Twelve-Class Brain Computer Interface Based on Motor Imageries and Cognitive Tasks

Aryan Mobiny, Ehsan Arbabi, and Tooraj Abbasian Najafabadi

***Abstract*— In order to provide locked-in patients with more effective control over their environment, brain-computer interfaces (BCI) with high performance are needed. One of the main concerns in common BCI systems is related to their degrees of freedom, which is usually limited to two to five mental tasks. This article presents a new asynchronously controlled twelve-class BCI giving the subjects high degrees of freedom. Mental tasks, including motor imageries and cognitive tasks, have been selected and their related scenarios have been designed in such a way that the tasks activate distinct cortical areas and produce different patterns, while considering ease of application. Afterwards, the number of EEG channels has been reduced by selecting the effective EEG channels corresponding to the activated areas within the brain. The resultant offline correct classification rates, 86.78% in average for eight subjects and by using Quadratic Baysian Classifier, confirmed that such set of mental tasks and channel selection is possible for all subjects without significant performance loss. Furthermore, the results obtained by feature selection indicate that spectral analysis has a more discriminative power than temporal analysis does in this twelve-class BCI system.**

***Index Terms*—Brain-computer interface (BCI), cognitive tasks, electroencephalogram (EEG), feature selection, motor imageries.**

I. Introduction

IN the last decades, the concept of Brain-computer interface (BCI) has emerged as an alternative means to provide "non-muscular" communication between the human brain and his surroundings. BCIs aim to provide assistive devices, especially for those with severe physical disabilities, such as patients suffering from late stage of amyotrophic lateral sclerosis (ALS) causing a locked-in syndrome [1]. For this, in noninvasive cases, electroencephalogram (EEG) has been widely used to measure the weak electrical potentials generated by activity in the brain.

Basically, BCI cannot read the users' mind and discover their thoughts; however, it can detect specific patterns of activity associated with the users' intents from the recorded EEG signals and translate them into pre-defined control signals [2]. In most cases, mental tasks have been used to produce these "endogenous" patterns, neurological phenomena generated as the result of cognitive responses of the brain. Among these mental tasks, motor imageries are more common in previous studies. That is because the preparation or imagination of movement changes the so-called sensorimotor rhythms (SMR) and results in a circumscribed desynchronization and synchronization in the Mu and Beta bands that are localized close to the sensorimotor areas. In fact, Event-Related Desynchronization/Synchronization (ERD/ERS) patterns produced by motor imagery tasks are similar to the patterns elicited by actual movements [3]. A complete review of the SMR-based BCIs is discussed on [4].

Among many research groups, having developed BCI systems using the patterns elicited from the Mu and Beta rhythms, works of two research groups are more prominent. Wolpaw and McFarland and their associates in Wadsworth center have focused on developing a CBR-based synchronized BCI system which allows users to control the amplitude of Mu and rhythms to move a cursor on the computer screen [5], [6]. Users of this system could achieve high accuracies (e.g. above 90%) after a few weeks of training [7]. The other group, the Graz BCI, designed synchronized BCI systems using the ERD/ERS of the Mu and Beta rhythms [8], [9], [10]. There are also other preliminary works considering different motor imagery tasks in BCI, and mainly focusing on using a lower number of features or channels [11], [12]. In several other studies, movement-related potentials (MRPs) have been used for the neurological phenomenon, such as work that has been carried out by Mason and Birch's research group [13], [14].

