A study on mental tasks discriminative power

Dan Marius Dobrea[1] and Monica-Claudia Dobrea[1],

[1] Technical University „Gh. Asachi“ Iasi,
Faculty of Electronics Telecommunications and Information Technology,
Carol I 11, 69121 Iasi, Romania
{mdobrea, serbanm}@etti.tuiasi.ro

Abstract. The present study was done as part of a more complex project whose final aim is to design and implement an autonomic self-organizing system, mentally commanded by an user giving one of the 4 possible commands: forth, back, left, right. For this, we used the most studied method for designing non-invasive brain-computer interface (BCI), namely, the electroencephalogram (EEG) signals acquired during mental tasks. To command, in real-time, the system requires very discriminative mental tasks to be used to trigger the corresponding device commands. The novelty of our paper consists in revealing the great importance the preliminary selecting process of subject-specific set of tasks plays within the implementation of any particular BCI application. In this idea, our research focuses on an extensive analysis of twelve mental tasks; the processing and classification approaches used by us are classical ones[1].

Keywords: Brain computer interface, mental tasks, EEG autoregressive model, Bayesian classifier, artificial neural networks

1 Introduction

The present study, as part of a more complex (on-line, EEG-based, 4-class) BCI project, aims to find, in a preliminary step, the paradigm which gives, for a given EEG processing methodology and for a specific subject, the most classifying process' advantages. Practically, in this research, we exploit the already suggested idea in the literature, namely the requirement to design a subject-specific BCI application in order to obtain high system performances. The novelty of this paper consists in quantifying the impact the subject-specific selected set of tasks has, by itself, on the classification performances, and thus, indirectly, on the global BCI performance. For this, for each of the participants to the study we find which are the 4 mental tasks (out of 12 proposed candidate tasks) that lead to the most discriminative EEG patterns.

The twelve covert mental tasks (attentively selected in this research based on the results reported in several psycho-physiological studies and brain imaging studies) consist in motor cognitive tasks as well as non-motor cognitive tasks. In general, in the BCI field, the choice of one or other particular set of mental tasks is done having

[1] AR method and Bayes classifier – for selecting the subject specific tasks –, and AR method and MLP classifier – for comparing the results with similar reported results in the literature.

in mind the assumed existence of different EEG-activation patterns during the performance of the respective selected tasks. In our case we considered some aspects like hemispheric asymmetries – i.e., the hemispheric asymmetries appear in processing positive and negative emotional experiences [1]; also, the right hemisphere is involved to a greater extend than the left in the performance of spatial and musical tasks. Verbal fluency [2], [3] and mathematical tasks primarily involve the left hemisphere [4]. Additionally, the motor tasks engage more asymmetrically the hemispheres than the non-motor tasks [4]; moreover, the two silent verbal fluency tasks – namely, phonemic (letter-cued) silent word generation and semantic (category-cued) silent word generation – were found as activating two overlapping but dissociable systems in the brain [5]. Not in the last, different components of mental calculation (e.g. tasks involving number comprehension and the calculation process) [6] suggest the participation of different cortical networks reflected in significant EEG-cortical area differences. However, the aforementioned relationships are not always as predicted [2], [3], [1] due probably to neuronal substrates specificities, differences in skill, degree of laterality, degree of vigilance [7] and, not in the last, due to interpretation of the task by the subjects [8].

Nowadays, the applications involving cognitive tasks discrimination abound in the different paradigms and experimental setups they use; but, most of all, the processing and classification techniques are those that are varying the most in all the BCI papers. In this context, the question of how good the methods are is quite difficult to respond because, often, for the same set of tasks the obtained results differ significantly from subject to subject. Thus, as good as these methods can be, they can not lead to excellent results if the selected mental tasks do not give raise fundamentally to different EEG pattern activations, at least in conjunction with a given subject, a given EEG feature extracting methodology and a given electrodes montage. From this point of view, the issue of finding the subject-specific most discriminative mental tasks appears to be at least as important as the processing methods themselves.

In what follows, using a set of 12 different motor and non-motor cognitive tasks and a commonly used EEG processing and classifying methodology[1], we reveal the significant achievable gain that can be obtained in the BCI performance only by selecting the most appropriate mental tasks for each investigated subject.

