

CZECH TECHNICAL UNIVERSITY IN PRAGUE



DOCTORAL THESIS STATEMENT

Czech Technical University in Prague

Faculty of Electrical Engineering

Department of Circuit Theory

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CLASSIFICATION OF HUMAN MOTOR ACTIVITY FROM EEG

Ph.D. Programme: Electrical Engineering and Information Technology

Branch of study Electrical Engineering Theory

**Doctoral thesis statement for obtaining the academic title of “Doctor”,
abbreviated to “Ph.D.”**

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Those interested may get acquainted with the doctoral thesis concerned at the Dean Office of the Faculty of Electrical Engineering of the CTU in Prague, at the Department for Science and Research, Technická 2, Praha 6.

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1. INTRODUCTION

Brain Computer Interface (BCI) is a very specific tool which bypasses traditional brain output pathways – peripheral nerves and muscles. The output commands are take directly from the brain instead [1]. The system designed in this manner can be used with paralyzed patients (*Spiral Cord Injury*), even with those with no remaining muscles control (*Amyotrophic Lateral Sclerosis*). The system can enable to control computer or any other device as well as to provide means of communication. Many brain activities can be used [2], but the most natural way to control our surrounding is to just think the movement like we do everyday and the movement-related activity also offers means to support the brain self-repairing capabilities in rehabilitation applications, e.g. after *Stroke*. The thesis deals with offline classification of EEG signals accompanying voluntary extension and flexion movements of an index finger in order to *improve resolution* of the existing BCI systems, and online classification of motor imagery using developed real-time processing system in order to find out optimal *training procedure* and *feedback* representation to support effective user training.

2. STATE OF THE ART

Classic movement-related BCI task identifies *left and right* hand movements [3][4]. Movements of foots and tongue are used to extend the number of classes [5]. Movements of different parts of the body are controlled by different parts of the somatosensory cortex (Penfield Homunculus) and have a different on-scalp spatial distribution of the EEG responses. Majority of BCIs utilize these differences, for example [6][7][4].

Different types of *same body parts movements*, e.g. wrist movements [8][9][10], hand opening and closing [11][12], or movements of closely localized body parts, e.g. different finger movements [13], are rarely used with noninvasive BCIs because the movements are controlled by closely localized and even overlapping parts of the brain [14] therefore spatial distribution of the on-scalp EEG responses can hardly be utilized [8]. Our group is therefore investigating the utilization of *temporal context* [15][13] by applying a *dynamic* Hidden Markov Models (HMM) classifier.

There is no other work known to me performing classification of extension and flexion movements of the same finger using noninvasive EEG recordings apart from my previous works [16][17][18] and preliminary study of my supervisor [19]. Other studies of our group dealt with individual fingers movements [13], or distal (index finger) versus proximal (shoulder) movements [20][21]. Classification of finger movements has been done successfully so far only using invasive data acquisition methods [22][23]. It must be emphasized, that in all cases of high-resolution studies, if movement classification was applied [9][8][24] it was performed offline only and using complex and manual signal processing. Most of high-resolution studies deals with activity detection only [25][12][26][11][27][28] and frequently using recording distinct movement types in distinct blocks [8][29] which is suitable only for rehabilitation applications.

The *Feedback* is a critical part as it provides a link from the BCI to the user and enables the user to learn controlling his brain activity. The feedback can be *uncontrolled*, i.e. reflecting directly the subjects activity or *controlled*, i.e. acting in some form of predefined way [2]. There are two main alternative approaches: *process control*, i.e. interactive ongoing complex interaction in order to carry the user's intent and *goal selection*, i.e. carrying the user's intent in a predefined way [1][2].

3. AIMS OF THE DOCTORAL THESIS

High movement-resolution classification: Number of the recognized states could be increased which could increase the information transfer rate as well as to improve rehabilitation techniques. A BCI could potentially facilitate restoration of paretic hand function, which would have substantial clinical impact [23].

- I aim to show the necessity of EEG *temporal context* utilization for improving resolution of the existing BCI systems by classifying extension and flexion movements of the same finger. For this purpose the thesis presents:
 - Comparison of results achieved using dynamic and static classification approaches and various feature extraction methods on the adopted EEG database [30][31].
- I aim to assess the *feasibility* of high-resolution classification in control applications. For this purpose the thesis presents:
 - Design of experimental recording respecting the drawbacks of the database [30][31] from the control application point of view, the performed *recording*, methods for processing the database, and method for merging recordings separated by a long period.
 - Problems met in BCI systems related to *high dimensionality* of the features in offline processing which may prevent to replicate results of existing high movement-resolution studies online.
 - Results achieved on the recorded database with fair analysis of *classification basis*.

Feedback influence: The user training may be the most important factor affecting the BCI capabilities [32]. In contrast to most BCI papers which focuses on development of complex methods on the computer side I shall use the simplest possible signal processing methods and focus on the influence of feedback itself.

- I aim to show that usage of simple signal processing methods is not only sufficient to achieve high-speed control but their usage in online processing is desired. I aim to find out how to present the feedback and how to conduct experiments online to support effective training of the users. For this purpose, the thesis presents:
 - *Design and implementation* of a universal real time EEG processing system.
 - Study on *feedback influence* using left and right arm motor imagery, where various ways of controlling the feedback are compared and guidelines for performing experiments are presented.

4. WORKING METHODS

4.1 Used data

The EEG database recorded in study [30][31] was *adopted*. Eleven subjects took part in the experiment; each of them performed brisk extension (extension followed by a return to the resting position) and flexion (flexion followed by a return to the resting position) movements of the right index finger. The distinct types of movements were recorded in distinct blocks; and the movements were performed on acoustic trigger (synchronous recording protocol), for more details see [30][31].

To evaluate the performance of our developed algorithms under “less laboratory” conditions I recorded *my own database*. The experimental set-up was changed from synchronous to asynchronous; the subjects performed the movements in time intervals of more than 10 sec and selected the movements based on their own will (i.e. self-paced and randomized recordings). To evaluate the stability of the whole system the recording was repeated after one year period. The recording took place at the laboratory of evoked potentials at the Medical Faculty of Charles University in Hradec Králové. Ten male subjects took part in the experiment. Four kinds of movements were performed during the recording – brisk extensions or flexions of left or right index finger.

To study the feedback influence using the developed real-time processing system I performed *online experiments* at our department. In contrast to the above mentioned databases, the data was recorded in an unshielded room not modified for EEG recording in any way during regular office hours. Eleven subjects took part in the recordings while seven subject took part in the study on user training. The experiments were performed under synchronous protocol as show in Figure 1, the subjects performed imagery of left and right arm to extend the bar or play a simple game. Finally asynchronous process control operation was tested.