Furthermore, it has been demonstrated that cognitive tasks or non-movement mental tasks (e.g. mental counting, solving a mathematical problem) lead to different changes in brain signals [15]. The works of Aunon and Keirn [16], [17] and, subsequently, Anderson *et al.* [18] are among the prominent BCI research implemented using cognitive tasks. In the 1980s, Aunon and Keirn used EEG signals related to five cognitive tasks. These tasks were recorded from seven subjects and six EEG channels, and each task was performed under both eyes open and eyes closed conditions. They eventually reported offline classification accuracy levels as high as 80%-90%. Anderson *et al.*'s works [18], [19] were a continuation of the studies instigated by Aunon and Keirn. They eventually reported an average classification accuracy of 91.4% [20]. Milan *et al.*'s works are another example of research carried out using cognitive tasks. In 2002 [21], they proposed a BCI system in which both cognitive tasks and motor imageries were used as mental tasks. These five mental tasks were

This paragraph of the first footnote will contain the date on which you submitted your paper for review. It will also contain support information, including sponsor and financial support acknowledgment. For example, "This work was supported in part by the U.S. Department of Commerce under Grant BS123456".

"relax," "left" and "right" hand movements, "cube rotation," and "subtraction" and they were chosen so as to activate cortical areas at a different extent. The experimental results showed that their proposed local neural classifier achieves classification rate of 70% (or more) for three mental tasks from online spontaneous EEG signals.

As it can be seen, the previous works concerning about BCI are usually based on a very limited number of mental tasks (usually two to five). Obviously, the more the number of mental tasks in a BCI system, the more degrees of freedom would be provided for users. However, the selected mental tasks must be easily imaginable and should activate separate areas of the brain. In the present study, we have proposed a BCI system based on twelve mental tasks, including: relaxation, six motor imagery tasks, and five cognitive tasks. The tasks and their performing scenarios have been selected and designed, respectively, by considering both ease of imagination and brain physiology so as to satisfy the above conditions. The proposed BCI system has been tested by eight subjects. Given the results, we believe that the selected mental tasks can create separable EEG patterns, improving our chances of successful classification. The remaining of the paper is as follows: The experimental condition, concerning about the mental tasks and the data collection procedure, are explained in section II. The data processing step, including noise/artifacts removal, feature extraction, EEG channel selection and feature selection, is covered in section III. In section IV, the experimental results are reported and discussed in details. Finally, the conclusion of the paper is drawn in section V.

II. Experimental Condition

A. Mental Tasks

Technically speaking, the first critical aspect in designing a BCI system is determining the set of mental tasks to be used. As mentioned in the introduction, we have utilized both motor imagery and cognitive tasks. These tasks have been chosen so as to maintain ease of imagination and also activate separated cortical areas at a different extent.

Totally, twelve mental tasks have been considered. Some of the mental tasks, i.e. imaginary movements of head and face, and auditory task, are not popular in other BCI related research. On the other hand, some other tasks have been utilized similar to the previous works, which provides us with a better basis for possible comparison of our results with those obtained by the other groups. However, we have also tried to make some modification in design of some of them to reach the most distinctive patterns, and subsequently enhance the classification results.

The following is a description of the tasks which have been performed by each subject. It should be noted that during recording sessions, subjects were seated on a comfortable chair in front of a monitor, in a sound controlled room with appropriate lighting, and they had no prior BCI experience or training hours.

Task 1: Relaxation

During this task, the subject was told to relax and try to think about nothing specific.

Tasks 2-7: Motor imagery tasks

These tasks include imagination of repetitive movements of the left hand, right hand, feet, tongue, head, and face. The respective cortical areas involved in these motor imagery tasks are comparatively large and topographically different in motor and somatosensory cortices. Thus, it is expected that ERD/ERS patterns, which are created by these mental activities, can be discriminated in the recorded EEG signals. The imaginary head movement includes moving the head forward, backward, right, and left. The imaginary face movement is, in fact, imagination of moving all face elements, including lips, nose, cheeks, chin, and eyebrows, in arbitrary directions.

Task 8: Cube rotation

The subjects were asked to visualize a rotating 3D Rubik's Cube (around its center) and also rotate some of its horizontal and vertical faces randomly. The EEG was recorded during the mental rotation period. This task is rather similar to Keirn's geometric figure rotation task [17] with some minor changes to make this task easy to imagine, as well as unifying the created patterns for all subjects.