2. Experimental protocol

In this study the EEG from 4 healthy, right-handed subjects, aged between 22 and 35 years, were recorded during 12 different mental tasks (4 motor and 8 non-motor imagery tasks). The subjects were instructed not to verbalize or vocalize and not to take any overt movement. For data acquisition, we used a MindSet 24 system. The subjects were seated in a noiseless room, with dim lighting. Measurements were made from 6 active electrodes (C3, C4, P3, P4, O1, and O2), with reference to electrically linked ears, A1 and A2. The data were pass-band filtered between 1.4 Hz and 35 Hz and sampled at 256 Hz. Signals were recorded for 20 seconds during each task, and each task was repeated 4 times. Successive tasks were separated by a resting period of 30 s. To obtain the results we used raw EEG data, with no explicit artifact removal.

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

(1) *Counting* (count): the subjects were asked to imagine a counting down operation beginning from a random number specified before the recording.
(2) *Left fingers movement* (fingerL): the subjects had to imagine opening and closing alternatively the left hand fingers, without doing the movements effectively.
(3) *Right fingers movement* (fingerR): The subjects had to imagine opening and closing alternatively the right hand fingers, without any overt movement.
(4) *Left arm movement* (armL): The subjects were instructed to imagine how they are slowly rising and falling down their left arm, without any overt movement.
(5) *Right arm movement* (armR): The subjects were asked to imagine how they are slowly rising and falling down their right arm, without any overt movement.
(6) *Mental letter composing* (letter): The subjects were instructed to mentally compose a letter (with a positive emotional content) to a friend or relative.
(7) *Mathematical adding* (math): The subjects had to add the number specified before the recording to its following number; then, the result had to be added further to its corresponding following number and so on. At the end of the recording, the correctness of the subject's result was checked.
(8) *Baseline-resting* (relax): The subjects were told to relax as much as possible and try to think of nothing in particular.
(9) *Geometrical figure rotation* (rotate): The subjects had to study a mug for 30 s before the recording and after that, with the mug removed, they had to visualize mentally the object being randomly rotated about its axes.
(10) *Letter-cued silent word generation* (wordG): The subjects had to find words beginning with the alphabetical letter specified before the recording.
(11) *Letter-cued silent names generation* (wordN): The subjects had to find as many as possible names beginning with the letter specified before the recording.
(12) *Reciting poetry* (wordP): The subjects had to recite mentally a poetry, without vocalizing.

3. Data processing and analysis

In a first step of analysis, the subject-specific set of 4 tasks was selected using the AR model and the Bayes classifier; then, in order to quantify the gains a such particular set could provide, we employed the EEG AR model in conjunction with a MLP classifier, trained with the backpropagation (BP) algorithm.

3.1. EEG AR 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. The AR parameters were extracted for each EEG channel and for each 0.25 s sliding windows (64 samples), overlapped by 0.125 s (32 samples).

For each sliding window we obtained feature vectors of 36 elements (6 AR parameters/window/channel * 6 channels). The order six for the AR model was determined by using the autocorrelation function criterion.

3.2. Bayes and MLP classifiers

The Bayes classifier – a well-known probabilistic method for data classification – finds the unknown posterior probability, $P(C_i|x)$ (see eq. 1), for each class C_i and for a specific feature vector x, we want to classify. Using the Bayes theorem, the posterior probability is actually determined based on the prior probability, $P(C_i)$, and on the likelihood function, $P(x|C_i)$, modeled in our case by a Gaussian process, $N(\mu, \Sigma)$ (see eq. 2). In eq. 2, d is the dimensionality of the feature vector and Σ_i and μ_i are the covariance matrix and, respectively, the mean vector parameters for class i. These last parameters were estimated on the training data set (i.e. 80% of the entire data set), using the formulas in eq. 3; the rest of 20% of data formed the cross-validation set.

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

$$p(x|C_i) \cong N(\mu_i, \Sigma_i) = \frac{1}{(2\pi)^{d/2} |\Sigma_i|^{1/2}} \exp\left(-\frac{1}{2} (x - \mu_i)^T \Sigma_1^{-1} (x - \mu_i) \right) \cdot \quad \textbf{(2)}$$

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

In the abovementioned formulas, N_i is the number of the training samples belonging to class i ($i \in \{1, 2\}$) 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:

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

To select the subject-specific most discriminative 4 cognitive tasks out of the 12 investigated in this paper, for each subject an exhaustive automatic analysis was done. For each subject, the all-possible four-task combinations were enumerated and the mean classification rates were computed for these based on the corresponding two-class correct classification rates compactly presented in tables 2 and 3. Of these calculated values, for each subject we selected the 4-task combination that led to the best mean classification rate. The results shown in table 4 were obtained using additionally a threshold criterion (i.e., if for at lest one pair of tasks – out of the 6 that can be derived for each 4-task combination – there were correct classification rates below a given threshold then, the corresponding 4-task combination was disregarded). Different and specific two thresholds were applied for each subject.