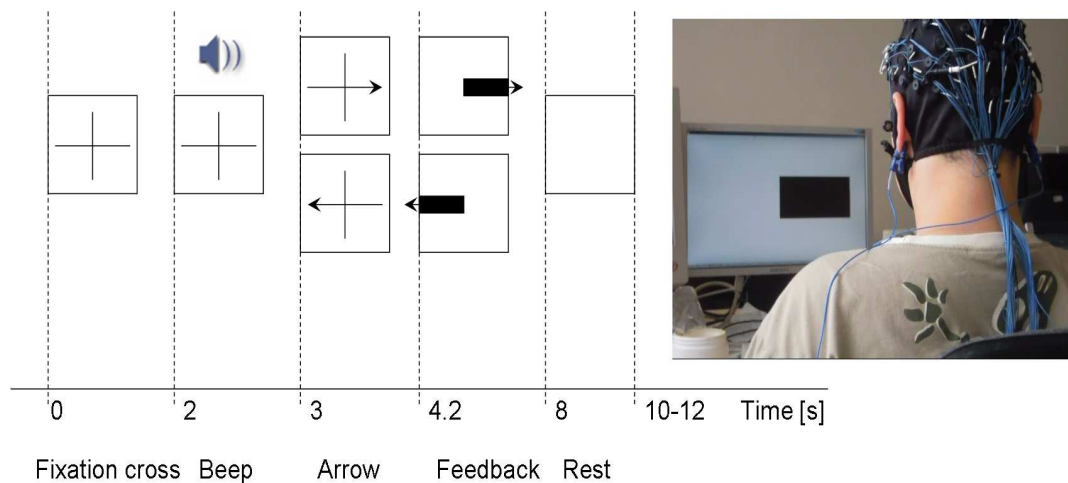


Figure 1: The original experimental protocol used in the synchronous experiments.

4.2 Temporal context utilization

The architecture of the used HMMs was designed by my supervisor [19][33][13] to capture the temporal development of movement-related EEG: Event-Related Desynchronization (ERD) and Event-Related Synchronizations (ERS). The used models have left-to-right, no skips architecture with four emitting states modeling the four significant phases of movement-related EEG, see Figure 2. The most important advantage of this approach is the physiological compatibility – the selected model architecture matches the underlying physiological process (this is actually insertion of a priori information on the EEG behavior to the classification system [13]). The movement-related EEG signal is not recognized based on ERD spatial scalp distribution but on its temporal context using only one signal source – based on differences between ERD and ERS parameters between both types of movements, more details can be found in [13][34]. To show the necessity of temporal context I compared the HMM with the following classifiers: Support Vector Machines (SVM), Learning Vector Quantization (LVQ), and one layer Perceptron. In contrast to other studies I used all these classifiers with a feature space extended to capture temporal dynamics – a Time Delay Neural Network

(TDNN) like approach, see Figure 3. Discrete Time Fourier Transform (DTFT) with frequency band of 6-40 Hz (called *full dimension* in further text), Autoregressive model (AR) coefficients, cepstrum and reflection coefficients features were used. Also, the DTFT features summed over the frequency dimension were used (called *reduced dimension* in further text) to mitigate curse of the dimensionality.

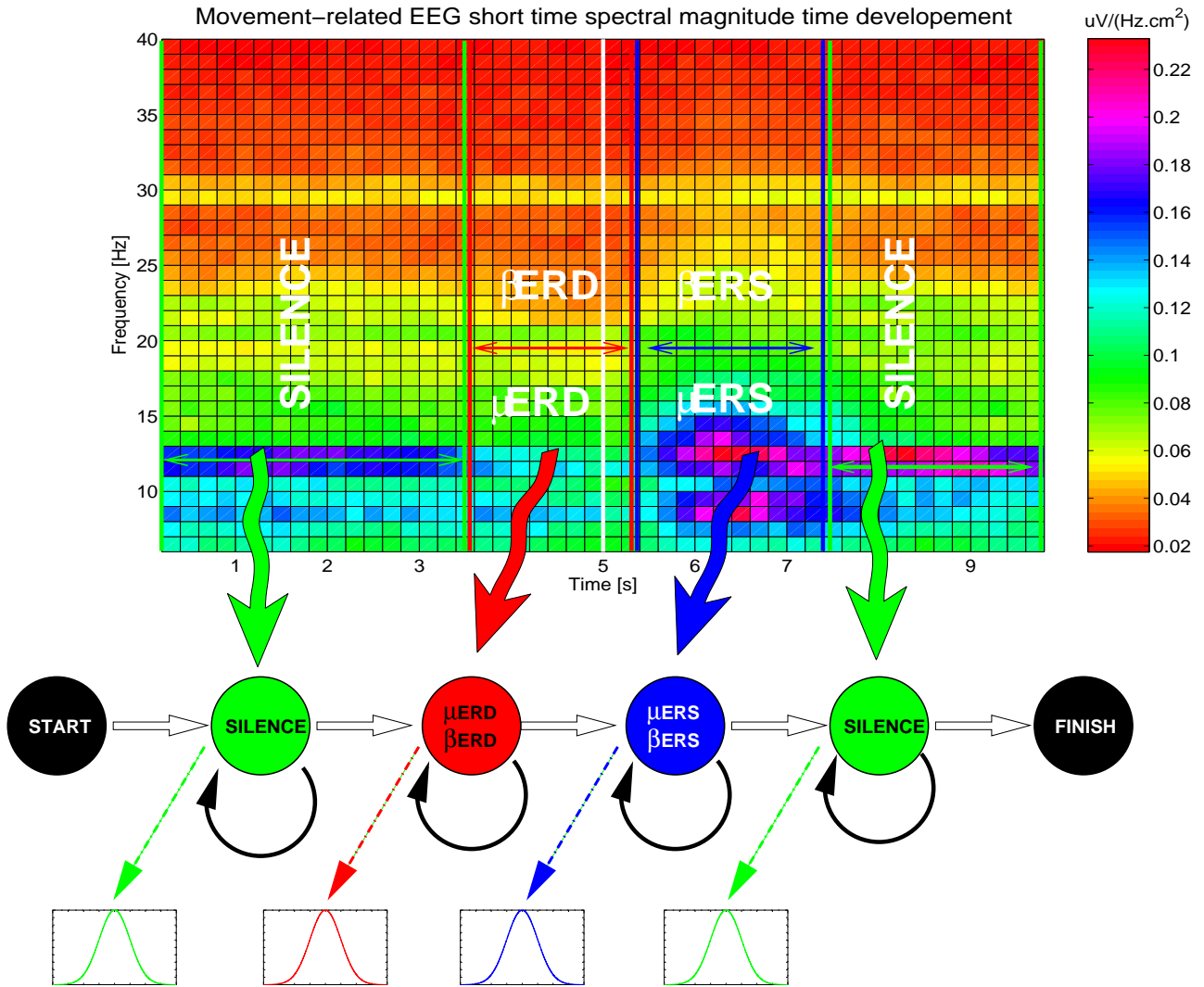


Figure 2: Hidden Markov Model architecture along with the EEG short time spectrum temporal development.