Task 9: Word generating (verbal task)

The Subjects were instructed to mentally name the months of the year, sequentially, without vocalizing them. This task is expected to result in specific patterns and potentials, specifically in Broca's and Wernicke's areas, which are linked to speech production and understanding [22].

Task 10: Auditory task

The subjects were asked to imagine hearing of a specific sound. In our experiments, sound of a crying baby has been chosen due to its ease of imagination and also its possible unique imagination among different subjects. Since the primary auditory cortex is known to be responsible for processing auditory information, this task activates this area, located at the upper side of the temporal lobe [22], as well as other possible areas.

Task 11: Visual task

In the 11th task, traffic lights were displayed on the screen as a cue for subjects. Afterwards, the subjects were asked to imagine flashing of its lights (red, yellow and green), respectively. This task is somewhat similar to Keiren's visual counting task [17]. However, we have changed its design in order to alleviate the probable interaction between verbal and visual tasks, as well as to make this task more straightforward, as subjects acknowledged.

Task 12: Math problem solving

Mathematic problem solving has been chosen in a number of other BCI researches in various forms. For example, Keiren and Aunon [17] used multiplication in their "complex problem solving" task. However, our chosen task is similar to that of Millan *et al.* [21]. The subjects were asked to perform a successive elementary subtraction, sequentially. This strategy for performing successive subtraction can reduce the possibility of an obvious and immediate answer.

B. Data Acquisition

A 20-electrode clinical NRSIGN3840 EEG system was used to collect data, referenced to an electrode placed on the forehead. These electrodes were placed based on the international 10-20 system, and the amplified EEG was sampled at 500 Hz. Eight healthy subjects, including five males and three females, all right-handed and between the ages of 23 to 25 participated in this study. The recorded data was transmitted to a PC for storage and offline analysis.

Data collection from each subject included ten runs and lasted for about an hour. Each run was consisted of three 10-second trials for each mental task (totally 12*3=36 trials per each run). The sequence of these trials was randomized throughout each experimental run, and the subjects were allowed to have a one-minute break between each two runs.

As it can be seen in Fig.1, each trial starts with presentation of a fixation cross, followed by a short warning tone ("beep") to inform a target subject about the beginning of the trial. Afterwards, a 1.25-second visual cue indicates the mental task that the subject should perform for the next five seconds. At the eighth second, a stop signal indicates the end of the trial.

III. Methodology

A. Preprocessing

The recorded EEG signals contain several perturbations. These noises and artifacts can overlap with the brain neural activity and modify the shape of a neurological phenomenon that drives a BCI system, and finally, result in an unintentional control of the device [23]. Preprocessing is all the processes that are usually performed to alleviate these undesirable noises and artifacts.

The effective frequency range of EEG, which is closely linked to human daily activities, is between 0.5Hz and 100Hz (especially below 60 Hz). Hence, a linear phase FIR filter was used to band-pass filter the raw signals between 0.5-100 Hz. Furthermore, a 50 Hz notch filter was applied to reject the power line noise.

Next, Independent Component Analysis (ICA) was used to remove the psychological artifacts, specifically those generated by eye or body movements. ICA is a statistical method in which the observed signals, measured from different sensors, are transformed into non-Gaussian components that are maximally independent from each other [24]. Several algorithms have been developed to implement ICA method. In this study, we used the FastICA algorithm [24] based on a fixed-point iteration scheme to maximize the non-Gaussianity (measured by the approximation of negentropy) and estimate the most independent components. Afterwards, EEGLAB has been used in order to determine whether each component is an artifact (to be eliminated) or is behaviorally relevant to our desired brain activity [25].

Having removed noises and artifacts, we divided the brain signals into one-second-long segments, where each of these segments has 50% overlap with its adjacent segments. Therefore, the stationary problem of EEG signals can be ignored since the size of segments is short enough.

