The selection of proper discriminative cognitive tasks – a necessary prerequisite in high-quality BCI applications

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***Abstract*—While in brain computer interface (BCI) field the research is focused basically on finding improved processing methods leading to both high classification rates and high bit transfer rates, in this paper the same BCIs performances are addressed but, this time, with the emphasis set on the subject-specific discriminative cognitive tasks selection process. In this respect, a set of twelve electroencephalographic (EEG)-discriminative mental tasks was proposed to be studied in conjunction with four different subjects. For each subject, a particular set of four mental tasks was selected. The classification performances corresponding to these particular sets of tasks were obtained using some standard processing methods (i.e., the autoregressive model of the EEG signals and a multilayer perceptron classifier trained with back-propagation algorithm). The superior classification rates achieved for the selected sets compared to other set of mental tasks commonly used in the 4-class BCI studies (i.e. the set proposed by Keirn and Aunon [3]) promote the idea of subject-oriented mental tasks selection process as a necessary preliminary step in any high-quality BCI application.**

Keywords-brain-computer interface application; EEG-discriminative mental tasks; autoregressive model; Bayes quadratic classifier; artificial neural networks

I. INTRODUCTION

Until now, the research in the EEG-based BCI field was concentrated mostly on the processing and, respectively, on the classification issues, with little or almost no emphasis put on the selection process of the subject-appropriate set of mental tasks. Usually, the selection of the mental processes used to command mentally a device involved the assumption of tasks' capacity to elicit specific differentiated EEG patterns. Based on the results reported by various psycho-physiological studies and brain imaging studies some motor and non-motor imagery tasks were selected more frequently. Such covert mental processes are the following imagined tasks: movements of tongue [1], of right or left hand, finger or foot [2], relax, counting, writing a letter, doing a mathematical calculus, rotating a 3D object [3], verbal fluency tasks like phonemic (letter-cued) silent word generation and semantic (category-cued) silent word generation etc. Of these mental tasks the sets of only motor imagery tasks are the most exploited [1]. However, some sets of only non-motor imagery tasks [3] or combined motor with non-motor imagery tasks [4] were considered also. In spite of this diversity of mental processes analyzed in the 4-class BCI applications – with the EEG data being either recorded, within particular conditions, from some volunteers or taken from freely provided on the internet databases [5] – we simply remark, as much as we know, that:

- the classification performances for any given set of overt [2] or covert cognitive [1] tasks vary significantly from subject to subject, thus making difficult the conclusions regarding a particular processing method or another (in general, the results of the best performing subject are reported); an elaborated example is a 4-class BCI application [1] where – for the same tasks but for subject-specific selected features – the reported correct classification rates are for one of the subjects (92, 92, 100, 70) while for the other three investigated subjects, the performances are significantly lower, namely (62, 86, 92, 96), (54, 92, 54, 73) and (62, 38, 80, 60), respectively. This example may well suggest not necessarily inadequate processing approaches but rather low subject-specific discriminative power of the respective set of mental tasks, at least in conjunction with the adopted EEG feature-extraction methodology.
- often, the classification rates obtained on the same set of tasks, but using different new or improved processing methods, are slightly (and only at times, significantly) better than some previously reported reference results – at least, for part of the subjects; we think this could be due also to the limitation imposed primarily by the subject inappropriate (in rapport with a particular EEG feature vector) selected tasks; frequently, in such conditions, small improvements in the classification scores are counterweighed by the increased complexity of the algorithms proposed, also reflected in more time consuming.

From the aforementioned comments, we assumed that in order to obtain high classification rates, a preliminary subject-oriented selection of the most EEG-discriminative tasks is necessary. In what follows we will show that such a proper selection of the subject–specific mental tasks could lead to high classification rates even when using some standard processing techniques (that are less time consuming) instead of using some new or improved, but also frequently more complex, versions of these techniques. This last advantage is critical especially within the on-line BCI applications where always there is a trade-off between the high classification performances obtained and the less time-consuming processing and classification methods that are used. Partly, the idea of our research has its roots in some researches that reveal the inter-subject variability of the way the same cognitive processes occur at the cortical level [6]. To some extent, these differences appears as a direct consequence of both the own native talents and sustained training, often reflected in the chosen profession (i.e., musicians, mathematicians etc.).

