Overcoming Inter-Subject Variability In BCI Using EEG-Based Identification

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Abstract. *The high dependency of the Brain Computer Interface (BCI) system performance on the BCI user is a well-known issue of many BCI devices. This contribution presents a new way to overcome this problem using a synergy between a BCI device and an EEG-based biometric algorithm. Using the biometric algorithm, the BCI device automatically identifies its current user and adapts parameters of the classification process and of the BCI protocol to maximize the BCI performance. In addition to this we present an algorithm for EEG-based identification designed to be resistant to variations in EEG recordings between sessions, which is also demonstrated by an experiment with an EEG database containing two sessions recorded one year apart. Further, our algorithm is designed to be compatible with our movement-related BCI device and the evaluation of the algorithm performance took place under conditions of a standard BCI experiment. Estimation of the μ rhythm fundamental frequency using the Frequency Zooming AR modeling is used for EEG feature extraction followed by a classifier based on the regularized Mahalanobis distance. An average subject identification score of 96 % is achieved.*

Keywords

Brain computer interface, subject identification, frequency zooming AR modeling, EEG classification.

1. Introduction

The large inter-subject variability of EEG signal parameters is known as a problem from the beginnings of BCI research [1]. Basically, a mental-state classifier trained on one subject's EEG used to classify EEG of a different subject achieves only a low classification score. This will pose an issue with BCIs used in the field of entertainment where a larger group of individuals can operate one BCI device. Also already published results (e.g., [2, 3, 4, 5, 6]) indicate that it can be advantageous to setup the BCI system (user interface appearance, BCI protocol, EEG filtering parameters, classifier parameters, and knowledge base for recognition) individually.

In this article we suggest a novel concept: combination of a BCI device with EEG-based subject identification. In this way the issue of large variability of EEG between subjects can be overcome by the BCI device being able to identify its user and switch its operating setup automatically to adapt to the current user instead of setting up the BCI manually. Since only one subject from just a small pool of device users is selected, there is no need for high identification accuracy in contrast to large-scale biometric applications. The practical application of the EEG biometry is thus presented in this article. Since the parameters of the EEG recording slightly changes in each session (e.g., impedances of electrodes, placement of electrodes), we present an EEG-based identification algorithm which is resistant to variations in EEG recordings between recordings sessions.

This contribution is organized as follows: Section 2 deals with the current state of the art; Section 3 describes the suggested method. The results are summarized in Section 4 and some conclusions are given afterwards.

2. EEG-Based Identification

A lot of papers support the idea of EEG-based subject identification. The EEG is partially linked to a subject's genes; about 30 % of all the genes are activated only in the brain [7]. Vogel [7] studied the interpersonal EEG differences and found many genetically-conditioned traits in the human resting EEG, and proved their genetic dependency and individuality. Review paper [8] summarizes a large number of results and claims that the EEG tends to be a stable individual characteristic varying considerably between subjects; these variations are attributed to the genetic predisposition. Paper [9] links the extroversion-introversion of the given subject with its frontal lobes 8 – 13 Hz rhythm characteristics. Similar findings are presented in [10]; it is shown that it is possible to discriminate between chronic alcoholics and healthy subjects based on the EEG traits. All the papers agree on the fact that the spectral features of EEG rhythms (central frequency, amplitude, and bandwidth) are genetically conditioned.