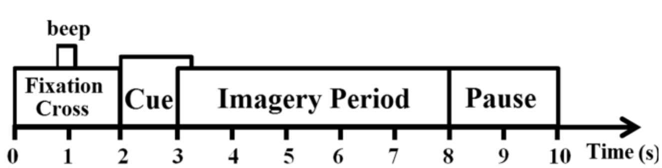

Fig. 1. Timing of each trial of the experiment

B. Feature extraction

In BCI systems, temporal and spectral analysis of the recorded EEG is more common, as the electrical activity of neurons is chiefly concentrated in time and frequency domains. In the present study, 72 features have been extracted and selected from each EEG channel for further analysis. These methods are described as follows.

The EEG spectrum is typically divided into four frequency bands (delta, theta, alpha, and beta), but in this study, we considered another band, called Sigma (similar to [26]), which has overlaps with both general alpha and beta bands. To start with spectral analysis, these bands can be divided to ten sub-bands. The relative spectral power (RSP) is computed as the ratio between the sub-band spectral power (BSP) and the total spectral power. The power spectral density (PSD) is estimated by applying an autoregressive method solved by the Yule-Walker algorithm [27].

Harmonic Parameters (HP), including central frequency (f_c), bandwidth (f_σ), and spectral value at central frequency, have been extracted from EEG segments according to [28]:

$$f_c = \sum_{f_L}^{f_H} f P_{xx}(f) / \sum_{f_L}^{f_H} P_{xx}(f) \quad (1)$$

$$f_\sigma = \left(\sum_{f_L}^{f_H} (f - f_c)^2 P_{xx}(f) / \sum_{f_L}^{f_H} P_{xx}(f)\right)^{1/2} \quad (2)$$

$$S_{f_c} = P_{xx}(f_c) \quad (3)$$

where $P_{xx}(f)$ denotes the PSD, calculated for each of the five frequency bands so as to allow the analysis of a specific frequency band in the EEG, instead of the whole EEG spectrum.

Slow wave indices (SWI) are more common in detection of sleep stages [29]. However, extracting them to highlight some spectral bands over slow wave bands can also lead to better classification results in BCI. Delta-slow-wave index (DSI), theta-slow-wave index (TSI), and alpha-slow-wave index (ASI) are computed according to [26]:

$$DSI = BSP_{Delta} / (BSP_{Theta} + BSP_{Alpha}) \quad (4)$$

$$TSI = BSP_{Theta} / (BSP_{Delta} + BSP_{Alpha}) \quad (5)$$

$$ASI = BSP_{Alpha} / (BSP_{Delta} + BSP_{Theta}) \quad (6)$$

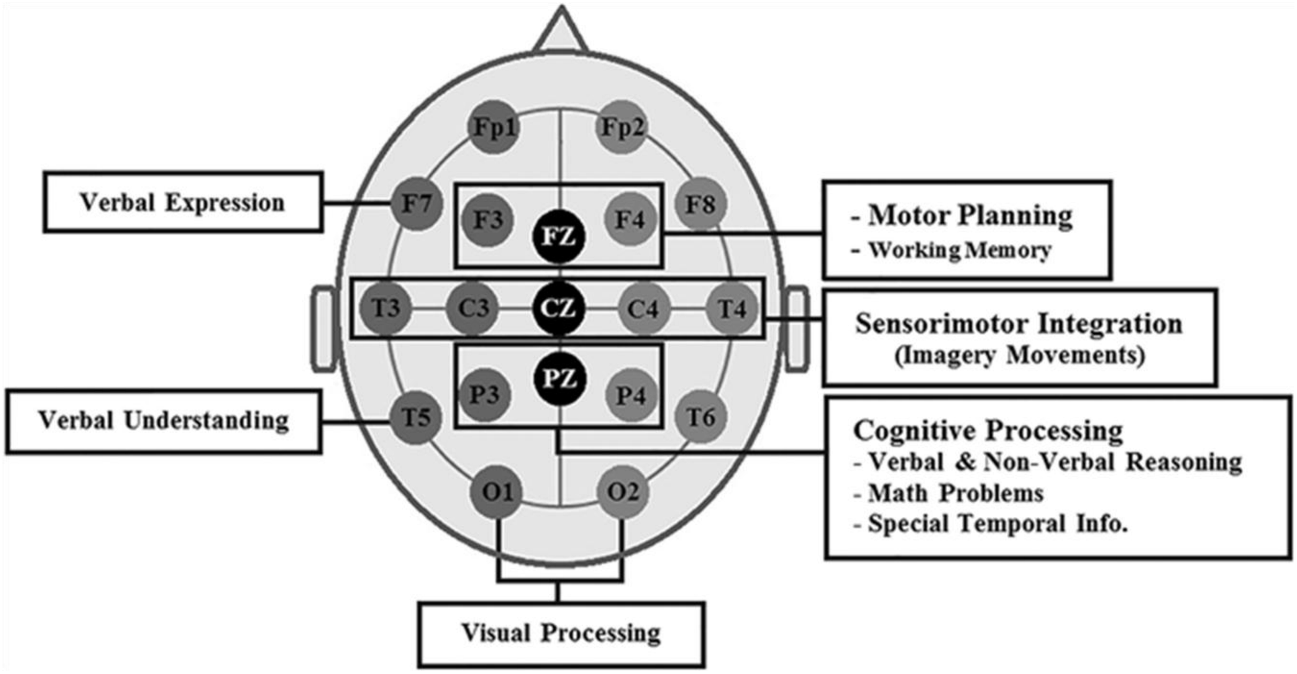

Fig. 2. Selected channels and the basic brain functions related to the brain regions located beneath them

Dynamic temporal information of EEG signal can be provided by Hjorth parameters (PHJ) [30]. For a signal x of length N, these parameters, namely *activity*, *mobility*, and *complexity*, are defined as follows:

$$Activity(x) = var(x) = \frac{1}{N}\sum_{n=1}^{N}(x(n) - \bar{x})^2 \quad (7)$$

$$Mobility = \sqrt{var(x')/var(x)} \quad (8)$$

$$complexity = \sqrt{var(x'') \times var(x)/var(x')^2} \quad (9)$$

where $\bar{x}$, x', and x'' stand for the mean, the first and the second derivatives of signal x, respectively.

In statistics and probability theory, skewness and kurtosis are among the most prominent criterions used to characterize the probability distribution of various data [31]. These criteria are also calculated and considered as the next feature group.

Autoregressive modeling (AR) has been used in different applications, especially in classification of bio-signals such as ECG and EEG, due to its simplicity and availability of efficient computational algorithms to estimate its coefficients [32]. In this study, model order of p=9 has been selected experimentally for the AR process and Burg's method has been applied to estimate the AR coefficient.

Frequency transforms are also common in EEG signal processing. We have used 30-point Discrete Cosine Transform (DCT) to extract features from each segment [33].

Having extracted the aforementioned features, we applied whitening transformation to the whole data to decorrelate the features and transform them to a new set of data whose covariance is the identity matrix. Furthermore, another point of high importance is our high-dimensional data. Linear Discriminant Analysis (LDA) has been applied for dimensionality reduction, as well as removing the linear dependencies among features. [34]. After applying LDA to our dataset, the separability could be retained by selecting the 11 combined features, no matter how many channels or features were selected beforehand.

