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# Motor Imagery Patterns Classification by Finding Discriminative Frequencies and Time Segments

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**Abstract:** An approach to classification of three different imaginary movements based on linear discriminant analysis transformations and applicable to brain-computer interface implementations is considered. First, search for discriminative frequencies individual for each subject and each movement is conducted. It is shown that this procedure leads to an increase in classification accuracy compared to conventional common spatial patterns algorithm followed by linear classifier considered as a baseline approach. In addition, an original approach to finding discriminative time segments for each movement is tested. This approach led to further increase in accuracy if Hjorth parameters and inter-channel correlation coefficients were used as features calculated for the found segments. Particularly, classification by the latter feature led to the best accuracy of 69,4% averaged over all subjects. Besides, scatter plots demonstrated that two out of three movements pairs were discriminated by the approach presented.

**Keywords:** brain-computer interface, EEG, Machine Learning, Frequency Spectrum

## 1. Introduction and Overview

Currently, intelligent methods of data processing start to play an important role in the personalization of various human activity areas. Among those, one can distinguish interactions between human and technical systems also called 'human-machine interfaces'. The availability and miniaturization of computer technology have created the prerequisites for the widespread use of new generation human-machine interfaces, such as the Brain-computer interface (BCI), or Neural interface [1], [2]. The development of BCIs is one of the most promising areas in applied research at the intersection of information technology and neuroscience. Its main goal is to create a new communication channel for the rehabilitation of people with speech and muscle disabilities [3], [4]. BCI implements communication by decoding the individual's mental commands that are formed in his brain activity. However, at present, the limiting factor for the practical implementation of such systems is the lack of sufficiently developed intelligent data processing methods that provide automated individual interface adjustment, taking into account the individual characteristics of the user. This leads to the unsolved urgent problem of bringing such systems out of scientific laboratories to the end-user environment. One of the unsolved problems hindering to achieve that is the exclusion of the laborious participation of an expert researcher, who forms training samples manually, from the process of tuning the neurocontrol system. That is why it is urgent to develop computational methods facilitating tuning BCI-systems in an autonomous mode.

In numerous BCIs based on the patterns of the ideomotor acts electroencephalogram (EEG), at the stage of setting up the system, stimulus-dependent experimental paradigm is used. In such systems a user is presented with different stimuli corresponding to execution of different movements (Berlin BCI [5], Graz BCI [6], Wadsworth BCI [7]. What is good in this paradigm, configuring, testing, and further use of control EEG commands classification methods are utterly convenient. However, external cues affect EEG and thereby distort the motor imagery pattern [8], [9]. Subsequently, this complicates the operation of the BCI configured in this way in the control mode, in which ideomotor activity is performed by the user in an arbitrary manner with no reference to external stimuli. Therefore, it is urgent to develop a BCI adjustment procedure that does not use external stimuli that induce the execution of single ideomotor acts. Methods for detecting EEG patterns of target ideomotor acts are a key element in the implementation of tuning autonomy in a completely stimulus independent BCI.

In stimulus-independent BCI, motor imageries – voluntary mental commands in form of imaginary movements of different limbs – are actively used. This approach is advantageous since such mental tasks do not require external cues and they are absolutely arbitrary, allowing the

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user to work at an arbitrary pace and mode, as well as to form commands for controlling external devices at arbitrary times at will. Existing methods of accounting for individual characteristics of brain activity and BCIs based on mental performance of movements [10], [11], [12], [13] were proposed only for particular tasks, with a fixed set of a priori known EEG commands and are difficult to implement for a completely stimulus independent autonomously tuned BCI.

The non-invasive approach based on electroencephalogram (EEG) signals proved to be extremely useful for the development of Brain-computer interfaces technology. The EEG method has convincingly proved its high safety and reliability, primarily in the framework of providing new a channel of communication with the outside world to patients if they are immobilized for various reasons [14]. The BCIs neural communication system does not require any pronounced muscular activity from the user, so it is actually able to function even in patients with severe neurodegenerative diseases of the motor system and disorders caused by spinal cord injuries [15], [16].