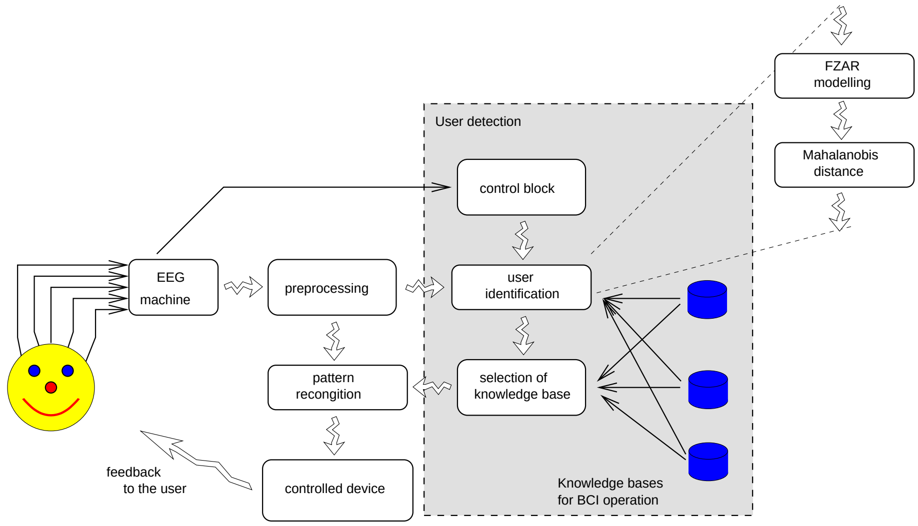

Fig. 1. A block diagram of the BCI interface (white boxes on the left side) equipped with user identification (grey box).

2.1 Experimental Evidence

Poulos et al. [11, 12] used Fourier transform and bilinear modeling for α band analysis and feature extraction of the 8 – 30 Hz EEG frequency band; 180 second segments were used for the classification in [11], 30 second segments in [12]. Recordings from one signal source were used. SVM, LVQ networks were used for the classification. Average classification scores of 95% with FFT and 78% with bilinear parameterization were reported.

Authors of [13, 14] utilized the 40 Hz EEG oscillations related to the visual processing for subject identification. Visual Evoked Potentials (VEPs) were recorded from 20 subjects while they were looking at a picture. Principal Component Analysis (PCA) was applied, fuzzy ARTMAP, k-nearest neighbor, and backpropagation network classifiers were used attaining performance of up to 95 % with 61 electrode EEG recordings.

Paper [15] applied maximum a posteriori trained Gaussian models on the EEG classification. Band 8 – 30 Hz was parametrized by means of PSD estimation, total energy was normalized. Eight sources from the centro-parietal scalp area were used; data were preprocessed by a spline Laplacian filter prior to the PSD computation. Authentication possibilities were tested, identification scores in the range of 60 % – 100 % were achieved. Interestingly, the authors observed a degradation of the identification performance over days.

A more recent paper [16] presents a biometric identification with EEG recorded over 14 electrodes placed over the whole scalp; EEG is parametrized using a 1358 – dimensional feature vector composed of autoregressive coefficients, power spectral density, integrated spectral power, interhemispheric power differences, and interhemispheric linear complexity. SVM is used for EEG data classification. Classification scores in the range of 97 % – 100 % were achieved.

However, none of the cited papers except [15] takes into account the variations in EEG recordings between experimental sessions separated by some period of time. Marcel et al. in [15] observe the performance degradation of the identification over days, and performance improvement if data from several days are used for training.

3. Methods

Fig. 1 shows a basic block diagram of the suggested BCI device extended with the identification algorithm. Prior to any use of the extended BCI, the BCI system shall be trained to correctly recognize mental activities of all its potential users. A set of knowledge bases (containing setups of the trained classifiers, instructions on how to organize the graphical user interface, etc.), one knowledge base per user, will be created as a result of this training. We propose the following operating protocol for the extended BCI system:

1. The control block of the BCI device detects that electrodes are mounted on the user's scalp; among others, measurements of electrode impedances can be used to accomplish this task.

2. The output of the identification algorithm is the estimated user's identity. The appropriate knowledge base (containing classifier setup, user interface setup, and other personalized settings) for the BCI is then chosen from the pool of the available ones according to the user's identity.

3. The BCI device continues to operate normally using the selected knowledge base until the control block detects that the electrode array was dismounted from the user's scalp. After this, the operation returns to step 1.