C. EEG Channel Selection

Generally, the more the number of channels to extract information from, the higher computational complexity will be resulted. Therefore, we need to reduce the number of EEG channels by selecting the channels which are highly linked to our chosen mental tasks. Several studies have been done so far to determine the specific functioning of different areas of the brain. For instance, it has been proved that activities invoked by imagery movements of the right hand, left hand, and feet are more prominent over electrode locations of C3, C4, and Cz, respectively [2]. These hypotheses get more complicated for cognitive tasks since several distinct parts can be involved in. However, certain channels, as well as the corresponding cortical areas beneath them, can be considered as the most important regions influenced by the activities related to each task. For example, Broca's area is a region in the frontal lobe of one hemisphere (usually the left hemisphere for right-handed subjects) with functions linked to speech production. Additionally, Wernicke's area is another region, located in the cerebral cortex, linked to speech, involved specifically in understanding of written and spoken language [22]. These two areas and their corresponding electrodes, namely F7 and T5, can be considered as the most involved channels for recording the brain activities invoked by the verbal task.

Similar analyses can be presented for other tasks. Since this channel selection approach is completely related to the brain physiology, we call it "Physiologic method." Fig.2 illustrates

TABLE I
REMOVED CHANNELS BY PHYSIOLOGIC AND DEFS METHODS FOR ALL SUBJECTS

Method			Removed Channels
Physiologic			Fp1, Fp2, F8, T6
DEFS	Subjects	1	F4, O2, T5, **T6**
		2	**Fp1**, **Fp2**, Fz, T5
		3	F4, **F8**, T4, **T6**
		4	F4, **F8**, P3, Pz
		5	P3, P4, Pz, **T6**
		6	Cz, **Fp2**, P3, T5
		7	**F8**, **Fp2**, T3, **T6**
		8	**Fp1**, P3, P4, **T6**

the selected channels using this method, as well as the basic brain functions related to the brain regions beneath these selected electrodes.

In order to ensure the proper performance of our selected channels, a population-based channel subset selection called Differential Evolution Feature Selection (DEFS) [35] has been used to compare its results (selected channels) with those of our defined method. In DEFS method, a population size of 50 has been used for all users, while the stopping criterion has been defined as reaching the maximum number of iterations, set to 100. We have utilized Quadratic Bayesian Classifier, which is a Bayesian optimal classifier under the assumption of normally distributed data [34].

D. Feature Selection

In statistics, feature selection is the process of selecting relevant features and removing redundant or irrelevant ones [34]. Our aim for applying feature selection method is to identify the most important types of feature-channel combinations in our 12-class classification problem (or even other subsets of these classes). Therefore, this test has been performed in the presence of all 15 physiologically selected channels and all 72 features. In the present study, we have used Orthogonal Forward Selection (OFS), a filter method, using the Mahalanobis class separability measure as the evaluation criterion [36]. Moreover, this method employs orthogonal decompositions in conjunction with Sequential Forward Selection (SFS) to reduce the redundancy problem of SFS (see, for example, [34]). Since the OFS method sorts all features according to their ability to provide large class separation, we can find the most informative features by selecting the highest ranked features. In this study, we have selected the 50 most informative features for all subjects.

IV. RESULTS AND DISCUSSION

The channels removed from the processing steps, using physiologic and DEFS methods, are presented in Table I. As it can be seen, the removed channels using DEFS is different from those of our proposed method, though there are some similarities for each of the users (bold ones). To evaluate the performance of each method, CCRs have been calculated for the test data considering all 12 classes and applying Quadratic Bayesian Classifier. In this study, 70 percent of the data from each of the classes has been chosen randomly to train the classifier, and the 30 percent left has been opted to test it. The random selection of train and test data has been repeated five times. The average values for the resulted CCRs are presented in Table II.

As it can be seen in Table II, considering CCR values, our method shows as good performance as DEFS method, if not better. However, the main advantage of our proposed method is that the effective channels have been selected only based on their placements, considering the related activated cortical areas of the brain. Thus, there is no need to apply complicated and time-consuming methods such as DEFS to select the most prominent channels for each subject independently. In other words, in our BCI system, we can simply use a unique set of channels for any subject.