Due to the nonstationarity of the analyzed activity, a very wide range of features can be distinguished in the EEG to describe the most informative patterns of a multidimensional EEG. In addition, there are significant differences in informative EEG features in different subjects [17]. In particular, despite the fact that within the framework of target motor imagery EEG patterns classification problem, the main significant frequency ranges, such as $\mu$ (10-13 Hz), $\beta$ (13-25 Hz) and $\gamma$ (25-70 Hz), have already been identified earlier [3], the most effective frequency range and its severity are purely individual [17]. It has been also shown that the ability of a person, in principle, to voluntarily induce patterns of brain activity, for example, when mentally performing a movement with a certain limb, is purely individual [18], [19], [20], therefore, the BCI user is not always able to operate with the set of control commands offered to him. Thus, in existing systems, there is still a problem of finding and consolidating a new pattern (command). In this regard, it is necessary to develop universal and noise-resistant approaches that make it possible to isolate informative signal components for detecting EEG patterns of target ideomotor acts.

In this paper an approach to the classification of the mental movements EEG is proposed (Materials and methods, D). It consists in i) determination of informative frequency ranges individually for each subject and class of mental movement, ii) determination of a short time segment containing a pattern of target mental movement, which also minimizes the noise; and iii) the selection of informative signal features by linear transformation of the high-dimensional original feature vector by linear discriminant analysis.

## 2. Materials and Methods

### *A. Dataset and Subjects*

The dataset used consists of 16 experiments conducted on 16 different subjects of different genders (12 men, 4 women), aged 18 to 25 (mean age 21.5 ± 3.5 years). Each subject signed a protocol of voluntary consent to participate in the study prior to the experiment. The experimental technique was approved by the Ethics Committee of the Southern Federal University.

### *B. Experimental design*

The experiments included 3 series of executing different voluntary movements. Duration of each series was 180 s (15-20 executions of each movement). Voluntary movement execution took place for 2 seconds in a randomly mode with, the the gaze was simultaneously fixed on the monitor screen. Hands movements implied clenching them into fists. Legs movements consisted in their simultaneous bending at knee joints and then unbending them back. The schematic of the experiments is given in Figure 1.

In the next series, the subjects executed the same real movements, but each of them was followed with the corresponding motor imagery.

Finally, the motor imagery preceded the actual implementation of the corresponding movement execution in the third series. After that, the epochs containing eye blink artifacts were removed from the sample in series 2 and 3 (eye blinks were detected using EOG signals). Ultimately, on average, the following numbers of MI classes examples were left for each subject: right hand MI (RHMI) - 35.9 ± 9.7, left hand MI (LHMI) - 35.1 ± 9.1, legs MI (LMI) - 32.9 ± 9.2). In total, 2240 non-artifact EEG epochs for resting state and motor imagery classes were analyzed.

### *C. EEG recording*

EEG signals were recorded using a biopotential amplifier Encephalan (Medicom MTD LLC, Taganrog, Russia) in a room protected from light and sound. 17 channels were used (F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2) with their locations defined as in the international 10-20 system. The sampling frequency was 250 Hz. To remove network crosstalk a notch filter was used (50 Hz).

### *D. Data labelling*

The surface electromyogram (EMG) of both hands was recorded in the superficial muscles on the hands (Brachioradialis and Flexor digitorum superficialis muscles) and the legs (Tibialis anterior muscle). Brain potentials associated with motor imagery (motor imagery-related potentials) were distinguished and stored relative to the tags of real movements onsets in electromyogram channels (EMG). Events were detected after the EMG signal was bandpass filtered (0.1-4 Hz). The threshold level of movement detection via EMG was 10 μV. The threshold of the movement onset was determined at the rising front of the smoothed EMG