Trait	Suitability for identification
Frequency of characteristic rhythms	Suitable for identification, [8, 19].
Topology of rhythms on the scalp	Suitable for identification – the sensomotoric μ rhythm is composed of various topologically localized movement-related rhythms [32]. There are also other individual differences [33].
Amplitude of the rhythmical activity	While the amplitudes of the rhythmical activities are individual characteristics [9, 8, 19], they are modulated by the induced responses to external events, movements, movement imagery [18], and change with age [20]. The amplitudes of rhythmical activities are also not stable over time during the recording session [20].

Tab. 1. Summary of the individual EEG features.

The proposed mode of operation leads to the following identification algorithm requirements:

1. The changes in EEG recordings between sessions shall have no influence on the identification performance. The method should be also robust to artifacts.

2. The feature extraction stage of the proposed identification method shall extract EEG features which are genetically influenced. On the other hand, features which are task-related (see Tab. 1) shall be avoided.

3. The identification method shall use similar signal features to the ones the BCI uses.

4. Fast identification is favorable in order not to introduce delays to the initial BCI setup. The method should also be simple and able to operate in real time.

3.1 Oscillatory Activity Selection

Since we recently developed a movement-related activity-based BCI system [17], we suggest an identification method based on the sensomotoric μ rhythm (8 – 13 Hz band, [18]). This choice has the following advantages: μ rhythm does not depend on eyes closing/opening [18], thus there is no need to close eyes during recording; μ rhythm is also present in about 95 % of the population. Finally, the α and μ rhythm frequencies are claimed to be genetically conditioned [8, 19]; our own observations [3] also indicate large inter-subject variability of this trait.

Based on the genetic properties of the EEG described above (see Tab. 1) we use frequencies $f^{\mu}_{1..p}$ of the p dominant components of μ rhythm for subject identification. Since more electrodes are used for EEG recording and the feature vector is composed of $f^{\mu}_{1..p}$ estimated from all the electrodes, the distribution of f^{μ} over the scalp gives additional information for subject identification. It is evident that usage of the f^{μ} has the advantage of not being dependent on the changes of EEG rhythms amplitude, subsequent EEG signal post-processing, and induced activity in the EEG. Furthermore, frequency features rather than power spectrum features are suggested for classification as dominant frequencies of EEG rhythms can be estimated more precisely from shorter EEG segments than signal band powers [20].

3.2 Frequency Zooming AR Modeling

AR modeling is a widely used technique in the field of the EEG processing as it attains a good frequency resolution, requires only a moderate number of signal samples, and has low computational cost. We assume that an EEG signal sample $x[n]$ is a linear combination of previous samples $x[n-i]$ and the zero mean white noise $v[n]$

$$x[n] = \sum_{i=1}^{p} a_i x[n-i] + v[n] \tag{1}$$

where p is the AR model order. The a_i coefficients can be computed in many ways; the most frequently used one giving satisfactory results with EEG signals [21] is the autocorrelation method. The a_i filter coefficients are set to attain a minimal power of prediction error $e[n]$

$$J = E[e[n]^2] = E[(x[n] - \sum_{i=1}^{p} a_i x[n-i])^2]. \tag{2}$$

This can easily lead to an AR modeling filter describing some parasitic signals in the processed EEG (slowly varying EEG components with frequencies below 5 Hz, superposed 50 Hz power network harmonic, etc.); this is one of the main AR modeling drawbacks. To mitigate this issue we use Frequency Zooming AR (FZ-AR) modeling originally developed for applications in the field of audio processing [22, 23]. The whole FZ-AR algorithm is performed in the following steps:

Step 1 : Modulation of the analyzed EEG $x[n]$ signal down; the desired frequency band of interest is centered at 0 Hz

$$x_m[n] = e^{j\Omega_m n} x[n] \tag{3}$$

where $\Omega_m = 2\pi f_m / f_s$; f_m is the modulation frequency, $x_m[n]$ is the modulated signal, and f_s the sampling rate.