In what follows, we investigate in what degree the use of subject-specific set of four mental tasks – in the context of some standard processing and classification methods (i.e., the autoregressive (AR) model of the EEG signals and a multilayer perceptron classifier trained with back-propagation algorithm) – influences the classification performances. For this, a set of twelve cognitive processes was first analyzed, out of which only four tasks were selected for each participant to the study. Within the selection step the same AR processing method was used together with a two-class Bayes quadratic classifier.

II. Experimental Setup

A. EEG signal recording

Four healthy, right-handed subjects (i.e., subjecs S1, S2, S3, and S4), aged between 22 and 35 years, participated to this study after informed consent. The subjects were seated in a noiseless room with dim lighting. The EEG signals were recorded during 12 covert mental tasks (4 motor imagery and 8 non-motor imagery tasks). In all tasks, the subjects were instructed not to verbalize or vocalize and not to take any overt movement. 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. For subject S4 a second session of recording was repeated after a week.

The system used for data acquisition was a MindSet 24 system. Measurements were made from 19 active electrodes, with reference to electrically linked ears, A1 and A2. Only 6 out of the 19 electrodes (with the positions defined by the 10–20 system of electrode placement.) were further analyzed (i.e., C3, C4, P3, P4, O1, and O2). The analysis of the data was done using raw EEG signals, with no explicit artifact removal. The sampling rate was 256 Hz and the data were band pass filtered with and antialiasing filter from 1.4 Hz to 35 Hz (-3 dB).

B. Different experimental conditions

There is a body of literature that suggest that there are measurable differences in the EEG signals that correlate with different types of mental processes. Based on such reported results we selected to investigate within our research a large set of mental tasks. During the study, the subjects performed the following twelve different mental processes, containing together motor and non-motor imagery tasks:

(1) *Resting task* (relax): The subjects were required to relax as much as possible and try to think of nothing in particular.

(2) *Counting* (count): The subjects were asked to imagine a counting down operation beginning from a random number specified before the recording.

(3) *Letter composing* (letter): The subjects had to mentally compose a letter (with a positive emotional content) to a friend or relative.

(4) *Geometrical figure rotation* (rotate): The subjects were instructed to visualize a mug for 30 s before the recording. Then, the mug was removed and the subjects were asked to mentally visualize the mug being randomly rotated about its axes.

(5) *Mathematical adding* (math): Before the recording the subjects were given a random number and were asked to add the number to its consecutive number; then, the result had to be added to its corresponding following number and so on. At the end of the recording, the subject's result was checked if it corresponded to one of the possible correct responses.

(6) *Left fingers movement* (fingerL): The subjects had to imagine opening and closing alternately the left hand fingers, without doing effectively the movements.

(7) *Right fingers movement task* (fingerR): The subjects were instructed to imagine opening and closing alternatively the right hand fingers without ay overt movement.

(8) *Left arm movement* (armL): The subjects were asked to imagine how they are slowly rising and falling their left arm without any overt movement.

(9) *Right arm movement* (armR): The subjects had to imagine how they are slowly rising and falling down their right arm without any overt movement.

(10) *Letter-cued silent word generation* (wordG): Before the recording, the subjects were told an alphabetical letter and they had to find words beginning with that letter.

(11) *Letter-cued silent names generation* (wordN): Before the recording, the subjects were told an alphabetical letter and they were asked to find as many as possible names beginning with that letter.

(12) *Mentally reciting a poetry* (wordP): The subjects were asked to mentally recite a poetry, without vocalizing.

Within this large set, beside the first five tasks corresponding to the set proposed by Keirn and Aunon [3] – set that we used as reference when reported and discussed the results – we also included some largely exploited motor tasks (i.e., movements of fingers and arms) together with not very used imagery tasks (i.e., verbal fluency tasks and poetry reciting task).

III. Data Analysis and Subject's EEG-discriminative Mental Tasks Selection

In order to select the subject' suitable set of four mental tasks we made an exhaustive analysis concerning the discriminative power of each out of the 66 possible pairs of

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tasks. In this case, the two-class classification problems were solved using a Bayes quadratic classifier. The feature vectors constructed with the estimated coefficients of the EEG-autoregressive model were the inputs of the Bayes classifier.

