GA Methods for Selecting the Proper EEG Individual Spectral Bands Limits

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***Abstract*—In a previous set of analyses and researches we have proved the strong relationship that exists between each particular subject and its corresponding particular set of imagery cognitive tasks (determined out of several proposed mental tasks); these individual sets of tasks were the ones on which the obtained classification performances were significantly superior than on the other possible combinations of tasks. Also, a remarkable aspect is that all these improvements in classification were achieved for the same EEG features (namely, AR parameters) and the same processing and classification methods, that, during the entire study, were kept unmodified. In consequence, the act of finding, for each individual subject, the appropriate specific set of cognitive tasks should be considered of great importance in any brain computer interface (BCI) implementation. The present paper continues these researches and focuses on the necessity to find (as it has been already suggested in the literature), for each subject, that set of custom band power coefficients for which superior classification rates on the subject optimal set of cognitive tasks - previously determined – will be the highest. Based on some specific GA methods, implemented in order to find the subject appropriate frequency band parameters, and using a neural network structure for the classification, the final new obtained classification performances considerably improved with 4 to 6 percents.**

I. INTRODUCTION

The EEG signal is a composite signal, structured from noise and some different types of waves (δ, θ, α, β and γ) that are considered to define and characterize different types of brain states (e.g. consciousness, relax, active thinking, active attention, a mindless state, focus on the outside world, solving concrete problems etc.). Even if these waves are quit well known and intensively studied, there is no standard definition of lower and/or upper limits for these bands; moreover, the limits may vary between different individuals on the same age segment, with the age, related to the brain activities etc.

For example, even if the upper limit of the beta waves (usually associated with active thinking, active attention focused on the outside world etc.) is bounded at around 35 Hz, during intense mental activity this wave can reach frequencies near to 50 Hz [1]. In a same manner, the alpha wave, superior bounded at around 13 Hz, can reach spectral components at 20 Hz [1], deep in the beta range.

Another important fact that questions the use of fixed frequency bands is based on the brain activity power "movement" phenomenon that can be observed anytime when there is an increasing in the task demands [2]. In such situations, the EEG power moves from the alpha band (through the mechanism of desynchronization) to the theta band (through the mechanism of synchronization). The transition of power between alpha and theta bands occurs within a narrow frequency range. If broad frequency bands, not adjusted to individual alpha frequency (IAF), are used to compute the power coefficients, these effects of an event-related increase (synchronization) and event-related decrease (desynchronization) in that band power will tend to cancel each other [2]. As a result, the border between the alpha and theta bands must be careful selected. But, as it has been already discussed in [2], the border of these frequency bands are subject dependent.

In conclusion, in order to obtain higher classification rates such phenomenons, like the one presented above, must be taken into consideration.

In what follows we aim to find a method that automatically determine the specific spectral band limits for each subject, limits that will conduct to higher classification rates when used in a power spectral features-based classification system. In this mode, the present research continues a previous research focused on finding the subject appropriate mental tasks that provided the higher tasks classification performance.

II. MATERIALS AND METHODS

A. Data Acquisition

In this paper, the EEG database is the same with the one used previously by us in a different set of studies [3], [4].

The EEG database was obtained from four healthy, right-handed subjects, not affected by any kind of mental disorders, aged between 22 and 35 years. The EEG signals were acquired during 12 different mental tasks – four of them were motor imagery and other eight were non-motor imagery tasks. In all the tasks, the subjects were instructed not to verbalize or vocalize and not to take any overt movement.

The system used for data acquisition, using a 256 Hz sampling rate, was a MindSet 24 system. The MindSet 24 system filtered all the EEG time series. For these, a band-pass

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filter, hardware-implemented, having the corner frequencies at 1.4 Hz and 35 Hz, was applied.

All the recordings took place in a noiseless room with dim lighting. Measurements were made from all 19 active electrodes, placed on the International 10-20 standard [8]. The EEG measurements references were the ears – A1 and A2 electrodes. In this study the classification was made based on the EEG data from only 6 channels – 3 pairs of electrodes placed on the scalp on the following positions: central (C3, C4), parietal (P3, P4) and occipital (O1, O2).

Signals were recorded for 20 seconds during each task and each task was repeated four times. Successive tasks were separated by a resting period of 30 seconds.