Step 2 : Decimation of the modulated signal $x_m[n]$ by the K_{zoom} factor giving a new low-pass filtered and down-sampled signal $x_d[n]$.

Step 3 : Application of the autocorrelation AR modeling method on the new signal $x_d[n]$.

As we analyzed μ band (8 Hz – 13 Hz), we chose $f_m =$ 10.5 Hz [24]. The μ band bandwidth is 5 Hz, so the theoretical maximal K_{zoom} value is $K_{zoom} = 256 \text{ Hz}/5 \text{ Hz} \approx 51$.

Subject	1	2	3	4	5	6	7	8
Resting EEG [secs]	961	925	780	1021	997	1220	1248	1355
Total EEG [secs]	3327	4045	3762	3872	3755	3802	3818	4386

Tab. 2. Length of the available EEG recordings.

We finally used $K_{zoom} = 28$. The final analyzed frequency band in the original EEG signal is < 5.92 Hz; 15.07 Hz $>$; applied frequency filtering suppresses any parasitic components lying outside of the μ band (e.g., low frequency artifactual component).

The second drawback of AR modeling is the model order selection ambiguity. Improper selection of p leads to either having an overly smoothed or too noisy spectral envelope, which affects the subsequent processing, see results below.

3.3 Tested Features for Classification

We tested the following features in our system:

FZ-AR coefficients (FZAR): we ran all the classification experiments using FZ-AR model coefficients. As these are complex-valued, real and imaginary parts were used to form a feature vector of $2 \times p$ elements per electrode. The disadvantages of the model coefficients are twofold. First, they do not have the Euclidean metric. This degrades the classification score when a distance-based classifier is used. Second, the FZ-AR coefficients also non-linearly depend on the short-time fluctuations of amplitude of periodic EEG oscillations, making the classification more susceptible to induced changes of EEG rhythm amplitudes.

Fundamental frequencies of μ rhythm (FREQ): To avoid both disadvantages of the FZ-AR coefficients, we propose using $f^{\mu}_{1..p}$ as the EEG features for classification. To do this we compute the positions of the FZ-AR modeling filter poles; we get p frequencies[1] (pole angular positions) for the FZ-AR model of model order p. Obtaining more than one frequency makes sense as the human arch-shaped μ rhythm is composed of several rhythms [25] and is a broad-band process in the μ band.

PSD estimation (PSD): PSD estimation is often used by EEG biometric papers; thus as the third type of tested features we interpolated the computed FZ-AR spectrum back to the original frequency band of 5.92 – 15.07 Hz and computed spectral envelope sampled in 16 points. This 16 point PSD estimation was used as a signal feature for the classification.

3.4 Classifier

A regularized Mahalanobis distance-based classifier [26] is used in our experiments. Mahalanobis distance is chosen as it takes into account the internal variance of the classified groups, and is simple to compute with lower required numerical load yet robust [27].

Before the classification, all available segments are divided between non-overlapping training $\mathcal{M}_{tr}$ (75 % of all segments) and testing set $\mathcal{M}_{te}$. Classification is repeated 10× with random divisions of data between both sets, and average classification scores were computed, see Fig. 4a.

Let us assume that $\mathbf{f}_{\mu}[s,m]$ is the $(N_{ele} \times p, 1)$ vector of μ rhythm frequencies estimated for all N_{ele} electrodes of the EEG recording, subject s, segment no. $m = 1,\dots,N_{seg}$. Then the mean value and covariance matrix estimations $\bar{\mathbf{f}}_{\mu}[s]$ and $\mathcal{S}_{\mu}[s]$ are computed from the $\mathcal{M}_{tr}$ data set,

$$\bar{\mathbf{f}}_{\mu}[s] = \frac{1}{N_{seg}} \sum_{n=1}^{N_{seg}} \mathbf{f}_{\mu}[s,n], \tag{4}$$