A. Autoregressive model

The parameters of the six-order standard parametric AR model of the EEG signal – adopted to obtain the feature vectors – were estimated using the Yule-Walker method [7]. The AR parameters were extracted for each 0.25 s sliding windows (64 samples), overlapped by 0.125 s (32 samples).

Having six acquiring EEG channels, for each time window corresponding to a sliding window we obtained feature vectors of 36 elements (6 AR parameters/window/channel * 6 channels). The order six for the AR model (adopted in other similar studies too [8]) was chosen here in order to easily report the results.

B. Bayes classifier

The Bayes classifier – an optimal, well-known probabilistic method for data classification – considers the feature vector as a random vector, and, in consequence, the parameters of the AR model are viewed as random variables. Through the inference process the Bayes method finds the unknown posterior probability $P(C_i|x)$ for each class C_i and for a particular feature vector x that has to be classify. Using the Bayes theorem, the posterior probability, $p(C_i|x)$, is actually determined based on the prior probability of the class, $P(C_i)$, and on the likelihood function $p(x|C_i)$:

$$P(C_i|x) = \frac{p(x|C_i)\cdot P(C_i)}{P(x)} \tag{1}$$

In the above formula the probability density $p(x|C_i)$ for the multivariate case was considered to be modelled by a Gaussian process, $N(\mu, \Sigma)$:

$$p(x|C_i) \cong N(\mu_i, \Sigma_i) = \frac{1}{(2\pi)^{d/2}|\Sigma_i|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu_i)^T \Sigma_i^{-1}(x-\mu_i)\right) \tag{2}$$

Here, d represents the dimensionality of the feature vector (i.e., 36 in our case) and Σ_i and μ_i are the covariance matrix and, respectively, the mean vector for class i. Each mean vector, μ_i, and each covariance matrix, Σ_i, were estimated based on the training data set which represented 80% of the entire data set, the rest of 20% of the data being used for the cross-validation set. The formulas used to estimate the above parameters were:

$$\mu_i = \frac{1}{N_i}\sum_{j=1}^{N_i} x_i^j \text{ , and } \Sigma_i = \frac{1}{N_i}\sum_{j=1}^{N_i}(x_i^j - \mu_i)(x_i^j - \mu_i)^T \tag{3}$$

In the abovementioned formulas, N_i is the number of the training samples belonging to class i and x_i^j is the sample j belonging to class i.

Finally, the Bayes classifier assigns the unknown feature vector x to class C_i if and only if:

$$P(C_i|x) = \max_k \{ P(C_k|x) \}, \quad k = \overline{1,2} \tag{4}$$

Here, the k variable (denoting the class index) takes only the following two values, {1, 2}.

C. Selection of mental tasks

To select the subject-specific most discriminative four cognitive tasks out of the 12 investigated in this paper, for each subject an exhaustive automatic analysis was done. For each subject, the all four-task possible combinations were enumerated and the mean classification rates were computed for all such combinations based on the corresponding two-class correct classification rates compactly presented in the tables II, III, IV and V, respectively. The applied formula was:

$$m_{T_1T_2T_3T_4} = \frac{1}{12}\sum_{\substack{i=\overline{1,3} \\ j=\overline{i+1,4}}} (r_{T_iT_j} + r_{T_jT_i}) \tag{5}$$

where: T_i symbolises a task out of the four analyzed tasks and r_{TiTj} and r_{TjTi} represent the correct classification rates obtained within the classification problem of the two tasks (T_i, T_j).

Of these calculated values, for each subject we selected the 4-task combination that led to the best mean classification rate. The results presented in tables VI, VII, VIII, and IX, respectively, were obtained using additionally a threshold criterion. Namely, if for at lest one pair of tasks – out of the 6 that can be derived for each 4-task combination – there are correct classification rates below a given threshold then, the corresponding 4-task combination was eliminated from our analysis. Different specific two thresholds were applied for each subject.