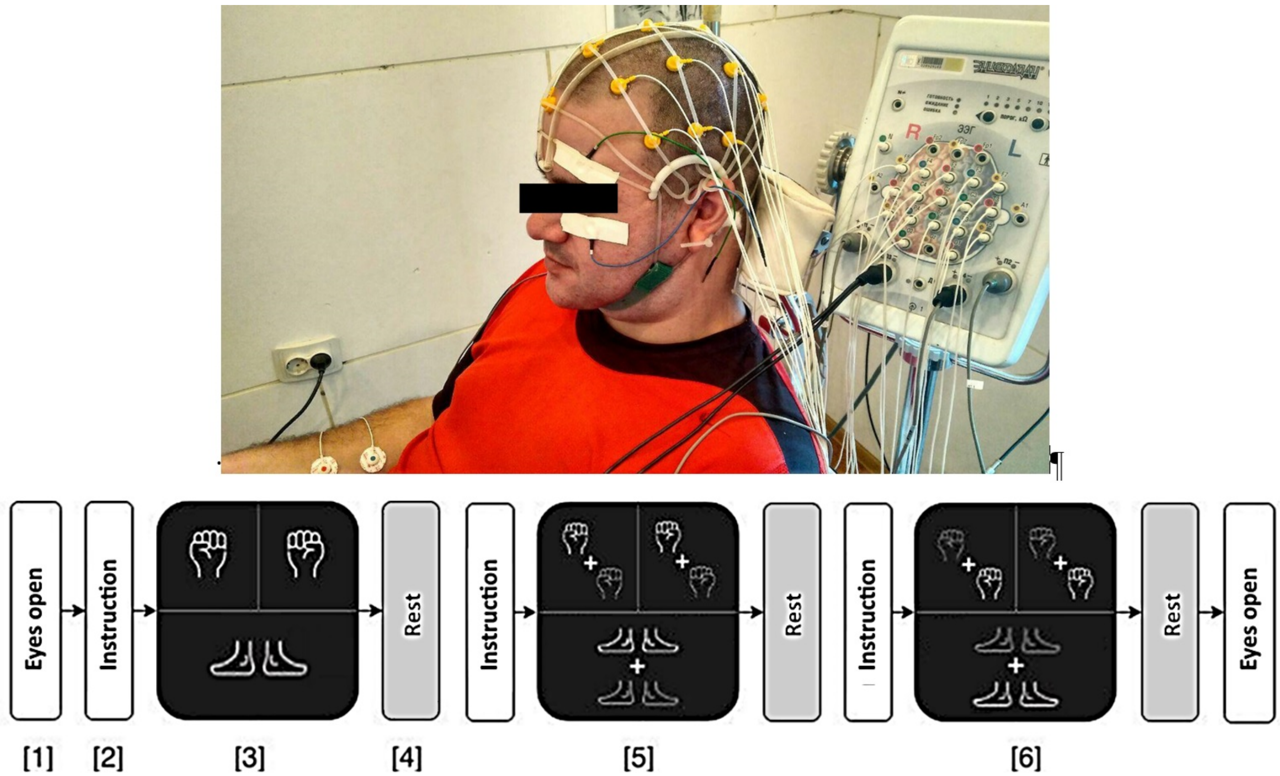


Figure 1. Timing representation of a scenario with the participation of volunteers in the task of movement execution (ME) and motor imagery (MI). (1) – Rest with eyes open (EO, 60 s); (2) – Instructions, 60 s; (3) - Series 1 (ME) (180 s), (4) - Rest after a series 1, 60 s; (5) - Series 2 (ME + MI repetition) (180 s), (6) - Series 3 (MI + M) (180 s)

channels. The EEG epoch of the analysis of motor imagery potentials was 2 s after the completion of myographic activity in series 2 and 2 s before the start of EMG in series 3.

### *E. Classification*

The logistic regression implemented in Python (scikit-learn library) was used for classification and further calculation of accuracy scores [21]. The L2 penalty function was used; for optimization, the L-BFGS algorithm was used with a tolerance (stopping criteria) of 0.0001. To find the optimal value of the regularization parameter C, we performed a grid search over the following values: 0.001, 0.01, 0.1, 1, 10. Next, accuracy score of two-fold cross-validation was used to evaluate the quality of classification. In the preprocessing stage, all feature values were converted to z-scores, and the entire sample of motor imagery examples was randomly mixed. The described classification procedure was applied separately to the data and the final score was calculated as the mean value of all scores of subjects.

### *F. Linear transformations*

For feature vectors transformation, linear discriminant analysis (LDA) with SVD (singular values decomposition) as a solver method and the tolerance (stopping criteria) of 0.0001 was used. To highlight the most informative, i.e., discriminative, frequency ranges, the transformation method based on LDA was applied to the raw feature vector of length 153 (17 channels $\times$ 9 frequency bands):

1. For each class of movements, a separate model of a 1-component LDA-transformer model was trained: the training sample included examples of the given class and as many background signal examples;

2. On the transformation completion, 153 values of features collapsed into one being a linear combination, while, for each class, there was a specific set coefficients;

3. Upon tuning all class-specific transformers, the final feature vector was 3-dimensional (1 feature for each class).

A schematic of this transformation procedure is shown in Figure 2.

During the complementing search for the most informative segments of time domain for each two-second segment of each motor imagery, a sample of examples of two classes was created: the movement considered and the background (resting state) signal. The feature vector was constructed of the differences between feature vectors of all windows combinations with each window having the length of 750 ms and a shift being 100 ms within a given motor imagery signal epoch and a 2-second long background signal epoch.