$$\mathcal{S}_{\mu}[s] = (\mathcal{M}_{tr} - \mathcal{E}\bar{\mathbf{f}}_{\mu}[s]) \times (\mathcal{M}_{tr} - \mathcal{E}\bar{\mathbf{f}}_{\mu}[s])^T \tag{5}$$

where $\mathcal{E}$ is the unity matrix. The $\mathcal{M}_{te}$ segments are classified by means of the regularized Mahalanobis distance [26]

$$d_s = (\mathbf{f}_{\mu} - \bar{\mathbf{f}}_{\mu}[s])((1-\lambda)(\mathcal{S}_{\mu}[s] + \varepsilon\mathcal{E})^{-1} + \lambda\mathcal{E}) \times \\ \times (\mathbf{f}_{\mu} - \bar{\mathbf{f}}_{\mu}[s])^T, s = 1,\dots,N_{subj} \tag{6}$$

where $\mathbf{f}_{\mu}$ is the classified pattern. The pattern is assigned to the subject which centroid is the nearest one in the Mahalanobis distance sense. Parameter ε controls the regularization and stabilizes the learning process when an inverse covariance matrix cannot be estimated reliably [26]. Parameter λ controls the trade-off between hyperspherical and hyperellipsoidal components of the distance (6) and its value shall be carefully selected.

4. Results

4.1 Simple Experiment

An EEG database originally recorded for our BCI experiments [3] is used for this study. 8 subjects took part in the experiment – 7 men and 1 woman, average age of 24.5 years ($\sigma = 3.59$). EEG was recorded with 41 unipolar scalp Ag/AgCl electrodes placed symmetrically and equidistantly with 2.5 cm spacing over both sensorimotor areas of the experimental subject, see Fig. 2. Sampling rate was 256 Hz.

[1] As the sequence of poles obtained by Matlab `root` function is each time permuted differently, the final frequencies $f^{\mu}_{1..p}$ were always sorted in ascending order.

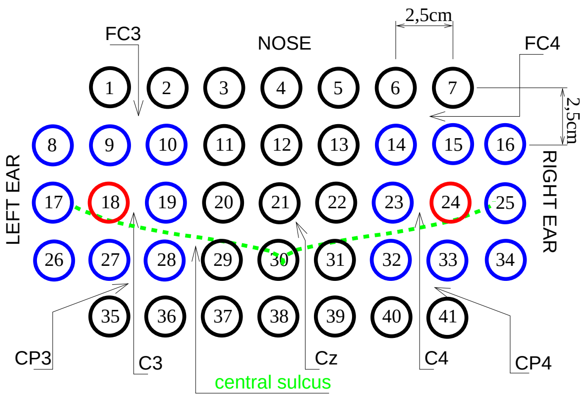

Fig. 2. Scalp electrode placement diagram. The 10 – 20 electrode positions C_3, C_4 and C_Z are denoted and *central sulcus* is roughly localized.

The EEG was recorded during one session, in four blocks of about 20 minutes. The subjects were performing a self-paced, voluntary brisk flexion of the right thumb and the right little finger during the first three blocks, and were resting during the fourth block. The total lengths of the recorded EEG segments are summarized in Tab. 2. The lengths of recordings differ between subjects since the primary goal of recording was to obtain 100 realizations of each type of movement per subject. As the movements were performed at the subjects' own rate, the intervals between movements varied and hence the recordings are of different length for each subject. To test the algorithm in an environment as similar as possible to the real application, we kept EEG with artifacts and EEG with movement-related activity in the database. Since our BCI experiments are performed with EEG filtered with a discrete Laplacian filter [3], we used the same filtered EEG for identification experiments. For a detailed description of the experiment, see [3].

ε/λ	0.05	0.1	0.2	0.4	0.8
0.01	84.8 %	85.2 %	87.1 %	89.7 %	93.7 %
0.1	89.1 %	90.0 %	91.2 %	93.0 %	93.2 %
0.2	90.5 %	91.2 %	92.4 %	**96.2** %	92.2 %
0.4	91.8 %	92.4 %	93.2 %	93.4 %	90.8 %
0.8	92.8 %	93.1 %	93.4 %	92.5 %	89.2 %

Tab. 3. Average classification score as a function of ε and λ.