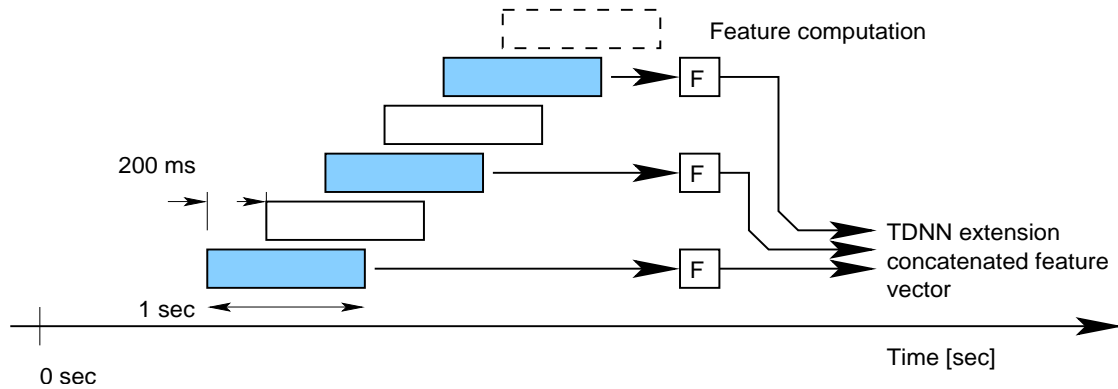


Figure 3: TDNN-like segmentation and feature extraction process.

4.3 Real time processing system

A modular real time processing system was designed and constructed in frame of obtained grant no. SGS10/178/OHK3/2T/13 of the student grant competition. Serious effort was taken in designing the system

and brand new system was implemented to allow easy future extensions of the system. The system allows performing experiments in both synchronous and asynchronous manner, present different representations of the feedback, control the feedback in different ways, and allow tailoring the feedback during the course of the experiment. The EEG Processing Pipeline (EPP) was build of loosely coupled blocks connected via network packet interfaces, see Figure 4. The *modular* and *distributed* architecture allows to freely distribute parts of the BCI EPP across network to extend the radius of the device as well as to exploit parallelism offered by the today's multi core systems. It is also possible to integrate existing standalone programs by implementing an appropriate interface module. The system is designed as *open* which means that all the settings as well as definition of the communication protocol are stored in standalone configuration files. This gives a great flexibility to the whole EPP.

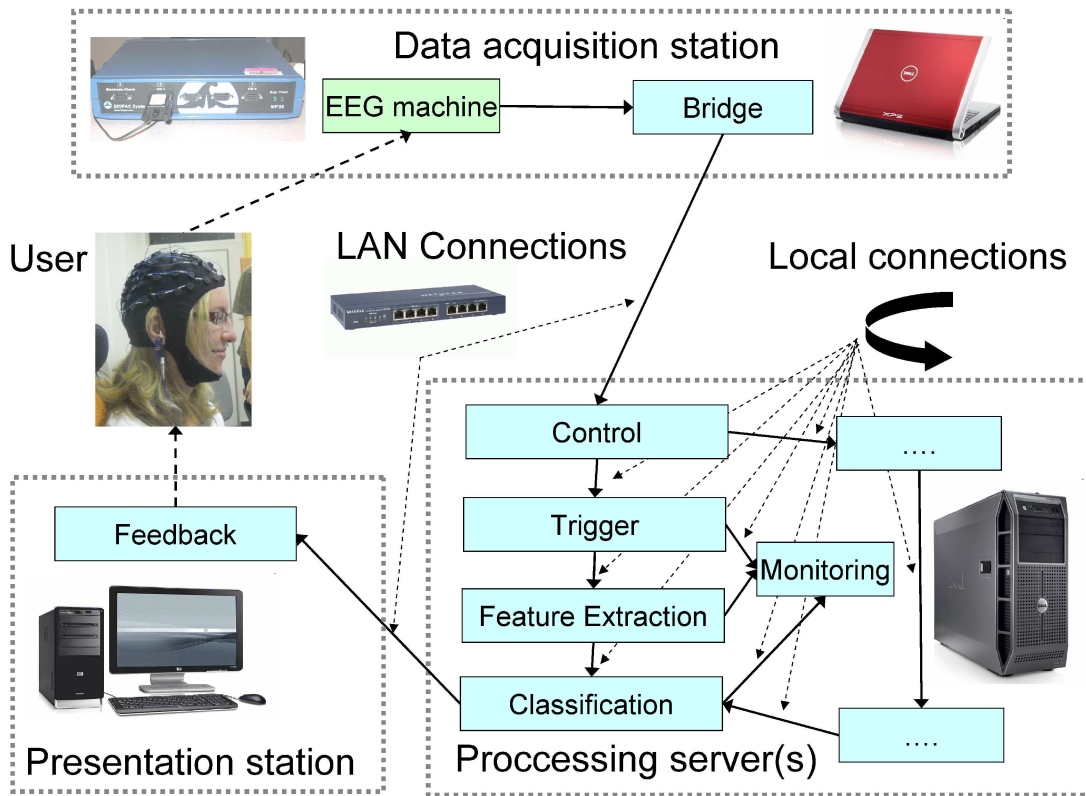


Figure 4: Modular architecture of the EEG Processing Pipeline (EPP).

The simplest possible methods were used: only two bipolar electrodes (placed over C3 and C4 locations), and one-dimensional 8-40 Hz band power asymmetry feature as defined by (1). Balancing of the feature was performed as some difference in signal power between the hemispheres is present while not performing the imagery due to background EEG activity, different electrode impedances etc.:

$$A_b = \frac{R(1+b) - L(1-b)}{R(1+b) + L(1-b)}, \quad (1)$$

where A_b is the balanced asymmetric ratio, R is the power extracted from channel recorder over right hemisphere, L is the power extracted from channel recorded over left hemisphere, and b is the balancing constant. The balancing constant b was automatically computed during the experiment as:

$$b = \frac{\text{Avg}(R) - \text{Avg}(L)}{\text{Avg}(R) + \text{Avg}(L)} \quad (2)$$

The simplicity of the processing enables straightforward analysis, easy tailoring during the experiment, and

allows to present the feedback without previous sessions devoted to training the classifier only. Snapshot of the modules graphical user interface is shown in Figure 5.