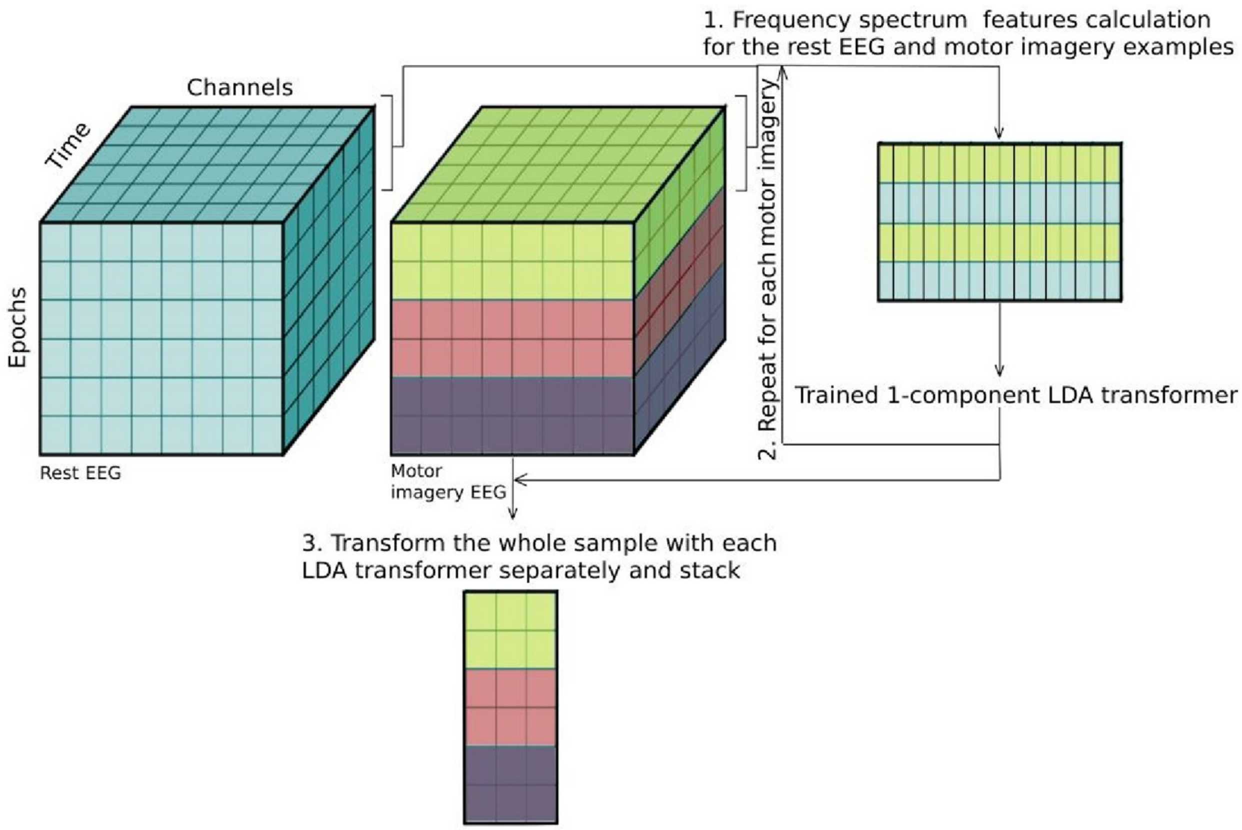


Figure 2. The procedure of transformation for finding informative frequencies

If frequency spectrum (power spectral density) features were used, they were converted to 3 components in the way described above. For other features, a single frequency band with the highest absolute weight value was extracted from the weights of each frequency LDA transformer. Finally, multiband filtering using the frequencies found in the previous step was applied to the signals processed.

The 750-ms window was used because of the best classification accuracies (compared to 500 and 1000 ms). In 2 seconds, 13 different 750 ms windows are accommodated with 100 ms shift. This gave us 13 examples of the target class of a given mental movement. Each of these examples consisted of differences between a particular background window and all 13 windows of a given motor imagery epoch. 13 additional examples presented the background class and consisted of differences between pairs of background signal epoch windows in the same manner. Thus, each motor imagery signal epoch was first presented as a $26 \times 153$ sample, and then the latter was used for training of a two component LDA-based transformer. Before adding to the final sample, each example was transformed in the following way: another example was created from the differences of the averaged feature vector over all background signal windows and all shifts of the given mental movement example, which was then transformed by a trained two-component LDA. A detailed stepwise description of this transformation is shown in Figure 3.