For the first set of experiments, only resting EEG (block 4) was used. First we estimated the appropriate model order p. The EEG was segmented into 1 minute segments with an overlap of 45 seconds. Because the shape of the AIC criterion curve did not exhibit any clear minimum, we did a set of experiments with varying model order p.

Then we had to find the optimal values of the ε and λ parameters in (6). Classification experiments with varying FZ-AR model order ($p = 1,2,3$) and segment length (60, 30, 15, 7.5, and 3.75 sec) were executed for all pairs of (ε,λ), with ε going through 0.01, 0.1, 0.2, 0.4, 0.8, and λ attaining values of 0.05, 0.1, 0.2, 0.4, and 0.8. This gave us 15 values of classification score for each (ε,λ) pair; these were averaged to obtain the final results, see Tab. 3. Based on this ε was set to 0.2 and λ to 0.4 for the next experiments.

We also analyzed the dependency of the classification score on the segment length because it defines the latency of the identification process. The shorter the segment, the better it is for the subject. On the other hand, with shortening segment the frequency estimation becomes more noisy and the classification score drops as well, see Fig. 3.

The final dependencies of the classification score on both model order and segment length, and the used feature vectors computed for the resting EEG are drawn in Fig. 3. The best reached result is 99.9 % for $p = 7$ and a segment of 30 sec, FREQ features used. The results for all the subjects with this configuration are listed in Tab. 4; note that the variations of the classification scores due to the cross-validation are rather low, the classification is stable and resistant to overlearning. Even for $p = 1$, segment of 15 sec, FREQ features, the achieved classification score is still 97 %; this configuration is a good trade-off between computational cost and identification accuracy. The computation of the pole frequency is simple and fast for $p = 1$ (linear analytical equation, no need for numerical methods).

The whole set of experiments was repeated with the complete EEG database (all blocks, including movement-related EEG) for segments of 60, 30, and 15 seconds to see how stable the process is with respect to the movement-related EEG changes. The achieved classification scores were within 2 % of the scores depicted in Fig. 3, $p = 1 \ldots 10$; only minor degradation in performance is observed. This is important from the BCI point of view.

To have a comparison with results achieved by other authors, we repeated the experiment of [11] with our data. The method published in [11] obtained an average identification score of 74 %. Comparison with other papers is not feasible since they either use a completely different paradigm (mental activities), or aim to authenticate instead of identify the user.

Finally, an experiment with a reduced set of electrodes was performed to emulate operation in a BCI interface with lower number of electrodes. As signal sources we used four differential channels: 1 – 9, 7 – 15, 19 – 28, and 23 – 32, see Fig. 2. These channels were chosen since they are suitable for movement imagery BCI, see [3]. With this configuration the best classification score obtained was 91 % ($p = 2$, segment length of 60 seconds, FREQ features used).

4.2 Sensitivity to Variations Between Sessions

To show that the algorithm is insensitive to variations in EEG recordings between different BCI sessions, we performed an experiment with a new database recorded in two sessions, one year apart. Originally, the database was recorded for our BCI experiment [28] to evaluate the stability of our BCI algorithms. Nine test subjects took part in the experiment. Data were obtained from 53 unipolar electrodes placed in the 10-10 system with referential ground electrodes