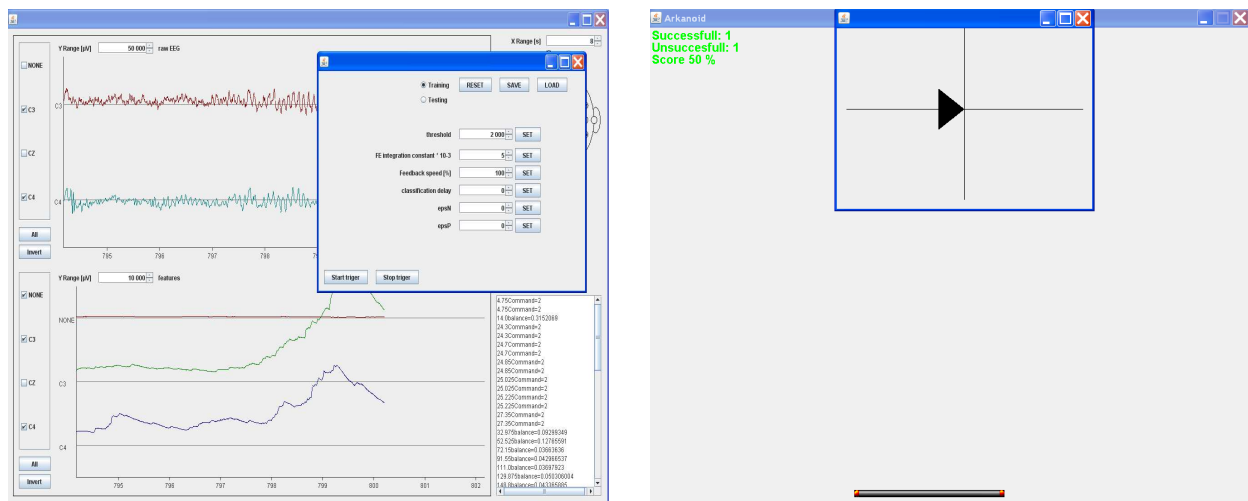


Figure 5: Snap shot of the modules GUI: a) control station: Control and Data Flow Monitoring modules; b) presentation station: Arkanoid game and Feedback modules.

4.3.1 Feedback

All the feedbacks were *continuous* (updated during the whole trial) and *cumulative* (the classification results was added) and 1 target to reach was given. *Optimistically controlled* feedback was used to avoid frustration from incorrect classification results. The feedback was provided only when classification was correct,

meaning the bar did not extend in the other direction but stopped or the player did not move in the other direction but stopped. *Uncontrolled raw* feedback was used to find limits of information transfer rate. The raw feedback directly represents classification result and is totally uncontrolled. Various feedback representation were tested: The *extending bar* was used in the first experiments as it is the most frequently used, see Figure 1. Animation was used to provide *realistic feedback*, see Figure 6. *Simple game* (called Arkanoid in the



Figure 6: Demonstration photo of experiment using realistic feedback. The feedback is reflecting the subjects imagery of rising hand.

further text) was used to provide meaningful control application and increase motivation of the subjects. See our web page [35] for demonstration videos of all the feedback types. The game supports both synchronous and asynchronous mode:

- In *synchronous mode*, a falling ball at left or right side of the screen is presented and the feedback is provided by movement of the player. The ball is falling directly down and the speed is set for the ball to reach the bottom of the screen at the end of the trial. The protocol depicted in Figure 1 is used but the feedback is provided by movement of the player instead of the bar extension.
- In *asynchronous mode*, the ball appears at random location on the top of the screen, and the user had

to position the player to bounce the ball; the ball then bounce at the screen boundaries. If the subject miss the ball the game is stopped for a while to give the subject a rest and then another ball falls from random location on the top of the screen. The feedback is always uncontrolled in the asynchronous mode and no instructions are presented, the subject just plays the game.

4.3.2 Study on user training

One recording lasted up to one and half hour and consisted of several 10-minutes long sessions. The sessions were done in each of the recordings as follows:

- First session was done without feedback, this was made to give time to the subject to get used to the task as well as be sure that the subject utilize movement-related activity later on.
- Second session was done using optimistically controlled bar feedback, this session was repeated until successful classification was achieved otherwise it would be futile to continue.
- Arkanoid game was used in the third, fourth and fifth session. The order of feedback control Optimistic-Raw-Optimistic (ORO) or Raw-Optimistic-Raw (ROR) was used. Half of the subjects started with one sequence and the other half with the other sequence. This was made to assess the usability of both types of control as well as the influence of feedback control on training the subjects.
- Arkanoid asynchronous free game was attempted at the last session if the subject was proficient in the previous tasks.

5. RESULTS

5.1 Adopted database

Examples of classification score time development with 95 % confidence intervals are shown in Figure 7. The movement was performed at the fifth second. The classification based on AR coefficient gives worse results because the AR coefficients does not constitute an Euclidean distance feature space, see Figure 7a. The FFT features performed the best with all the classifiers.

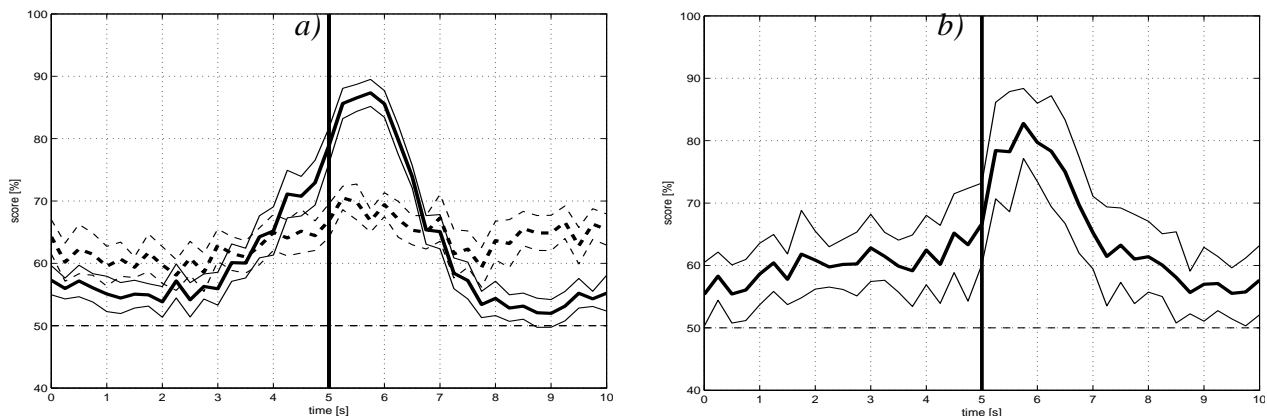


Figure 7: Classification score time development 95 % confidence intervals: a) Movement detection (vs resting EEG). Comparison of cepstral (solid line) and AR (dashed line) features. b) Movement classification, Perceptron classifier, FFT features.

Overall results are shown in Table 1, the HMM achieved the best results due to a priori information on physiological behavior of EEG inserted to the HMM classifier. The TDNN-like extension capturing temporal dynamics helped to reach higher classification scores with the remaining classifiers [34].