### G. Frequency spectrum features

We used nine commonly recognized EEG frequency bands: $\delta$ or delta (1-3 Hz), $\theta$ (3-7 Hz), $\alpha$ (7-10 Hz), $\mu$ (10-13 Hz), $\beta$-1 (13-25 Hz), $\beta$-2 /$\gamma$-1 (25-45 Hz), $\gamma$-2 (55-70 Hz), $\gamma$-3 (70-90 Hz), $\gamma$-4 (90-110 Hz). PSDs (power spectral densities) of these bands were computed via the Welch method (Hanning filtering window, 50% overlap of consecutive windows) [22]. Once the PSDs were calculated, we converted them to the feature vector by summing the PSDs of frequencies lying between the boundaries of each band.

### H. Frequency filtering

Frequency filtering was conducted using a Butterworth filter with an infinite impulse response of the 5th order.

## 3. Results and Discussion

In order to conduct further comparative analysis, accuracy was initially obtained using the traditional combination of Common Spatial Patterns (CSP) + linear classifier [17] (logistic regression). Wherein, in addition to the described

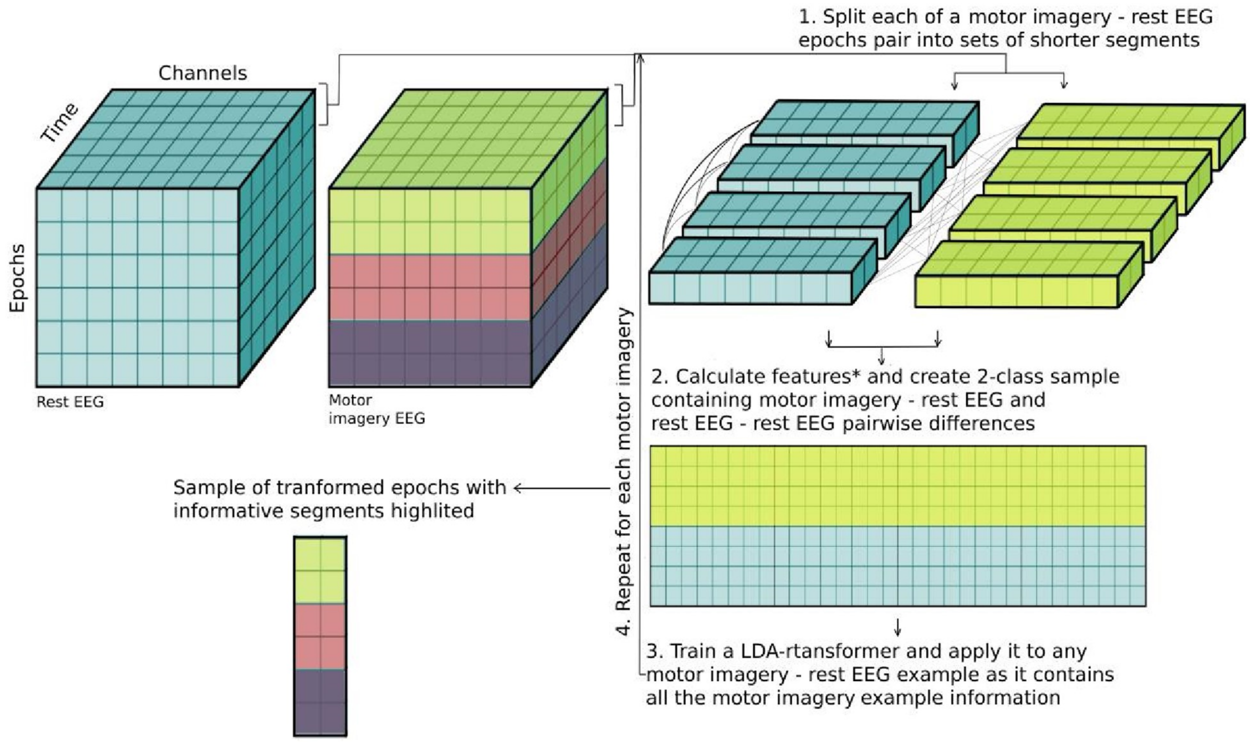


Figure 3. The procedure of transformation for finding informative segments (*if the frequency spectrum features are used then spectrum is computed and the previously trained informative frequency LDA-transformers are applied; otherwise, if Hjorth parameters or inter-channel correlation coefficients are used as features, 3 frequency bands corresponding to the biggest absolute values of the previously trained informative frequency LDA-transformers weights are extracted, then multiband frequency filtering is performed, and features are calculated*)