The 12 mental tasks performed by the subjects were as follows:

- Counting task (Count): The subjects were asked to imagine a counting down operation started from an integer number, randomly specified before session.
- Left fingers movement task (FingerL): All the subjects were instructed only to imagine the action of opening and closing, alternatively, the left hand fingers, but without doing the movements effectively.
- Right fingers movement task (FingerR): The same task as previously-mentioned, but this time mentally performed with the right hand fingers.
- Left arm movement (HandL): The subjects were asked to imagine how they are slowly rising and falling their left arm without doing the movements effectively.
- Right arm movement (HandR): The same task as that presented above, but mentally performed with the right arm.
- Mental letter composing task (Letter): The subjects were instructed to mentally compose a letter. The letter meaning should have a positive emotional content.
- Mathematical adding task (Math): Before each recording session, a random number was given to each subject. The subjects were instructed to add this number to the following one; then, the result will be added to its corresponding following number and so on.
- Baseline-resting task (Relax): The subjects had to relax as much as possible, trying to think of nothing in particular.
- Geometrical figure rotation (Rotate): The subjects were instructed to study a mug for 30 s before the EEG acquisition session. Then, the subjects were asked to close their eyes and to visualize the object being randomly rotated around its axes.
- Generating common words (wordG): Before the session, the subjects were given an alphabetical letter and they were asked to find continuously different ordinary words beginning with that letter.
- Generating names (wordN): Before the session, the subjects were given one alphabetical letter and they were asked to find as much as possible names beginning with that letter.
- Mentally reciting a poetry (wordP): The subjects were asked to mentally recite a poetry but without vocalizing.

B. Relative power spectrum coefficients

Relative band power was estimated for seven frequency bands – δ_2 (2 – 4 Hz), θ (4 – 7Hz), α_1 (7 – 10 Hz), α_2 (10–13 Hz), β_1 (13–18 Hz), β_2 (18–35 Hz) and γ (35 – 128 Hz) –, within all 8 s sliding windows (2048 points) (overlapped by 100 ms and obtained for all 6 acquiring channels). The sliding step's duration of only 100 of milliseconds ensures an appropriate tracking of the temporal cortical activations (placed in the range of 100 – 200 ms), thus corresponding to the sequence of cognitive processes. Also, the assumption of time invariant properties of the EEG signal was supported by the signal's breakdown into time sliding windows [5].

Relative power spectrum coefficient at each frequency band was expressed as a percentage of the EEG power in the 2 – 128 Hz band:

$$RP_i = \sum_{j=k_i}^{k_{i+1}} P_j \Bigg/ \sum_{i=1}^{7} \sum_{j=k_i}^{k_{i+1}} P_j \qquad (1)$$

where: i is the frequency band, k_i and k_{i+1} are the limits of the band range divided by the spectral resolution, *df* (*df = sampling frequency/window's size* = 0.125 Hz in our specific case) and P_j represents the power of the j-th component of the frequency spectrum. In this way we obtained a feature vector of 42 components (6 channels * 7 frequency bands) and 119 such vectors per each recording.

Finally, we got 1904 artificial neuronal network (ANN) input feature vectors (119 vectors per each recording * 4 recordings * 4 mental tasks).

III. Results and Discussions

In order to compare the obtained results, presented in this paper, and to conclude on the classification improvements due to the user specific frequency bands, we focused only on one single subject – subject 2. The subject 2 was previously reported by us [3], [6] as having the worst classification performances in comparison with the other 3 subjects. For this subject, in the analysis to be presented here, we have used only the optimal set of tasks previously determined [3], [6].

From the subject 2 input database we used 80% of data for the training set (1524 feature vectors) and 20% of data for the cross validation (CV) set (380 features vectors). All the classification results, presented further for this subject, were obtained by using raw EEG data without any artifact removal procedures in the pre-processing steps.

Two different studies were done. In the first study, ANN was used in order to classify the four tasks based on the relative power spectrum coefficients computed in the fixed bands, previously presented. Further, the results of this classification process were used as reference for the second study in order to reveal the classification improvements one can get by using the user-specific spectral bands limits. The ANN topology and the parameters used in the second study were identical with the ones resulted and exploited in the first analysis.

The second analysis used a GA method to determine and to select the specific individual spectral band limits.

A. Classification of EEG features with fixed spectral band limits

The first requirement for the ANN was to obtain higher classification rates.

The GA optimization technique required the ANN to be trained multiple times in order to find the optimal combination of power spectrum bands that produced the smallest error (e.g. a population of 100 chromosomes requires, in each generation, 100 ANN trainings). This reason generated at least one important constrain. This constrain was related to the ANN; namely, it was necessary to find – before starting the GA optimization –, an optimal multilayer perceptron (MLP) ANN (topology, learning rates, moment rates, nonlinearity types, etc.) that had optimal convergence characteristics; that is, first, the networks had to have a stabile dynamics and, second, the ANN had to have a lower convergence time. In this mode, the time spent by the ANN was minimized and, as a result, each GA generation took less time.