Classifier	Ext/Flex/Rest	Ext/Flex	Ext/Rest
HMM	88.7 ± 5.84	83.0 ± 10.7	99.9 ± 00.2
Perceptron	Not applicable	71.2 ± 11.6	93.6 ± 05.3
SVM	51.7 ± 14.2	74.3 ± 08.9	95.4 ± 03.4
LVQ	61.4 ± 11.6	71.3 ± 08.8	90.3 ± 03.7

Table 1: Grand averages of the best classification scores in percents reached in the experiments, for detail see [34].

5.2 Recorded database

Real EEG short time spectral magnitude time developments (spectrograms) for extension movement from both recording sessions are shown in Figure 8. One can see that the responses are similar in grand averages, therefore merging the sessions make sense. The signals were normalized to unit power and automatic evaluation of spectra similarity was used to remove bad contact/noisy electrodes from both session before the merge. A generative HMM classifier was selected to validate the merge due and assess the stability of movement-related responses. The overall subjects movement detection scores on the single recording was of 92.4 ± 4.9 , and 80.9 ± 6.0 on the merged recording. The scores achieved on the merged recordings are lower, yet movement detection is still possible indicating that the activity is stable.

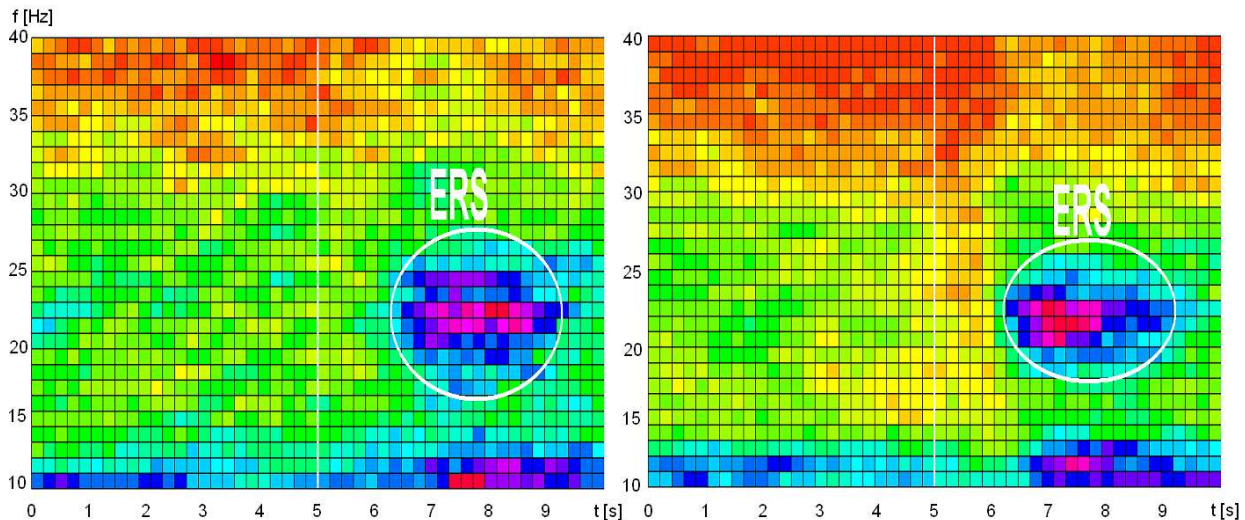


Figure 8: Short time spectral magnitude EEG time development (spectrogram), executed finger extension movement, first session (left) and second session (right). One can clearly see the marked ERS in both recordings. Experimental subject 1, electrode 36.

The results achieved on the first recording session are summarized in Table 2. The scores were computed as average over all the movement types (or movement types combinations) to provide a more precise estimate of performance. *Movement detection* was possible with all the subject even using reduced dimension of features. Classification of movement on the *opposite side of the body* was also possible with all the subjects when utilizing the difference of features between the hemispheres.

Task	Classifier	Electrode(s)	Dimension of features	Subjects with successful classification	Score averaged over these subjects [%]
Detection	LVQ	difference	1	All subjects	71.3±7.44
Opposite side	LVQ	difference	1	All subjects	66.6±9.51
Same finger*	LVQ	one	35	1, 4, and 5	67.4±5.32
Detection	HMM	one	1	All subjects	78.8±8.89 (82.8±7.37)
Opposite side	HMM	difference	1	1, 4, 5, 6, and 9	70.0±10.2 (77.3±8.73)

Table 2: Summary of selected results achieved on the first recording session. Classification scores using resubstitution method are shown in brackets with the HMM classifier - the fact that both scores are close indicate that the results are not false positive due to overtraining. * Best movement type combination for each of the subject taken into account to show that classification is possible.

Classification of extension and flexion movement of the same finger was possible only with 3 subjects

(whom had the strongest ERD and ERS responses visible in the grand average spectrograms) and only with the LVQ classifier; the classification is not reliable for practical use. Large individual differences were found in the achieved classification scores, with some subjects the classification scores were low however this is because of the fact that not anyone can use a motor activity based BCI [36]. To illustrate the variability between the subjects and compare the results with work of other authors, scores varying from 56 % to 95 % (74 % in average) were achieved using executed left and right index finger movements in online study [37] with synchronous cue based mode and the benefit of feedback. The result are different as the aim was not to replicate the experiment [30][31] but to assess the performance under more realistic conditions. Examples of classification between extension and flexion movements with LVQ classifier are shown in Figure 9.

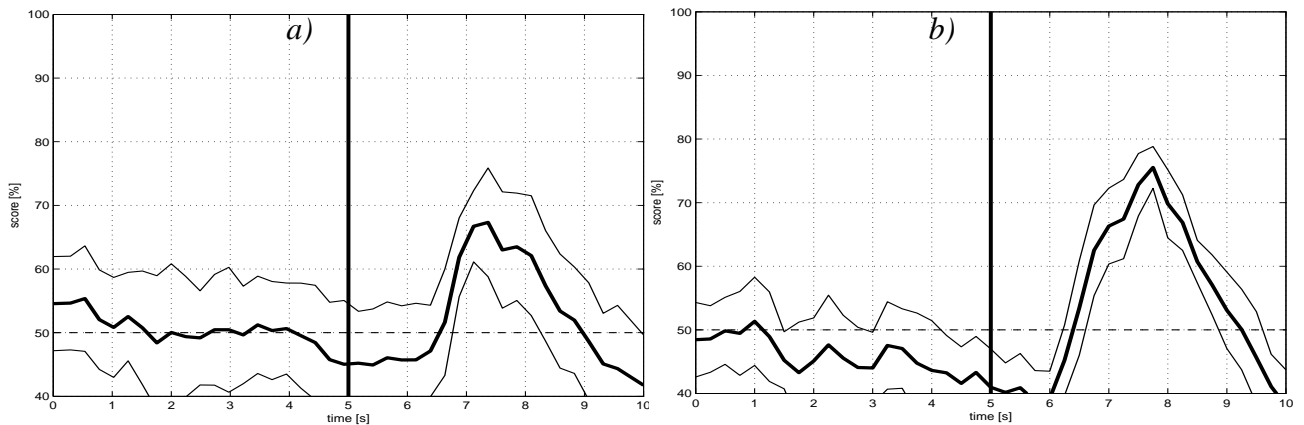


Figure 9: Movement classification score with 95 % confidence intervals, experimental subject 1, electrode 36, right finger: a) reduced dimension (FFT features summed over the frequency dimension); b) full dimension (all the FFT features).