IV. TESTING THE CLASSIFICATION ACCURACY ON THE SELECTED SETS OF MENTAL TASKS

As we have already mentioned, we applied the Bayes rule only in the best discriminative two-task selection phase. In a second step of analysis, we compared the performances obtained by us (with the previous selected sets of tasks) with similar results reported in the literature

A. Multilayer perceptron classifier

The classifier used in the second step of analysis (i.e., in the four-class problems) was an artificial neuronal network of multilayer perceptron type (MLP), trained with the backpropagation algorithm. Mainly, this particular choice was done based on the good performances and extensive utilization of the neuronal networks in the BCI systems [9].

The employed MLP network had one hidden layer of 35 processing elements (PE), with activation functions of tanh type. The input layer consisted in 36 PEs corresponding to the 36 components of the input feature vectors. The output layer had 4 PEs, corresponding to the 4 cognitive tasks' associated classes. For the output PEs the activation functions were of sigmoid type.

V. RESULTS

The classification results (extracted from the confusion matrixes corresponding to the cross-validation sets, for each of the four subjects and for the all 66 pairs of tasks out of the 12 proposed cognitive tasks) are compactly presented in **Table II**.

To exemplify, this compact representation was done as follows: the classification rates from the first diagonal of the CV confusion matrix – presented, as an example, in **Table I,** for S1 and for the pair of tasks (**wordP**, **rotate**) – can be drawn from **Table II (S1)** also, from the intersections of the line *wordP* with the column *rotate* (this is the *true positives rate* for the *wordP* task) and of the line *rotate* with the column *wordP* (this is the *true positives rate* for the *rotate* task). Notice that the two abovementioned values correspond to the same two-class discriminating problem, namely, (**wordP** versus **rotate**).

TABLE I. THE CONFUSION MATRIX ON CV SET, FOR THE PAIR OF TASKS (**WORDP**, **ROTATE**)

Bayes results / **True classes**	**WordP**	**Rotate**
WordP	**90.08 %**	9.92 %
Rotate	6.72 %	**93.28 %**

Further, using the already presented tasks' selecting approach, we obtained for each subject the following best combinations of tasks – listed in their decreasing mean classification rates (see **Table III**). A summary of the finally selected sets of tasks, corresponding to the four investigated subjects, is presented in **Tabel IV**. In **Tabel V** the performances obtained with these selected sets of tasks are comparatively presented, together with the performances achieved for a reference set of tasks, comprising in 4 out of the 5 proposed by Keirn and Aunon mental tasks [3] – i.e., the (**count**, **letter**, **math**, **rotate**) set.

As expected, the results showed in tables III and IV confirm the inter-subject great variability regarding the selected 4-task combination. Additionally, the results presented in table 5 give us a measure of how much such preliminary subject analysis can improve the classification results without any improvements within the algorithmic part of the BCI developed system. Here, for exemplification, we took into discussion the commonly used set of tasks of Keirn and Aunon and showed that using this particular set for all investigated subjects, without any discrimination, may lead to lower performances as in table VI (S2).

The consistence of the above reported results was further tested on subject S4, for which a second session of recording was repeated after a week. On the resulted new set of EEG data the same processing steps (as those applied on the first set of data) were employed.

The single main difference consisted in the classifying process of the extracted EEG feature vectors which, this time, was done with a MLP network trained with the entire feature vectors' set obtained on the EEG data acquired in the previous week.