In the first analysis, after an extensive search, we found that an ANN – with two hidden layers of neurons, with 11 processing elements on the first hidden layer and 5 processing elements on the second hidden layer, having all moment rates equal to 0.7, and a learning rate of 4 on the first hidden layer, 0.6 in the second hidden layer and 0.2 on the output layer – had the best convergence characteristics for our specific case.

The best results obtained for the above proposed ANN are presented in Table I.

TABLE I
THE CONFUSION MATRIX OBTAINED FOR THE 4 TASKS CLASSIFICATION CASE AND FOR THE POWER SPECTRUM COEFFICIENTS (IN PERCENTS)

Real Classes \ Assigned Classes	**HandR**	**Relax**	**Rotate**	**WordP**
HandR	**90.11**	0	0	9.89
Relax	0	**100**	0	0
Rotate	3.81	9.52	**86.67**	0
WordP	11.11	1.01	0	**87.88**

The results obtained using an artificial neuronal network of multilayer perceptron type (MLP), trained with the backpropagation algorithm, and having an EEG sixth-order AR model are presented in Table II.

TABLE II
THE CONFUSION MATRIX OBTAINED FOR THE 4 TASKS CLASSIFICATION CASE AND FOR THE AR MODEL (IN PERCENTS)

Real Classes \ Assigned Classes	**HandR**	**Relax**	**Rotate**	**WordP**
HandR	**62.69**	21.64	10.45	5.22
Relax	12.73	**59.09**	9.09	19.09
Rotate	7.5	3.33	**82.5**	6.67
WordP	2.78	18.75	3.47	**75**

Using the power spectrum coefficients the results considerably improved. If we count only the average of correct classification rates the improvements are from 69.82 (see Table II) to 91.16 (see Table I).

In the second analysis, a chromosome used by the GA was composed from a series of values. These values encoded one of the 7 spectral band limits. For each spectral band limit a lower and an upper bound values were supplied to the genetic algorithm in order to limit the optimized spectral parameter. The lowest and the highest values for each spectral parameter are the following ones: f1 $\in$ [1.5, 2.5], f2 $\in$ [3, 5], f3 $\in$ [6, 8], f4 $\in$ [9, 11], f5 $\in$ [12, 14], f6 $\in$ [15, 34] and f7 $\in$ [35, 100].

B. Classification of EEG features with individual spectral band limits

In order to solve the problem of the subject specific band power features determination, a GA was used. The GA method changes continuously the frequency limits of the bands, see Fig. 1, on which the relative power spectrum coefficients are computed. The root-mean square cost of the network's output of the cross validation set was used as the fitness criteria for the GA. This cost had to be minimized by the GA.

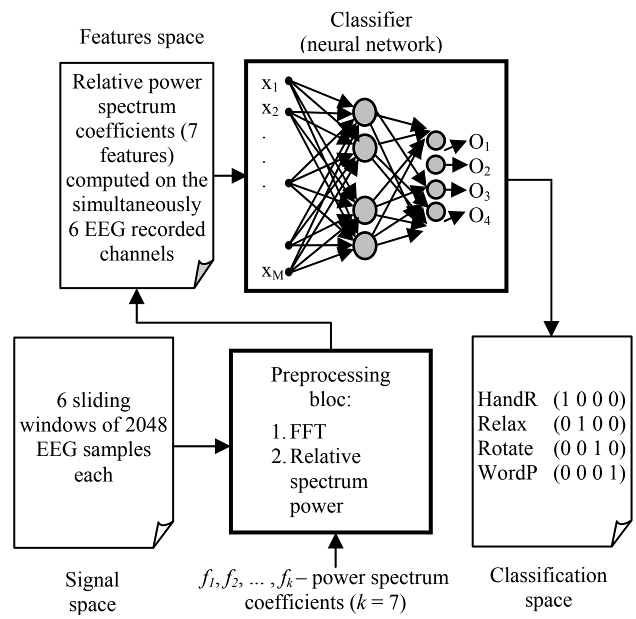

Fig. 1. System data flow schematic

Two of the main parameters of the GA, with an important impact on both – the convergence time to a solution and the quality of that solution –, are the population size and the crossover operator. In our case, related with this particular problem and based on a previous experience [7], a population of 15 chromosomes was used. The second parameter was managed in this analysis based on three different trials, with three different types of crossover operators.