Results of two-class (extension, flexion) classification with the most proficient subject no. 1 were analyzed in detail, see Figure 10. The Figure 10 shows mean values (horizontal lines) for all the four states of our model. Blue line indicate values from each of the cross validation folds, green line indicates mean computed from all the cross validation folds and red line indicate values using resubstitution method. Vertical lines indicate standard deviations. One can see that the HMM is able learn both ERD (Figure 10a, model of 9 Hz spectral line) and ERS (Figure 10b, model of 20 Hz spectra line, compare with Figure 8), but the differences in the responses between the movements were too low for classification. The HMM classifier was able to learn both the ERD and ERS as in [19] but now it was verified that this is possible even with less laboratory conditions of the experimental recording respecting control application.

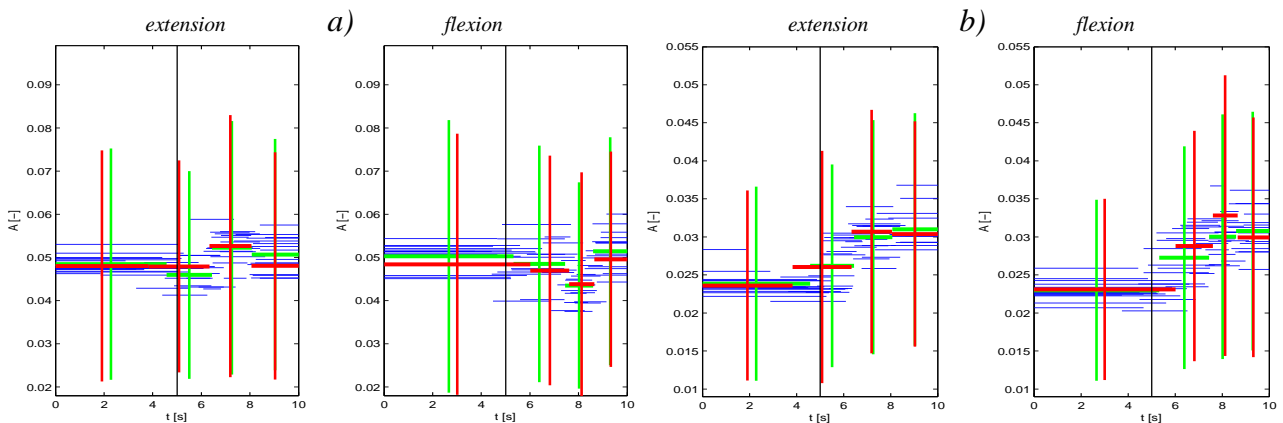


Figure 10: Analysed HMM models. The horizontal lines indicate mean values of the four state of our model. Blue lines indicate values from each of the cross validation folds, green lines indicate values averaged over all the cross validation folds and red lines indicate values when all the data was used for training. Subject 1, electrode 36, left extension (left part) and flexion (right part): a) spectral line 9 Hz (ERD); b) spectral line 20 Hz (ERS).

5.3 Study on user training and feedback influence

The feedback was proven to increase the movement-related changes in EEG and consecutively the classification scores, see Figure 11. Left part of the Figure is showing feature distribution of session without feedback; the right part is showing feature distribution from the consecutive session using optimistically controlled bar feedback, randomized recording was applied.

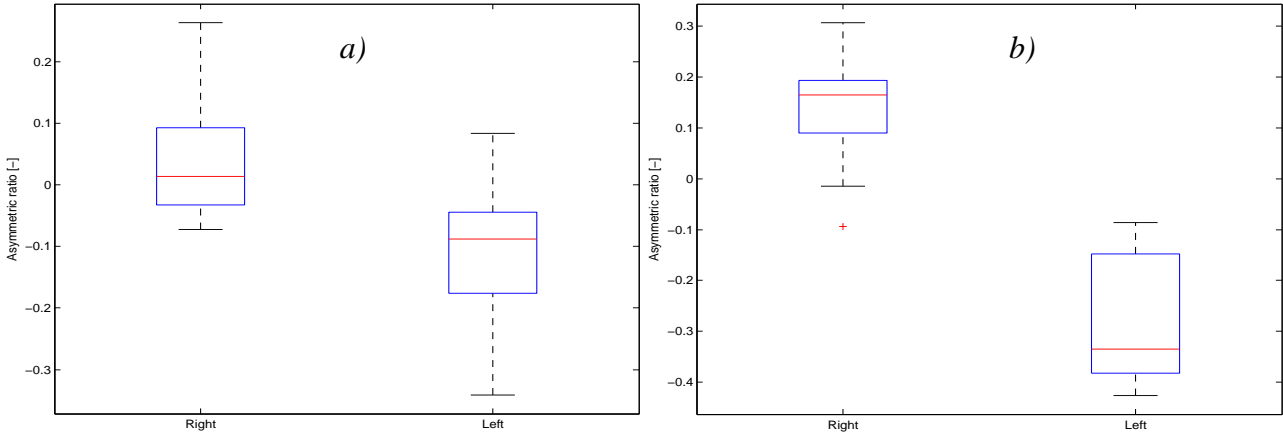


Figure 11: Distribution of feature from experiment 23: a) session without feedback; b) session with optimistic bar feedback. One can see that the feedback session produces more diverse responses.

Experiments without feedback and with block recording were made to verify the hypothesis that block recordings facilitates imagining/performing the movements in more consistent way, which could explain why classification was working significantly better using the adopted database. The block recording helped to reach higher scores. The distribution of the feature is shown in Figure 12. One can see in the Figure that the feature from resting blocks after the imagery block for both left and right tasks shows remaining asymmetry, while the feature from the initial resting block shows nearly zero asymmetry.