Mean and standard deviation values (%) for each mental task are presented in Table III. Mean CCR values are obtained from averaging the diagonal elements of the confusion matrices over all subjects. Considering this table, all mean values are highly acceptable and close to each other, which can emphasize the proper performance of our applied method, including selected mental tasks, extracted features, and proposed channels. However, the imagery movement of left hand and the visual task can be considered as the most separable tasks, respectively. Moreover, all of the standard deviations are appropriately low and admissible.

TABLE II
CORRECT CLASSIFICATION RATES (%) FOR ALL SUBJECTS CONSIDERING BOTH PHYSIOLOGIC AND DEFS METHODS

	Subject / Method	1	2	3	4	5	6	7	8	Mean	STD
CCR%	Physiologic	93.61	85.46	92.69	83.33	86.11	85.09	83.33	84.63	86.78	4.05
	DEFS	91.39	87.31	91.30	82.22	90.00	83.62	82.96	82.41	86.40	4.06

TABLE III
MEAN AND STANDARD DEVIATION (%) FOR EACH DIAGONAL ELEMENT OF CONFUSION MATRICES OF ALL SUBJECTS

	Right hand	Left hand	Verbal	Math	Face	Cube Rotation	Relaxation	Visual	Auditory	Feet	Tongue	Head
Mean CCR (%)	85.00	89.72	87.50	84.58	86.67	85.97	86.53	88.61	87.36	85.28	88.33	85.83
STD (%)	6.69	5.47	5.78	5.49	5.44	4.16	7.89	5.81	5.57	5.33	5.48	6.33

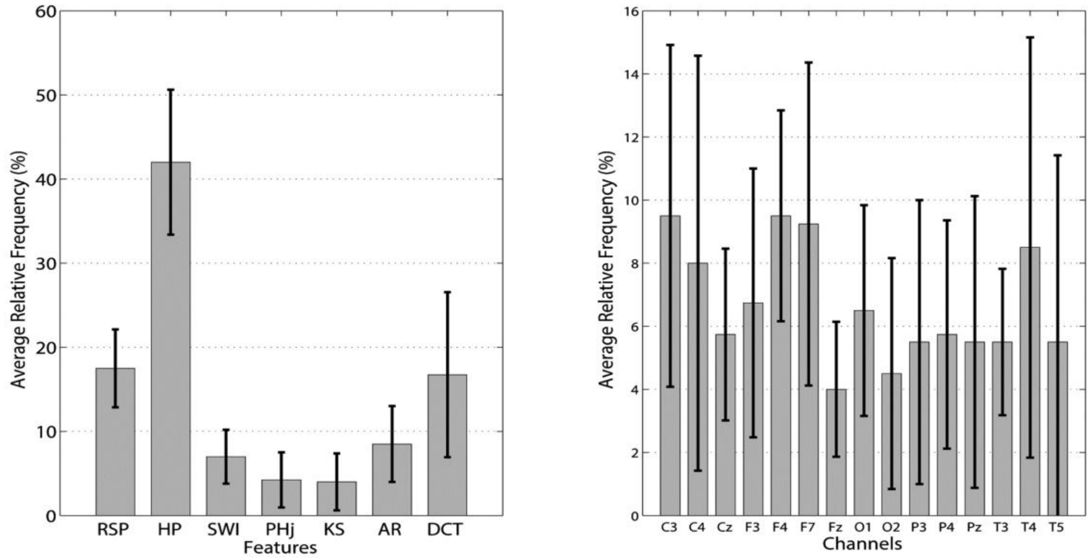

Fig. 3. Average relative frequency (%) of each feature type and channel, within the 50 most informative features using OFS method, considering all users

In order to find the most informative feature-channel combinations in our twelve-class BCI system, we have applied OFS method on all the extracted features considering all 15 selected channels.