adjustment of the logistic regression regularization coefficient, the optimal number of CSP filters in the 1-9 range was optimally selected during cross-validation. This approach showed an accuracy of 51.1 ± 10.8%, i.e., even with a fairly efficient and tuned model, the accuracy was low. In the next stage, the original algorithm was tested to select the most informative frequency ranges. For each class, the best combination of the ranges considered was determined for its separation from the background signal, but this also contributed to the separation between three classes themselves. In other words, in such an offline approach, for each subject, we first trained different 1-component LDA models for each of 3 types of motor imagery. In practice, this procedure can be done in the same manner as training is usually done in the conventional BCI paradigm. So, at this stage, there is not a single model trained to classify several motor imagery types, rather there are 3 models, each one to independently discriminate a single motor imagery type with background signal. Surprisingly, the application of these models to transform the raw EEG signal and obtain 3 output features (one by each motor imagery type specific model results in better discrimination of 3 motor imagery types themselves: after applying such a transformation, the accuracy increased to 65.4 ± 9.1% if power spectral densities are used as features. This increase with respect to CSP-LDA was statistically significant according to t-test results ($t = 4.05$, p-value $< 0.001$). Additionally, Hjorth parameters [23] and the coefficients of inter-channel correlation were tested as features. The classification accuracy by the Hjorth parameters and the correlation coefficients was 53.9 ± 11.4% and 53.7 ± 8.2%, respectively (Table I). The advantage in accuracy caused by power spectral densities is most likely due to their frequency domain origin, that is, despite ignoring temporal effects, these features may still reflect if there was some short and specific frequency event within the longer signal analyzed. In contrast, inter-channel correlation and Hjorth parameters focus mostly on bulk spatial peculiarities, and some shorter events may be suppressed while calculating the features for longer signal.

Moreover, in this approach, the dimension of the feature vector has decreased by more than 50 times, which is important for the computational efficiency and compact representation of the feature space [24]. Further refinement was the addition of the search for the most informative segment within 2 seconds of each mental movement act. Since the moment and duration of its execution was completely arbitrary, it seems reasonable to search for the informational segment separately for each act of mental movement. This approach was tested on three features: power spectral den-

TABLE I. Classification accuracies in different approaches

| Approach | Feature | Classification accuracy |
|---|---|---|
| CSP + LR | CSP-patterns | 51,1 ± 10,8% |
| Search for informative frequencies | Frequency spectrum | 65,4 ± 9,1% |
| | Hjorth parameters | 53,9 ± 11,4% |
| | Inter-channel correlation coefficients | 53,7 ± 8,2% |
| Search for informative frequencies and segments | Frequency spectrum | 59,5 ± 4,8% |
| | Hjorth parameters | 68,2 ± 4,2% |
| | Inter-channel correlation coefficients | 69,4 ± 2,3% |

sities, Hjorth parameters, and inter-channel correlation coefficients. The corresponding classification accuracies were 59.5 ± 4.8%, 68.2 ± 4.2%, and 69.4 ± 2.3%. The latter accuracy is significantly higher than that obtained for CSP-LDA conventional approach (t=6.63, p-value < 0.001), however, there was no significant difference between this accuracy and that of pure informative frequency search (t=-1.7, p-value=0.09 > 0.05). Nonetheless, one cannot deny that there is an improvement in accuracy caused by informative time segment search. Moreover, the p-value obtained is not much higher than the conventional threshold of 0.05, and it is more likely caused by the large standard deviation of the search for informative frequencies accuracies. When comparing the mean values and standard deviations of these two searches, although there is no significant difference, the mean accuracy of the more extensive approach comprising the search for informative time segments is greater, while the corresponding standard deviation is lower. The latter indicates higher stability of this approach among subjects in addition to a somewhat improved accuracy. In detail, what was done for each subject is consecutive application of the search for informative frequency ranges resulting in 3 LDA models described above and the search for the most informative time segments within each motor imagery epoch based on the features determined during the first step. At this stage, initial search for informative frequencies was performed using power spectral densities by default, as they were previously shown to lead to better accuracies for the search. As one can see, the accuracies obtained in this approach for different features are opposite compared to those obtained for the pure search for informative frequencies, that is, while searching for informative time segments, Hjorth parameters and inter-channel correlation coefficients provide better results than power spectral densities. The decrease in accuracy based on the power spectral densities is probably due to the use of only 750 ms of the signal rather than all 2 seconds. Indeed, it is nearly impossible to obtain high-quality spectrum for such a short signal, especially when using windowed FFT-based methods such as Welch's. In contrast, Hjorth parameters and inter-channel correlation coefficients are practically not affected by the small signal length and are capable of reflecting signal peculiarities even in smaller time scales. However, it can be argued that the sequential search for informative frequency ranges and for the informative time segment, albeit using different features (power spectral densities and inter-channel correlation coefficients, respectively), leads to an improvement in the classification results. It is noteworthy that the signals of each ideomotor act are processed independently, but accuracy growth is also observed when they are combined back again, i.e., the method identifies general invariant patterns. Another advantage of the method is resistance to noise, because all pairwise differences between background and the target signal windows are used in the calculations. Thus, by using different subtractions for each time segment, one can expect that at least some of them minimize the noise and highlight informative events.