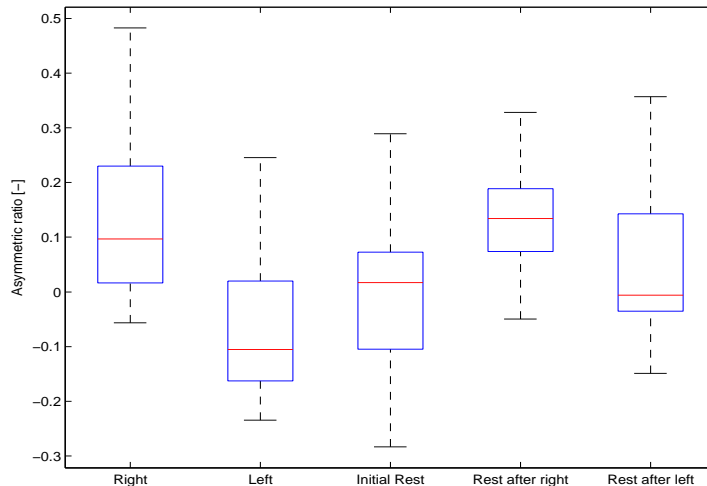


Figure 12: Distribution of the feature in experiment no. 30 without feedback using block recording. One can see that the resting blocks after the movement blocks show remaining asymmetry.

5.3.1 User training and feedback control

The results are shown in Table 3, one row of the table corresponds to one recording. Two types of scores are shown: Strict score is computed over all time instants of all the trials together (better describing process control operation) while the discrete score is computed by taking each of the trials separately (better describing goal selection operation). Classification using the optimistically controlled bar feedback achieved high classification scores (78.9 % in average over all sessions) and the classification was possible even when

subject attended the experiment for the very first time. This is an easy task as there is nothing more to further focus on which can distract the attention, thus this task is the most frequently used in BCI systems, for example [5]. The Arkanoid game feedback increases motivation of the subjects but it is more distracting as the subjects also focused on the ball. Also, as there is a given target, the subjects frequently grow frustrated from the inability to reach the target. This can make the experiment fail easily. However, when frustration was avoided high classification scores were achieved using both controlled and uncontrolled feedback. Classification scores averaged over all sessions of 76.2 % (controlled feedback) and 73.4 % (uncontrolled feedback) were achieved.

TYPE	BAR - O		Arkanoid - O		Arkanoid - R		Arkanoid - O		Arkanoid - R	
SUB.	STR	DIS	STR	DIS	STR	DIS	STR	DIS	STR	DIS
8	75.5	78.9	70.9	75.0	73.8	81.4	75.6	72.7		
8	71.4	78.9			61.4	58.8	76.6	94.1	70.5	84.6
8			70.1	87.5	75.9	93.6	74.5	91.7		
6	64.2	75.1			71.0	83.3	64.3	70.0	67.5	75.0
6	58.5	58.8	69.2	77.7	52.2	50.0	54.2	62.5		
6	69.5	75.0			63.9	68.8	70.2	69.0	77.0	87.5
5	75.5	78.9	71.0	75.0	59.8	67.4	75.5	72.8		
5	65.0	72.0			52.7	52.3	73.8	82.4	67.7	75.0
5	61.3	75.0	77.1	92.3	69.6	73.3	71.2	93.8		
7	66.7	76.5	55.6	52.0	55.7	61.5				
7	69.7	76.4	60.2	63.6	55.1	46.6	49.2	50.0		
7	69.5	85.0			60.5	81.2	65.3	79.1	64.0	62.5
4	63.0	80.0	57.4	68.7	57.3	57.5	49.6	47.0		
4	58.0	67.8			64.7	72.4	71.5	84.6	65.9	73.7
10	75.2	80.8			63.8	73.7	74.4	90.0	75.4	88.0
10	79.8	100	71.5	82.4	71.5	80.0	74.7	94.1		
10	78.8	100			82.6	93.3	93.8	93.8	82.6	93.3
11	61.0	75.0			52.9	58.8	61.0	64.7	59.4	72.7
11	75.4	85.7	70.5	73.6	75.4	88.8	62.3	73.9		

Table 3: Summary of results archived in the final protocol. The columns show classification score for the consecutive sessions. STR indicate strict score; DIS indicate discrete score. O indicate optimistic feedback (no potential in moving towards the wrong target); R indicate raw feedback. The discrete scores higher than 75 % are marked by boldface. The value of score achieved by chance is of 50 %.

5.3.2 Guidelines for performing feedback experiments

The most important thing is to provide increasing difficulty of the tasks and adjust the difficulty to the subject's immediate capabilities to avoid frustration from the inability to control the system.

The first sessions should be performed without feedback in order to give the subject time to get used to the task, even if the subject was proficient in previous experiments. It is helpful to provide additional instructions on which movement to imagine and how to imagine it based on classification results before presenting the feedback.

It is helpful to instruct the subjects to train the imagery before attending the experiments. The subjects were instructed to image the movements on the way to university, and those who did it had less difficulties in the experiments.

The frustration can be partially avoided by controlling the feedback: if the subject grow frustrated it is helpful to show him or her optimistically controlled or even fake feedback (but not tell the subject that the feedback is fake) and switch to real feedback afterwards. It is also helpful to stop the experiment and let the subject calm down afters sessions when the classification has failed completely.

It is necessary to interact with the subjects during the experiment to encourage then and provide additional instructions on how to cope with the fact that the classification is never perfect. If the classification is incorrect the subject automatically tries to correct his or her mistakes by starting the imagination again or trying to imagine the movement harder but this just worsens the situation. The classification has improved almost immediately when the subjects were instructed to ignore the feedback and to continue with imagery as if nothing happened. This effect was significant even with the optimistically controlled feedback.

It is equally important to keep the subject motivated and maintain his attention by providing a task that the subject can enjoy. Previous experiments when only bar feedback was used in all the sessions were not successful also because the subjects grew tired more quickly. The classification was working better when the subjects enjoyed using the interface as well as after they deliberately tried to fool the system by performing the imagery in opposite to the instructions or by performing other mental activities and convinced themselves that the system is utilizing the motor imagery.

5.3.3 Asynchronous free game task

The results are summarized in Table 4. One must compare the achieved score to the baseline (chance level value) shown in the last column of the Table. As the ball bounce randomly and no correct game strategy can be arbitrary decided only game score (number of bounced balls divided by number of all balls needed to be caught) is presented. All the subjects were able to catch the balls falling on sides of the screen; but had difficulties catching balls falling in the middle of the screen as there is no non-control state in the system. The subjects therefore took strategy to wait at one side of the screen and switch to the imagery at the right moment to intercept the falling ball. Also, it was most difficult to catch ball in beginning of the trials; after the subjects bounced the ball successfully they were frequently able hold the ball in the game.

Subject	8	8	5	5	1	10	10	10	11	6	7	S1*	S1*	S1*	X**
Score	46.9	56.0	47.2	54.3	37.5	34.4	53.5	47.9	50.0	47.6	44.4	57.9	65.3	62.9	30.8

Table 4: Result summary of the asynchronous gaming. * Sessions performed in the supervised work [38] using optimistic feedback only; asynchronous gaming was also tested in the last session. ** Value of score baseline assessed by using randomly generated signals.