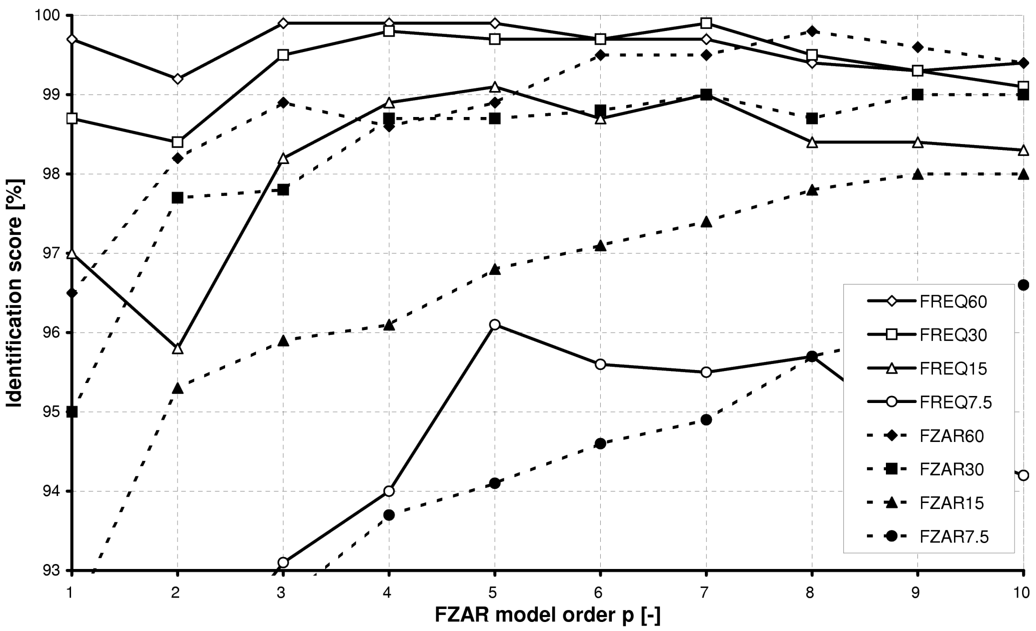

Fig. 3. Mean classification score as a function of segment length and FZ-AR model order. Only resting EEG used, classification scores computed from PSD estimations are not shown (they were in the range of 12 % – 74 %). Also the results for segments of 3.75 secs are not shown as they were mostly below 90 % of the classification score.

placed on both ears with sampling frequency of 1024 Hz decimated down to 256 Hz. Subjects performed voluntary movements (extension or flexion of right or left index finger) during recording [28]. Four 20-minute blocks of EEG were obtained for each subject and session – three blocks containing the movements and the fourth block containing only resting EEG. Only blocks 2 and 3 of both sessions are used for the experiment since our preliminary database analysis [29] showed they give the best results. The most likely explanation of this is that blocks 1 and 4 contain far more artifacts than blocks 2 and 3; while in the beginning of the block 1 the subject (previously unexperienced with BCI) was getting used to EEG recording equipment, in the end of block 4 recording subject was already tired of the long recording. The experimental protocol emulates the real world usage of the BCI system: data from the first session is used for system training (user used the system for the first time) and the data from the second session are used for testing (user returned to the BCI after some time), see Fig. 4b.

First, we showed that the differences between EEG recordings in both sessions are significant. To show this we compared EEG band powers between both recording sessions. EEG was filtered to 5 – 40 Hz band (linear phase FIR filter used, order of 256) to suppress DC component, low frequency components, and also high frequency parasitic components (e.g., AC line noise). Blocks 2 and 3 were used, the first and last minutes of each recording were discarded to avoid transients in the beginning and end of recordings. Data were segmented to 7.5 sec long segments with no overlap and signal power was computed for each segment, electrode, subject, and session. Then we removed 5 % of the maximal values for each electrode, subject, and session to suppress influence of outliers on the statistical test. Toolbox [30] was used to implement these computations. After this we applied Mann-Whitney non-parametric [31] U test to compare medians of signal powers between sessions for each electrode and subject; we realized that we can deny the hypothesis of the same mean power values in both sessions for 422 out of 477 electrode sets (9 subjects per 53 electrodes) at the 5 % significance level. The same test was repeated with EEG filtered to 8 – 14 Hz band, in this case powers in both sessions significantly differed in 416 out of 477 electrodes. The achieved results show that there are statistically significant differences between powers of EEG between sessions. These findings also comply to the fact that it is not possible to successfully classify movement-related EEG in both sessions merged together without the specific EEG preprocessing merging method [28].