As it can be seen in Fig.3, harmonic parameters (HP), relative spectral power (RSP), and discrete cosine transform (DCT) are the most discriminative types of features, respectively. Especially, the harmonic parameters have been selected far more than other feature types for all subjects. On the other hand, it appears that the time-domain features, namely PHJ (Hjorth parameters) and KS (kurtosis and skewness), are less important. Finally, it can be concluded that in the proposed BCI system, the frequency-domain features show better performance than the time-domain ones. This result emphasizes the fact that it is difficult to obtain useful information from EEG signals by temporal signal analysis since the resultant time-domain features are highly related to signal shape, which is extremely random. For further analysis, since the number of features in each feature type differs from one another, we can normalize the resulted relative frequencies. To this end, we have divided the number of selected features of each feature type (presented in Fig.3) by the total number of extracted features of that type. Normalized average relative frequencies are presented in Fig.4. This figure emphasizes the importance of harmonic parameters. It also shows that the large number of selected features from DCT is due to the multiplicity of extracted features of this type, not the suitable performance of each DCT feature, necessarily.

Furthermore, by analyzing the EEG channels, it can be seen that almost all of the 15 selected channels provide decent features, and each channel plays a prominent role in our BCI system. However, by taking the total number of features selected from each channel into account, some of them can be considered as more or less important ones. For example, the total number of 16 features has been selected from Fz. These selected features are almost uniformly distributed among all subjects. This eventually makes Fz the least important channel. On the other hand, according to Fig.3, C3, F4, and F7 make major contributions in discriminating 12 mental tasks. However, when we look at each subject independently, it is clear that the channel performance strongly depends on the subjects. For instance, ten features have been selected from channel C4 for subject number 3, whereas it is only one feature for subject number 7, which makes C4 the best and the worst channel for subject 3 and 7, respectively.

V. Conclusion

Several applications can be counted for brain-computer Interfaces, in particular for people with severe disabilities who have minimal or no muscular control over their body and environment. For example, they can move their wheelchair to either sides, or control home appliances, like switching on/off a television, a radio, or a fan only using their thoughts.

In this study, an asynchronously controlled twelve-class noninvasive BCI has been proposed and developed based on mental tasks, including imagery movements and cognitive tasks. These tasks and their performing scenarios have been selected and designed specifically so as to produce different patterns as much as possible, while maintaining users' convenience. This BCI system enjoys twelve different tasks,

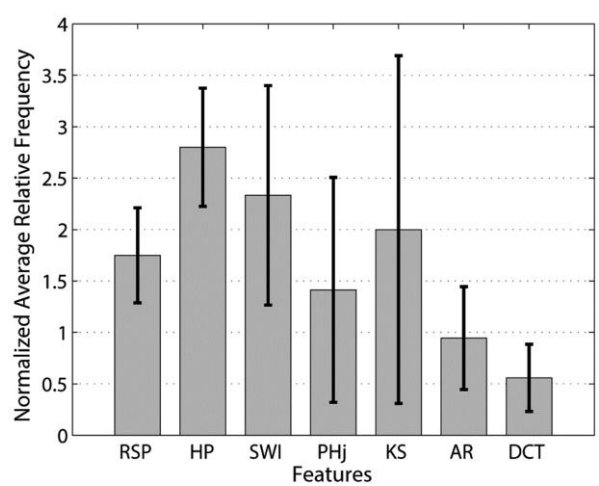

Fig. 4. Normalized average relative frequency of each feature type, within the 50 most informative features using OFS method, considering all users

which provide users with a great number of choices, much more than similar BCI systems developed by other research groups so far. Moreover, high correct classification rates (about 87% in average) demonstrate the impressive performance of our proposed system.

Next, considering the confusion matrices for all subjects, each mental task has been evaluated separately in Table III which demonstrates that all the selected mental tasks have been performed and classified properly. The best classifications have been achieved for the left hand imagery movement (89.72%) and visual task (88.61%), respectively.

As a future work, since these primary offline experiments were performed on healthy subjects, further real-time analyses on patients are indispensable. Moreover, other methods of pattern recognition can be applied and tested to investigate the possibility of extracting more distinctive features and selecting the most informative ones.

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