Finally, this two-step subject-specific approach can also be implemented in the conventional BCI paradigm as initial training and the following operation. The classification results using various features and approaches are summarized in Table I. The scatter diagrams in the space of the LDA components obtained are shown in Figure 4 for the two most successful features. In these figures, two detached clusters can be distinguished, which corresponds to two out of 3 motor imagery types being completely discriminated and the corresponding accuracy of 65-70%. Unsurprisingly, motor imageries of feet and left hand are almost the same in this space since it is a common problem caused by most of the subjects being right-handed.

Currently, spontaneous EEG analysis methods, including both linear classifier models [25] and ANNs (artificial neural networks), have become widespread for solving neural communication problems [20], [26]. The comparison results show the superiority of nonlinear neural network algorithms, especially in terms of the efficiency and adaptivity [27], [28], [29]. This is achieved via the development of new ANN methods [30] that integrate great customization capabilities and the advantages of various approaches that can effectively detect specific and invariant motor imagery patterns of bioelectric brain activity. However linear classifiers are still a clear and easy-to-interpret method; moreover, their computational load is low.

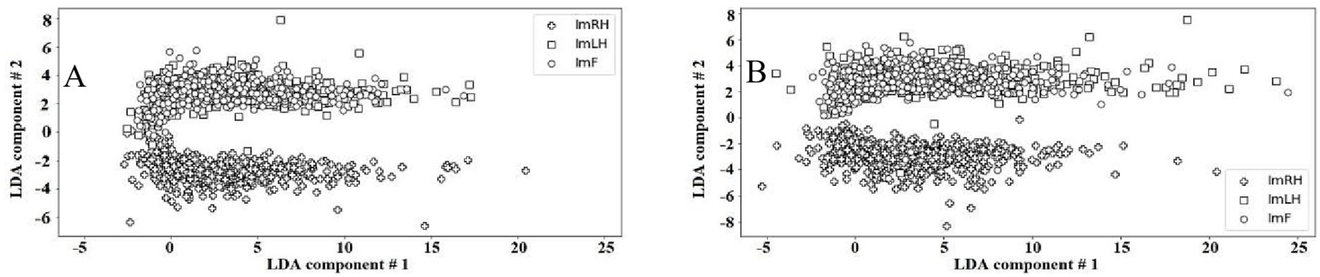


Figure 4. Scatter plot for all subjects in LDA components space after search for the in-formative frequencies and segments using Hjorth parameters (A) and cross-channel correlation coefficients (B)

However, since quasi-stationary EEG can form non-linear discriminant functions, such classification is not always highly accurate at detecting control commands in the BCI framework. Therefore, improving the accuracy of linear methods needs additional preprocessing and highlighting significant features to find invariant EEG patterns [31]. Thus, the results of the classification of multiclass motor imagery patterns based on our original approach showed that the method is capable of increasing the accuracy (on average up to 70%) of detection of randomly generated control commands in the BCI circuit. These results are consistent with available data indicating that neural interfaces based on motor imagery (MI) and approaches for solving neurofeedback problems can provide a reliable and effective non-muscular communication channel. On the other hand, it requires the development of new techniques and scenarios for user training, as well as via training and adaptation of the methods themselves [32], [33]].