Scores above the chance value were achieved in all but two sessions, and the subjects improved between the experiments; yet the scores are not very high. This is not surprising as there was only one session of the game task at the end of the recording so the subject had to develop the game strategy during this session and the session ended when the subject self reported that can no longer continue. Good process control performance was achieved with 5 subjects and impressive control was achieved by one subject in the supervised study [38] despite of using the most simple methods. This leaves a big potential for future improvement of the system. Clearly, it would be needed to perform another study devoted to the self-paced operation only and use additional no-control state (for example imagery of foot movement, or more thresholds) to improve the results.

6. Conclusions

An uncharted field of noninvasive high movement-resolution classification was explored in the task of classification of EEG accompanying performed voluntary extension and flexion movements of the same finger and the influence of feedback and user training was explored in the task of left and right arm motor imagery classification. Outcomes of the thesis are the following:

The modular EEG toolbox [15] was extended by support for new version of HTK, multi-CPU support, database processing and creating support, support for merging EEG recordings with automatic detection of bad contact/noise electrodes [39], support for generating artificial signal, model analysis, other feature extraction methods and classification systems [34], and other error estimate methods.

New database of EEG accompanying performed voluntary extension and flexion finger movements was created in two recording sessions separated by a year period [40][41][42]. The recording was performed in less laboratory conditions compared with the conditions in recording of the database [30][31] and reflected the aim of control rather than rehabilitation application [43]: the performed movements were self-paced, self-selected and the subjects decided which movement to perform just before the actual movement.

A universal real-time BCI system was designed [44][45], constructed [46], and finally process control operation was achieved using imagery of left and right parts of the body [35].

The contributions in accordance with goals of the thesis are the following:

Necessity of temporal context: Comparison of feature extraction methods and classification systems proved the necessity of using the EEG temporal context [17] as no spatial differences in the scalp EEG are present. It was verified that HMM achieves the best performance due to a priori information on physiological behavior of EEG inserted into the HMM classifier in comparison with other classification systems [34]. The capture of temporal development was also confirmed using the new database recorded in less laboratory conditions respecting control application.

Feasibility of control application: I have shown that high-resolution classification can not be used to increase the information transfer rate by extending the number of states: While high classification accuracies were achieved on the database where distinct movements were recorded in distinct blocks, classification was possible only with some subjects [43] and low accuracies were achieved using the new database.

Feedback influence: I have shown that simple methods are not only sufficient but their usage is desired. In contrast to majority of BCI papers focusing on development of complex methods, comparable classification accuracies with motor imagery of left and right arm were achieved by using the simplest possible methods [46] which can be more easily adapted. I have shown that the methodology of conducting the experiment has a critical influence. The key to achieve good performance is to keep the subject motivated, maintain his attention by providing a task that the subject can enjoy [35], and most importantly by avoiding frustration from the inability to use the interface in the beginning. This can be done by adjusting the difficulty and tailoring the feedback to the immediate capabilities of the subject. If the subject grows frustrated it is helpful to show him or her controlled or even fake feedback and switch to real feedback afterwards.

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List of candidate's works relating to the doctoral thesis

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Patents

No patents

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ANOTACE

Práce se zabývá problematikou konstrukce a využití rozhraní mozek-stroj (BCI), které je založené na klasifikaci pohybové aktivity na základě jejích projevů v EEG. Práce si klade následující cíle: ukázat, že využití časového vývoje je nezbytné pro zvýšení rozlišení existujících systémů pomocí klasifikace drobných pohybů, ověřit, zda lze drobné pohyby klasifikovat za podmínek nahrávání respektujících využití systému pro ovládání, případně dosáhnout zvýšení rychlosti přenosu informace skrze rozhraní a stanovit optimální postup provádění experimentů pro trénování uživatelů za použití zpětné vazby.

V experimentech na převzaté databázi, která obsahuje EEG doprovázející volní extenzní a flexní pohyby ukazováčku, je ukázáno, že využití časového vývoje je zásadní pro klasifikaci takto drobných pohybů ovládaných stejnými svaly. Není totiž možné použít obvyklého přístupu prostorové lokalizace projevů EEG na skalpu. Pro zachycení časového vývoje je použit dynamický klasifikační systém skrytých Markovských modelů (HMM), který dosahuje lepších výsledků ve srovnání s dalšími klasifikačními systémy díky předem vložené informaci o fyziologickém principu pohybové aktivity.

Na základě nedostatků převzaté databáze, která byla nahrávána pro účely analýzy odezev, jsou navrženy modifikace nahrávacího protokolu tak, aby lépe odrážel potřeby BCI rozhraní. Bylo provedeno nahrávání ve dvou fázích s časovým odstupem jednoho roku a vytvořena nová databáze pohybového EEG.

V experimentech na vlastní databázi je ukázáno, že projevy pohybové aktivity jsou stabilní v čase, ale klasifikace pohybů stejného prstu není dostatečně spolehlivá pro zvýšení přenosové rychlosti rozhraní. Předkládaného časového vývoje signálu lze lépe využít pro klasifikaci pohybů prováděných různou rychlostí nebo v rehabilitačních aplikacích, kde je možné využít i pouhou detekci aktivity a provádění stejných pohybů v blocích a kde není kladen takový důraz na úspěšnost klasifikace a rychlost přenosu informace.

Pro účely studie vlivu zpětné vazby je navržen a zkonstruován BCI systém pracující v reálném čase.

V experimentech s představovanými pohyby na levé či pravé straně těla je ukázáno, nakolik je zásadní vliv zpětné vazby a učení na straně uživatele. Metodika provádění experimentů má zásadní vliv a je málokdy prezentována v pracích dalších autorů, které se zaměřují především na vývoj stále komplexnějších metod zpracování signálu, zatímco málo úsilí je zaměřeno na potřeby a vyvíjející se schopnosti účastníků experimentů. Systém využívá jednodušších metod, které mají při zpracování v reálném čase výhodu ve snazší adaptaci. Zatímco při zpracování offline dosahují komplexní metody lepších výsledků, při zpracování v reálném čase je situace často obrácená. Navzdory použití jednoduchých metod jsou dosaženy výsledky srovnatelné s konkurenčními BCI systémy, což ponechává velký prostor pro další vylepšování systému. Provedená studie vlivu zpětné vazby ukazuje, že při provádění experimentů v reálném čase je nezbytné interagovat s účastníkem experimentu, podporovat ho a upravovat zpětnou vazbu na míru. Klíčem je zajistit, aby osoba byla motivována, udržela pozornost a především nebyla frustrována z neschopnosti ovládat systém v prvních experimentech, čehož je možné dosáhnout pomocí přizpůsobování zpětné vazby. Pokud dojde k frustraci uživatele systému, je přínosné ukázat mu optimisticky ovládanou, či dokonce falešnou zpětnou vazbu, a pak se vrátit ke skutečné zpětné vazbě.

Klíčová slova: BCI, EEG, ERS, ERD, HMM, FEEDBACK