TABLE II. CLASSIFICATION PERFORMANCES FOR EACH SUBJECT AND FOR ALL 66 PAIRS OF TASKS

S1	**count**	**fingersL**	**fingersR**	**armL**	**armR**	**letter**	**math**	**relax**	**rotate**	**wordG**	**wordN**	**wordP**
count	•	85.71	**93.33**	81.95	87.02	76.98	69.23	72.73	74.62	87.3	**93.98**	**91.34**
fingersL	**96.12**	•	76.80	86.36	80.65	**90.70**	**94.03**	77.78	**95.65**	64.44	81.10	78.76
fingersR	**93.33**	67.69	•	85.94	76.98	89.92	88.72	74.81	**90.77**	63.33	82.73	72.27
armL	82.79	**91.87**	**91.34**	•	79.69	84.50	83.33	78.86	82.54	89.60	**93.62**	**90.16**
armR	87.10	88.55	85.27	52.76	•	75.21	85.16	66.13	77.24	**90.78**	**91.34**	**90.16**
letter	76.74	**92.06**	**92.86**	77.78	82.09	•	80.77	68.38	77.94	**92.25**	93.50	87.60
math	78.26	89.26	**94.26**	79.26	85.04	75.20	•	80.16	78.83	89.78	**95.24**	**90.08**
relax	84.55	82.95	82.33	69.70	74.05	68.12	77.52	•	75.59	81.15	88.98	83.72
rotate	65.60	**92.86**	**95.20**	63.57	71.82	62.18	57.63	64.84	•	82.84	**93.70**	**93.28**
wordG	**91.47**	66.67	79.26	80.00	85.09	89.68	**94.07**	84.21	**90.91**	•	73.28	72.93
wordN	**93.44**	78.90	82.76	89.47	84.39	**97.73**	**95.35**	87.50	**94.53**	64.75	•	75.61
wordP	85.16	76.76	73.53	84.96	84.21	83.33	87.10	73.81	**90.08**	66.39	76.52	•
S2												
count	•	80.77	54.07	65.75	78.33	80	77.31	61.90	55.45	77.04	77.86	82.01
fingersL	65.50	•	62.20	58.70	62.81	70.77	58.59	68.86	63.20	66.42	54.81	76.80
fingersR	68.33	77.34	•	68.75	78.81	79.31	70.4	67.41	68.18	68.42	75.21	74.82
armL	59.63	70.09	45.67	•	80.29	80.00	81.40	60.38	52.71	67.39	77.52	83.19
armR	71.11	63.43	67.88	57.63	•	65.77	58.91	79.31	73.81	61.40	67.41	78.08
letter	71.54	80.80	59.71	73.60	78.47	•	69.84	71.55	79.14	72.58	76.47	76.30
math	73.33	70.87	61.54	75.40	78.57	67.44	•	58.02	75.91	53.68	64.81	74.81
relax	79.84	85.00	75.83	80.51	83.45	77.70	73.39	•	83.74	77.30	65.87	76.92
rotate	68.97	81.54	68.29	72.22	82.17	81.03	74.58	68.94	•	79.30	80.45	85.60
wordG	75.83	69.42	59.57	61.54	81.56	76.34	68.91	70.18	67.63	•	68.75	74.40
wordN	76.61	87.50	61.59	69.05	84.17	75.00	61.22	60.47	72.95	64.57	•	63.43
wordP	81.9	79.23	68.97	73.94	80.73	70.00	74.17	74.40	82.30	70.00	55.37	•
S3												
count	•	83.59	**92.86**	82.84	84.44	83.33	81.82	76.64	80.49	82.96	81.6	86.07
fingersL	85.04	•	**99.22**	**90.77**	**90.15**	60.33	72.95	88.72	66.67	80.15	70.90	65.00
fingersR	**92.31**	**98.43**	•	66.13	**90.51**	**97.60**	**97.67**	84.38	**90.70**	87.31	86.36	**94.96**
armL	**92.56**	87.20	76.34	•	82.91	**96.12**	**94.81**	80.99	83.62	75.57	83.97	75.41
armR	89.17	88.62	82.47	76.09	•	82.76	**90.98**	89.15	76.42	86.09	84.21	79.07
letter	86.05	79.10	**99.23**	**94.44**	87.05	•	71.22	87.68	87.79	89.47	86.92	**93.75**
math	75.61	79.70	**99.21**	**96.67**	**96.99**	43.97	•	80.53	62.50	87.02	81.82	86.26
relax	80.51	**90.98**	89.76	73.13	84.92	85.47	84.51	•	80.69	78.26	73.02	83.06
rotate	**90.15**	**94.07**	**97.62**	89.21	**93.18**	**95.16**	**96.30**	86.36	•	**95.00**	87.93	86.40
wordG	82.50	82.35	83.47	66.13	89.29	89.34	82.26	62.39	64.44	•	78.05	65.32
wordN	86.92	81.82	86.18	85.48	72.13	82.40	84.55	73.64	74.10	70.45	•	79.31
wordP	**91.73**	86.96	**94.85**	86.47	**92.06**	**92.91**	**94.35**	**91.60**	73.08	89.31	89.93	•
S4												
count	•	88.41	72.36	86.67	80.6	60.58	58.99	74.22	72.48	85.29	**95.20**	**94.16**
fingersL	89.74	•	72.31	59.09	82.95	85.95	82.44	76.12	82.86	85.05	**90.16**	83.33
fingersR	81.06	76.80	•	67.77	69.23	76.00	75.44	73.38	78.79	88.89	**92.31**	89.93
armL	85.19	80.49	75.37	•	61.94	72.79	69.67	75.51	76.92	**90.98**	**95.24**	84.62
armR	68.60	73.81	68.00	59.50	•	58.99	65.52	76.86	63.91	89.15	**93.89**	**93.85**
letter	69.49	76.87	70.77	78.15	72.41	•	58.78	66.93	67.20	81.16	82.71	**93.28**
math	77.59	**90.32**	83.69	75.94	74.10	66.13	•	73.53	74.81	89.43	87.40	**95.24**
relax	86.61	82.64	81.90	81.20	78.36	70.31	77.31	•	87.72	72.97	82.91	**94.70**
rotate	71.70	82.61	59.35	72.80	65.57	66.15	65.00	73.76	•	**94.35**	**92.25**	**95.49**
wordG	**94.96**	89.86	89.92	**91.73**	**97.62**	**93.16**	**91.67**	**90.48**	**93.89**	•	63.24	87.69
wordN	**98.46**	89.47	**92.00**	**93.80**	**95.97**	**91.80**	**92.97**	**90.58**	**94.44**	69.75	•	**91.80**
wordP	**95.76**	80.62	**93.33**	**92.00**	**92.00**	**92.65**	**92.25**	**92.68**	**96.72**	87.20	**90.98**	•

