applied existing classification system on more difficult task of EEG movement direction classification. Used setting was the same as in our previous work dealing with classification of distal and proximal movement. We can assume that the same model will be possible to use for other types of movement activity classification.
We have proved that the results of classification are not random for 9 out of 11 experimental persons by chi square test application on α=99.5 % confidence level.
Further we analyzed reached classification score with the EEG data using the data mining techniques. We concluded that the classification system truly recognizes movement components of the EEG signal. Localization of electrodes achieving the best classification score is in a good accordance with the results of physiological analysis of EEG presented in [3] and [5].

These results indicate with high confidence level that the classification system truly recognizes movement components in EEG.

Our next work will be focused on increasing the classification score by additional analysis of other parameterization and studying the trained models with the data mining algorithms [7].

Acknowledgement

This work was supported by grant Transdisciplinary Research in Biomedical Engineering No. MSM 684 0770012 of the Czech University in Prague, and the Grant GACR 102/03/H085: Biological and Speech Signal Modeling.

Further we would like to thank prof. Andrej Stančák (The 3rd Medical Faculty of the Charles University in Prague, The Department of Normal, Clinical and Pathological Physiology) for his support and invaluable comments.

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