Finally, our results agree with the well-known characteristics of event-related desynchronization (ERD) and synchronization (ERS) phenomena in the mu- and beta-rhythm of the EEG. They are primarily considered as events reflecting the performance of motor imagery or mental movements [34], [35], [36]. The ERD phenomenon do not only occur while performing a real movement, but also during motor imagery (mental movement or sensation) [37], [38], [39]. The authors also note a specific somatotopic localization of the effects: in the contralateral hemisphere tj the hand involved, the ERD is more pronounced [40]. These EEG phenomena are usually obtained statistically by averaging (summation) EEG signals obtained during different mental tasks of identical content using lower (delta-, theta-, alpha- (mu-)) or higher (beta- and gamma-) rhythms. Analysis of single events in the EEG is used quite rarely, especially if time intervals are short [41], [42]. Comparative analysis has shown [43], [44], [45] that using single implementations of short (up to 500 ms) EEG segments, one can identify the visual stimulus indicating the movement direction and the brain areas involved in its processing. Moreover, even shorter EEG epochs (up to 200 ms) may be sufficient to identify the readiness potential, indicating the lateralization of the upcoming motor act. However, analysis epochs not shorter than 500-700 ms seem to be the most reliable motor intent identification [46], [41] . We have also shown previously [47], [9] that motor imagery leads to additional activation of both the central motor cortex and the frontal and temporal cortical areas. Additionally, sufficiently pronounced phenomena at gamma frequencies associated with motor imagery. We suggest that the growth of the power of gamma frequency band can be considered as a consequence of the growth of specific information processes associated with voluntary forms of motor behaviour regulation. The specificity of these changes is indicated, in particular, by their close connection with the target areas of the cortex that are contralateral to the motor imagery being performed, as well as those involved in the formation of spatial images and their relationships. This is confirmed by studies involving fMRI and MEG methods, in which local growth of high-frequency gamma activity was observed within the somatosensory cortex in the motor imagery task [48], [49].

## 4. Conclusions

Thus, it is clearly shown that brain motor imagery activity is accompanied by a number of electrographic phenomena useful for BCI. Motor imageries are used by a number of groups [2], [25], [29] to create such systems and are not inferior to systems operating on other phenomena in terms of efficiency (reliability, speed control, etc.) , in particular, on the basis of P300 evoked potentials. Their great advantage is that they do not require external cues and are associated with comparatively local cortical phenomena, and. On the other hand, their peculiarity is a relatively short duration, which is crucial for real-time systems. Nevertheless, currently, it is only possible to form a pretty limited alphabet of control MI commands. This, apparently, is due both to the lack of effective MI activity skills in a person, in addition to mental or inner speech [50], and the complexity of classifying electrographic patterns correlated with visual and proprioceptive types of MI. The development of BCI technology depends on a number of factors, an important one of them is improving the reliability of methods for detecting and classifying invariant EEG patterns in the brain of a person forming control commands in an voluntary and anthropomorphic mode. The successful solution of the above mentioned problems can provide effectiveness and stability of neural communication systems, which will lead to the rapid spread of the technology among disabled individuals. These technologies are highly demanded both in the scientific research and in the mass market for monitoring the functional state of a person, as well as for the creation of a new non-muscular, auxiliary control channel for external devices for various purposes [51], [52]. In this work, it was shown that the problem of classifying the mental equivalents of real movements is most effectively solved by searching for specific frequency ranges for both each subject and for different types of mental movements. The procedure for finding the best time segment to classify target patterns within the entire time range of an ideomotor act also contributed to improving the classification accuracy. The best accuracy was obtained when the following steps were conducted: a) search for informative frequency bands as separate LDA-components for different types of motor imagery for a given subject using power spectral densities as features; b) search for shorter informative time segments using inter-channel correlation coefficients calculated for EEG filtered in the bands found in a) (i.e. bands corresponding to the greatest weights in LDA-components in a)). Moreover, unlike similar investigations [53], our approach does not rely on prior knowledge of an approximate wide informative frequency band, so it is universal in some sense. The preliminary results obtained will form the basis for further development of BCIs. However, in order to create successful classification models for practical applications, significant improvements and development of the exploited experimental paradigm are required. In particular, the use of deep learning methods may improve the accuracy and reliability of the classification of mental equivalents of real movements. The development of such models based on the present study's results is the subject of our current work.

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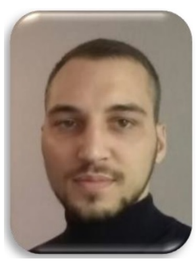

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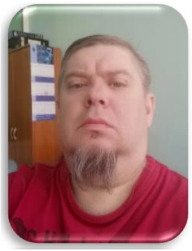

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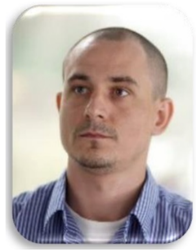

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