The GA was implemented based on a population of 15 chromosomes (only in one trial a population of 20 chromosomes was used), using a roulette selection method, three types of crossover operator and a classical mutation operator. The chance of a chromosome to be selected was based on the rank of the fitness for each chromosome. The probabilities for the crossover and the mutation operators were set to 0.9 and 0.01, respectively. Three types of crossover operators were used: two points, heuristic and uniform.

A genetic training ran until the maximum number of generations was achieved (i.e. 150 generations).

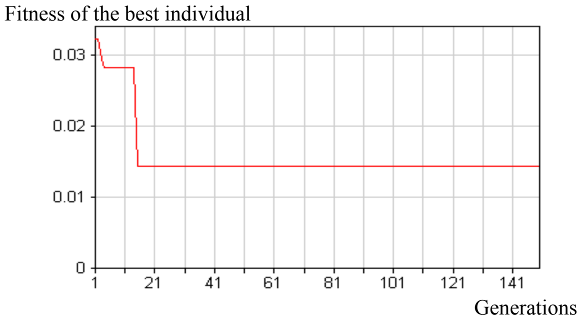

Fig. 2. The evolution of the genetic algorithm GA1, see Table VI, for a population of 15 chromosomes

The GA running time was of 15 hours and 50 minute on an Intel(R) Core(TM)2 Duo CPU (E7400) at 2.8 GHz, with 4GB of RAM. The obtained system subscore for processor and RAM memory was 6.3 as part of a Windows Experience Index score computed by the operating system.

TABLE III
THE CONFUSION MATRIX FOR THE 4 TASKS CLASSIFICATION CASE AFTER THE GA1 POWER SPECTRAL BANDS OPTIMISATION (IN PERCENTS)

Real Classes \ Assigned Classes	**HandR**	**Relax**	**Rotate**	**WordP**
HandR	**90.91**	0	0	9.09
Relax	0	**100**	0	0
Rotate	0	4	**96**	0
WordP	7.23	0	0	**92.77**

In Fig. 2 we present the evolution of the GA displaying fitness of the best individual (the root-mean square cost on the cross-validation set for the best chromosome of each generation). From this figure one can note the ability of the GA algorithm to improve the classification performances using for this an optimal set of spectral bands limits specifically selected for subject 2 during the evolution process. The associated classification performances obtained at the end of the GA evolutions are presented in Table III – with an average of correct classification rates of 94.92. These results correspond to a GA based on a two-point crossover operator. Comparing the results from Table III with the ones displayed in Table I and Table II, one can easily be aware of the gain obtained in the classification rates. Compared to the reference values, obtained in the first analysis, the performance obtained using the specific subject spectral band limits improved with more than 3.75 percents. Comparing the same result with the one obtained in the classification system based on the AR coefficients the improvements are of more than 25 percents.

In Tables IV and V there are presented the classification results obtained with the optimal combination of spectrum bands determined by the GA when using for this a heuristic (see Table IV) and, respectively, a uniform (see Table V) crossover operator. The obtained average of the correct classification rates was 95.41%, for the heuristic crossover operator, and 97.16%, for the uniform crossover operator. When comparing these results with the reference ones, one can notice that the average correct classification rate improved with a minimum of 4.25% up to 6%.

TABLE IV
THE CONFUSION MATRIX FOR THE 4 TASKS CLASSIFICATION CASE AFTER THE GA2 POWER SPECTRAL BANDS OPTIMISATION (IN PERCENTS)

Real Classes \ Assigned Classes	**HandR**	**Relax**	**Rotate**	**WordP**
HandR	**88.89**	1.01	0	10.1
Relax	0	**100**	0	0
Rotate	0	0	**100**	0
WordP	7.23	0	0	**92.77**

All the results presented in Tables I, III, IV and V were obtained on the cross validation data set. When, after 150 generations, the GA finished the adaptation process, the best obtained parameters (those that produced the lowest cost – f_1, f_2, ... , f_k) were automatically loaded into the system and the corresponding results were obtained at the outputs of the neuronal network, Fig. 1.

TABLE V
THE CONFUSION MATRIX FOR THE 4 TASKS CLASSIFICATION CASE AFTER THE GA3 POWER SPECTRAL BANDS OPTIMISATION (IN PERCENTS)

Real Classes \ Assigned Classes	**HandR**	**Relax**	**Rotate**	**WordP**
HandR	**93.94**	0	0	6.06
Relax	0	**95.92**	4.08	0
Rotate	0	0	**100**	0
WordP	1.2	0	0	**98.8**

For each specific implemented GA, the corresponding resulting parameters of the classification system (the band limits values, f_1, f_2, ... , f_k) are those presented in Table VI.