TABLE III. THE BEST DISCRIMINATIVE 4-TASK SETS OBTAINED FOR S1, S2, S3, AND S4, RESPECTIVELY

Subject	**1st task**	**2nd task**	**3rd task**	**4th task**	**Mean performance**
S1	**Threshold value: 75**				
	fingersR	letter	math	wordN	89.09
	Count	fingersR	letter	wordN	88.94
	Count	**fingersR**	**armL**	**wordN**	**88.72**
	fingersL	letter	math	wordN	88.65
	fingersR	armL	letter	wordN	88.51
	Threshold value: 80				
	Count	**fingersR**	**armL**	**wordN**	**88.72**
S2	**Threshold value: 60**				
	armR	**relax**	**rotate**	**wordP**	**79.12**
	armR	letter	rotate	wordP	77.78
	Count	armR	relax	wordP	77.33
	Letter	relax	rotate	wordP	77.3
	fingersL	letter	rotate	wordP	77.23
	Threshold value: 70				
	Count	letter	wordG	wordP	75.66
	Letter	relax	wordG	wordP	73.97
S3	**Threshold value: 70**				
	Count	**fingersR**	**letter**	**wordP**	**92.14**
	fingersR	letter	rotate	wordP	92
	fingersR	armR	math	wordP	91.61
	fingersR	letter	relax	wordP	91.27
	Count	fingersR	letter	rotate	91.11
	Threshold value: 83				
	Count	**fingersR**	**letter**	**wordP**	**92.14**
	fingersR	Letter	relax	wordP	91.27
S4	**Threshold value: 60**				
	Count	**armL**	**wordN**	**wordP**	**91.99**
	Count	armR	wordN	wordP	90.94
	Count	rotate	wordN	wordP	90.79
	Count	fingersL	wordN	wordP	90.67
	Count	relax	wordN	wordP	90.67
	Threshold value: 84				
	Count	**armL**	**wordN**	**wordP**	**91.99**
	Count	armL	wordG	wordP	89.69

TABLE IV. FINALY SELECTED SUBJECT-SPECIFIC SETS OF TASKS

Subject	**1st task**	**2nd task**	**3rd task**	**4th task**	**Mean performance**
S1	count	fingersR	armL	wordN	**88.72**
S2	armR	relax	rotate	wordP	**79.12**
S3	count	fingersR	letter	wordP	**92.14**
S4	count	armL	wordN	wordP	**91.99**

TABLE V. THE CLASSIFICATION PERFORMANCES OBTAINED FOR EACH SUBJECT – FOR THE SELECTED AND FOR THE REFERENCE SET OF TASKS, RESPECTIVELY