Then we performed identification experiments using all the three types of features, see Tab. 5. While all the types of features failed to properly identify subjects 6 and 7, the results for the remaining subjects are conclusive. The FREQ parameterization provides the best results and is the most resistant to both variations in EEG recordings and task-related EEG changes; the PSD and FZAR features are more sensitive to either variations in EEG recordings or to the induced changes of the EEG activity. This is in compliance with the reasoning in Section 3.3. The degradation of performance when PSD features are used is in compliance with the findings presented in [15]. The low identification performance with subjects 6 and 7 is attributed to specific EEG patterns of these subjects (subject 7 would not even be able to use a movement-related BCI device, so it does not matter a lot that the system does not recognize him properly).

Subject	1	2	3	4	5	6	7	8
Score	99.4 %	97.5 %	96.2 %	92.6 %	94.5 %	98.0 %	96.7 %	100.0 %
σ	±0.8 %	±1.8 %	±1.8 %	±3.5 %	±2.5 %	±1.4 %	±2.2 %	±0.0 %

Tab. 4. The best classification results we achieved per subject.

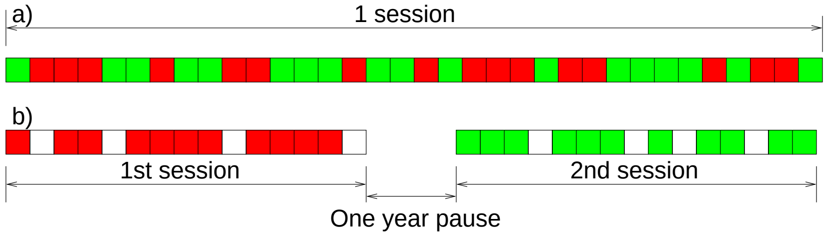

Fig. 4. Distribution of training and testing realizations, each box is one EEG realization, red designates use for training, green for testing, blank is not used. a) Training-testing scheme used by the simple experiment. b) The training-testing scheme used in the experiment with two sessions.

Interestingly, we cannot rule out that the induced movement-related activity in the EEG improves identification performance with FREQ parameters [29]. However, this hypothesis has yet to be further examined.

Feature	All subjects	All subjects except 6,7	Subjects 6,7
PSD	39.6 %	49.3 %	40.9 %
FZAR	70.5 %	85.7 %	51.2 %
FREQ	87.1 %	96.0 %	50.5 %

Tab. 5. Performance of the identification algorithm, experiment with two sessions.

5. Conclusions and Next Steps

The article presents a novel approach to solving the problems arising from the inter-subject variability in the BCI field – the extension of the BCI device to include a subject identification block. Using the biometric algorithm, the BCI device automatically identifies its current user and adapts parameters of the classification process and of the BCI protocol to maximize the BCI performance. Along with this we present an algorithm for EEG-based identification designed to be robust to variations between EEG recordings. The robustness is achieved by using extracted frequencies of the fundamental components of the μ rhythm and demonstrated using real life BCI EEG database recorded in two sessions one year apart. Because we analyze only frequency features, the gradual band power changes reported in [20] cannot influence classification performance. The frequency extraction is robust in resisting artifacts and induced EEG activity and the identification procedure works without the subject's interaction. Since the μ rhythm does not depend on eyes closing/opening, there is no need to close eyes during recording, and also no visual stimulation is needed with our method. And because it is intended to be used in the field of brain computer interfacing for simple user identification and not for large-scale reliable biometric application, the achieved classification score is satisfactory.

The proposed algorithm can easily be implemented in real time; actually, our current work aims at integration of the presented method into our BCI prototype [17]. The first tests of the real-time implementation demonstrate performance in line with the results presented in this paper. The architecture of the extended BCI is protected in Czechia by a utility model and a patent application [34].

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