Also, in the second study, the influence of a larger population was analyzed. Using the same parameters for the ANN and GA (excepting the population size that was increased from 15 to 20 chromosomes), the relative power spectrum features for subject 2 were determined once again.

The results are presented in Fig. 3 (the evolution of the GA given by the displaying fitness of the best individual of each generation), Table VII (the confusion matrix for the cross validation data set) and Table VI (the bands limits values and the average of correct classification rates).

Based on the results presented in Tables VI and VII and on the Fig. 3, one can conclude that a larger GA population may offer superior classification performances.

TABLE VI
THE CONFUSION MATRIX FOR THE 4 TASKS CLASSIFICATION AND FOR ALL THREE GA IMPLEMENTATIONS

		GA1		GA2	GA3
Population size		15	20	15	15
Crossover	Type	Two points		Heuristic	Uniform
	Parameter	-		Number of tries = 3	Mixing ratio = 0.5
f_1 [Hz]		1.751	2.433	2.467	1.5
f_2 [Hz]		4.145	4.804	3.473	3.306
f_3 [Hz]		6.451	7.616	6.435	7.472
f_4 [Hz]		10.739	10.439	10.704	10.802
f_5 [Hz]		12.479	12.482	13.849	12.0
f_6 [Hz]		15.108	24.576	22.737	15.0
f_7 [Hz]		40.893	73.413	70.714	99.072
Average of correct classification rates		**94.91 %**	**96.12 %**	**95.41 %**	**97.16 %**

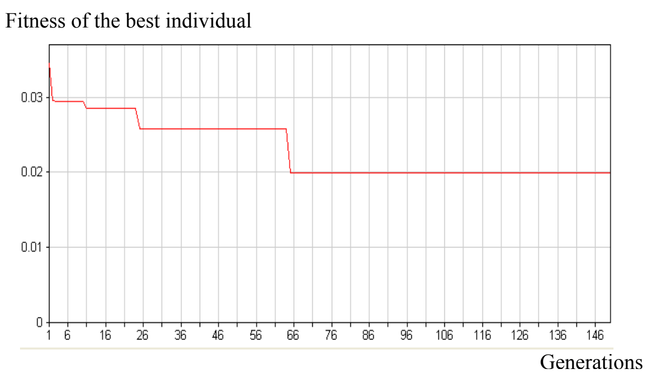

Fig. 3. The evolution of the genetic algorithm GA1, see Table VI, from a population of 20 chromosomes

IV. CONCLUSIONS

Once again, the obtained results suggest and support one of our previous observations, namely: the relative energy within the "standard" frequency bands is more useful in discriminating the mental tasks than the AR parameters [4].

The GA method, used to determine the spectral band limits for a specific subject and for the relative power spectrum features, proved its efficiency, increasing the average of the correct classification rate by 6 percent reaching thus an average of correct classification rate of 97.16%, as presented in Table V. It is important to mention that these results were obtained on the EEG database obtained from subject 2 for which the worst classification performances were obtained compared to the other 3 subjects [3].

The improvement of 6% obtained based on subject-specific frequency band limits compared to the "classical" or standard fix frequency bands, see Table I, is a significant improvement in a field of research were each small mental tasks classification rate improvement (of 1-2%) is desirable in order to obtain a reliable system.

TABLE VII
THE CONFUSION MATRIX FOR THE 4 TASKS CLASSIFICATION CASE AFTER THE GA1 POWER SPECTRAL BANDS OPTIMISATION (IN PERCENTS)

Real Classes \ Assigned Classes	**HandR**	**Relax**	**Rotate**	**WordP**
HandR	**93.94**	0	0	6.06
Relax	0	**97.96**	2.04	0
Rotate	0	5.0	**95.0**	0
WordP	2.41	0	0	**97.59**

A secondary result highlights the ability of the uniform crossover operator to find the optimal combination of frequency band limits that produces the smallest error. Like in our case, we suppose that the uniform crossover have the ability to maintain the genetic diversity even in the case of a small population.

The GA method, used to select the optimal combination of spectrum bands, is a very time consuming operation; but after the band limits – for a specific BCI system user – are founded these limits can be then used without any computation burden.

As a final result, the classification performance significantly increases when we are using the subject appropriate frequency band limits.

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