Selected set of tasks							
S1		**S2**		**S3**		**S4**	
count	78.48	**armR**	62.69	**count**	79.03	**count**	83.46
fingerR	73.92	**relax**	59.09	**fingersR**	95.65	**armL**	74.44
armL	73.47	**rotate**	82.50	**letter**	87.02	**wordN**	91.74
wordN	82.02	**wordP**	75.00	**wordP**	85.22	**wordP**	92.08
Reference set of tasks							
count	35.77	**count**	21.64	**count**	81.16	**count**	56.93
letter	60.47	**letter**	34.55	**letter**	67.20	**Letter**	40.98
math	48.06	**math**	30.00	**math**	56.45	**Math**	46.22
rotate	59.06	**rotate**	46.53	**rotate**	85.12	**Rotate**	43.85

TABLE VI. THE CLASSIFICATION PERFORMANCES FOR S4 (SECOND EEG DATA SET)

	count	**fingersL**	**fingersR**	**armL**	**armR**	**letter**	**math**	**relax**	**rotate**	**wordG**	**wordN**	**wordP**
count	•	**96.61**	88.55	89.52	**96.88**	87.68	85.5	83.45	87.79	83.58	87.3	**91.6**
fingersL	**93.42**	•	83.09	90.32	**90**	87.5	84.06	88	**95.2**	87.9	80.17	79.03
fingersR	88.71	84.87	•	64.89	67.57	67.41	62.96	78.15	84.13	83.05	69.63	84.5
armL	88.55	79.39	66.13	•	68.5	45.16	64.54	80.67	85.59	83.33	81.94	**91.41**
armR	**93.7**	73.91	66.67	55.47	•	55.73	70	84.3	70.73	82.4	81.3	85.47
letter	**91.45**	75.59	67.5	70.23	64.52	•	67.18	85.71	80.83	79.83	71.93	85.6
math	86.29	76.92	70.83	70.18	74.81	70.97	•	88	78.29	76.27	71.64	79.66
relax	87.07	89.23	72.79	77.21	88.81	82.95	80	•	80.17	59.03	68.5	84.09
rotate	89.52	**91.54**	72.87	81.02	81.06	77.78	69.05	71.64	•	73.57	78.4	79.69
wordG	**94.21**	**90.84**	85.4	89.36	**93.08**	**90.44**	88.32	86.49	85.22	•	56.03	87.18
wordN	**91.47**	**91.79**	86.67	**90.09**	87.88	86.52	83.47	87.5	89.23	78.07	•	**91.73**
wordP	**95.16**	87.79	**94.44**	**96.06**	**97.83**	**98.46**	87.59	**91.87**	88.98	84.78	77.87	•

TABLE VII. THE DISCRIMINATIVE 4-TASK SETS OBTAINED FOR S4 (SECONDEEG DATA SET)

1st task	**2nd task**	**3rd task**	**4th task**	**Mean performance**
Threshold value: 70				
count	armR	wordG	wordP	90.49
count	fingerL	armR	wordP	90.12
count	armR	relax	wordP	90.02
count	fingerL	armL	wordP	89.91
count	armR	wordN	wordP	89.85
count	fingerL	armR	wordG	89.71
count	fingerL	rotate	wordP	89.69
count	armL	wordG	wordP	89.56
count	**armL**	**wordN**	**wordP**	**89.39**
Threshold value: 83				
count	armR	relax	wordP	90.02
count	armL	wordG	wordP	89.56
count	fingerR	wordG	wordP	88.43
count	fingerL	fingerR	wordG	88.35

TABLE VIII. THE CLASSIFICATION PERFORMANCES OBTAINED FOR S4 WITH FIRST AND WITH SECOND DATA SET, RESPECTIVELY

	First set of EEG data				**Second set of EEG data**			
	count	**armL**	**wordN**	**wordP**	**count**	**armL**	**wordN**	**wordP**
count	**83.46**	11.02	3.94	1.58	**81.24**	5.69	9.66	3.41
armL	15.04	**74.44**	3	7.52	7.29	**76.23**	8.36	8.12
wordN	1.84	2.75	**91.74**	3.67	1.91	4.89	**89.33**	3.83
wordP	0	4.32	3.6	**92.08**	0.25	4.1	4.64	**91.01**

The cross-validation set was, in this case, given by the all feature vectors obtained in the second session of recording. The results obtained for S4 on the second set of EEG data are presented in tables VI, VII, and VIII, respectively.

In **Tabel VII** the first most discriminative 4-task sets for S4 are listed in the decreasing order of their mean classification rates. The best 4-task combination selected for the first EEG data set was found as corresponding, for the second EEG data set, to the 9-th combination out of the 66 combinations. This combination was obtained for a threshold value of 70 but the maximum threshold value for this set could be 77.88.

In **Tabel VIII** it can be seen that the classification performances obtained for subject S4 on the first data set, as well as, on the second data set (when using the same selected 4-task combination) are only slightly apart ones from another. This essentially sustains the idea of consistency of the subject-specific selected set of tasks – an important aspect in any BCI application. We stress here that the recordings were done in non-stress conditions and with subjects rating them as not being tired or drowsing at all.

VI. DISCUSSIONS AND CONCLUSIONS

The idea of designing a subject-specific BCI application is not quite innovative. Also, this conclusion can be drawn from several papers were the need for subject specific both electrode-montage [1], [6] and features extraction [1], [10] is reported.

In [11] it was suggested that even if improvements remain possible in all areas of the BCI field from preprocessing to classification, one of the best areas in which improvements in classification accuracy can be made is by discovering new EEG extracted features. If one take this last approach it still remains unsolved the issue of inter-subjects variability of classification accuracies for a given feature vector [6]. Unlike this frequently used approach in this paper we proposed a new BCI-problem approaching. Although our research obeys the same idea of subject dedicated BCI design, the novelty of this research consists in revealing the great importance the particular most discriminative mental tasks' selecting process (employed in a first step of analysis) has for a given subject. Exactly, if in others papers [6] the deduction that different individuals have varying classification performances due to the putative different individual thought patterns is only a derivative of their main analysis, in our research the focus is put on the important role the subject-specific selected mental tasks play within the implementation of a specific BCI application. Thus, in order to reveal what improvements in performances could be obtained only by making such preliminary analysis, we made a comparative study between two different sets of tasks (i.e., one set was the subject-specific selected set of tasks while the other was the imposed set composed of four out of five mental tasks proposed in [3]). In order to obtain a valid comparative result in both cases the same EEG processing methodology was used. In such conditions, the significant differences obtained in the classification performances between the two sets (see Table V) were due entirely to the new, more appropriate, paradigms used (i.e., the use of subject-specific mental tasks).

However, one must pay attention to the fact that we can talk about the best subject-specific set of tasks only in conjunction with a given feature vector. Thus, for a given subject and for different feature vectors one can expect to obtain other different best 4-task combinations.

The advantage of exploiting such a result is straightforward. Thus, using some simple (less time consuming) but, in the same time, largely recognized useful EEG extracted features (e.g., AR coefficients that incorporate cortical processing temporal information, the frequency band asymmetry ratios that take advantage of the hemispheric asymmetries, the coherence function that quantifies the local or distal synchronised activity of different cortical networks etc.) in synergism with the corresponding determined best set of tasks, one can now easily develop high quality subject-dedicated BCI applications.

A further observation that can be drawn from our above-presented results is that each of the four selected sets of tasks was composed of both motor and non-motor cognitive tasks. Practically, through the large and diverse set of covert cognitive tasks we used in this study, we conferred more flexibility to the subject-appropriate tasks' selection process.

In conclusion, in the on-line BCI applications, in order to obtain high performances, two approaches could be taken into consideration: (*i*) first, for a given set of mental tasks one could search for both, the best EEG discriminative features and the less time-consuming feature extraction methodology and (*ii*) second, for given EEG features and extraction methodology one could find the subject' most discriminative tasks out of a proposed set of mental tasks. The last approach gives to the researcher the liberty of choosing the mental tasks according to the particularities of the subject's cortical dynamics avoiding thus some possible constraints mainly imposed by the selected paradigm. However, none of the above approaches can guarantee to be the best solution. What matters is to exploit completely the relation that exists between the EEG features proposed in the literature and the corresponding selected mental tasks in order to obtain high on-line BCI performance.

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