In a second step of analysis, the performances of the previous selected sets of tasks were tested using a 4-class MLP classifier, trained with the BP algorithm [9], and having: one hidden layer of 35 processing elements (PEs), (with *tanh* activation functions), an input layer of 36 PEs (related to the 36 components of the input feature vectors) and an output layer of 4 PEs, with activation functions of sigmoid type.

4. Results

The Bayesian classification results, achieved for the 4 subjects, are presented in tables 2 and 3. These tables are compact representations of the confusion matrixes obtained on the CV sets, for each subject, and for all 66 possible pairs of tasks. To exemplify for S1, the rates presented on the first diagonal in Table 1 for the (*wordP*, *rotate*) pair of tasks (i.e. the *true positives rates* for the *wordP* and, respectively, the *rotate* task) can be drawn from Table 2 also, from the intersections of the line *wordP* with the column *rotate* and of the line *rotate* with the column *wordP*.

Table 1. 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 %**

The first 4-task combinations (enumerated in decreasing order of their mean classification rates), obtained for each subject, are shown in **Table 4**. The finally selected sets of tasks, for the 4 investigated subjects, are those presented in bold type in **Tabel 4**. In **Tabel 5**, the performances obtained with these selected sets are comparatively presented, together with the performances achieved for a reference set of tasks, comprising in 4 out of the 5 mental tasks proposed by Keirn and Aunon [10].

Table 2. Classification performances for subject S1, 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	•

As expected, the results in **Tables 2** and **3** confirm the inter-subject variability regarding the particular way the subject EEG patterns are activated when performing the same cognitive tasks; this is primarily reflected in the various classification performances obtained by the investigated subjects for the same sets of tasks. Also, this subject-specificity is exhibited in the particular 4-task combinations we found as given the best classifying results for the 4 subjects as well as in the corresponding calculated mean classification rates which vary considerably from subject to subject. Another important result of our study is that for all investigated subjects, the suitable sets of tasks were combinations of motor with non-motor imagery tasks.

Table 3. The classification performances for subjects S2, S3, and S4, for all 66 pairs of tasks

		Count	**fingersL**	**fingersR**	**armL**	**armR**	**letter**	**math**	**relax**	**rotate**	**wordG**	**wordN**	**wordP**
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 4. Most discriminative 4-tasks obtained for each subject and for two different thresholds.

Subject	Threshold value	1st task	2nd task	3rd task	4th task	Mean performance
S1	**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
	80	**count**	**fingersR**	**armL**	**wordN**	**88.72**
S2	**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
	70	count	letter	wordG	wordP	75.66
		letter	relax	wordG	wordP	73.97
S3	**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
	83	**count**	**fingersR**	**letter**	**wordP**	**92.14**
		fingersR	letter	relax	wordP	91.27
S4	**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
	84	**count**	**armL**	**wordN**	**wordP**	**91.99**
		count	armL	wordG	wordP	89.69

The results presented in **table 5** give us a measure of how much a preliminary phase of selecting the subject's appropriate tasks can improve the classification results without any improvements within the algorithmic part of the developed BCI system.

Table 5. Confusion matrixes for the selected and for the reference sets of tasks, respectively

Selected set of tasks							
S1		**S2**		**S3**		**S4**	
count	78.48	**armR**	62.69	**count**	79.03	**count**	83.46
fingersR	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

5. Discussions and conclusions

The major result of this study consists in that the quality of an EEG-based, multitasks BCI application can be drastically improved by finding firstly the most discriminative cognitive tasks for a given subject and for a particular EEG feature extracting methodology. In this perspective, within a BCI application, in order to obtain better performances, one should: first find which are the best EEG features confining the most discriminative information that reflects the way in which the cognitive tasks are processed at the cortical level (i.e., hemispheric asymmetries, local and long-range synchronizations of brain activities, etc.), then, with the selected EEG features, the most subject-specific discriminative set of mental tasks (out of an extensive set of candidate tasks, including both, motor and non-motor imagery tasks) should be chosen and finally, improved versions for the already used processing methodology should be search for. The large variation in the classification performances obtained for the best-selected sets of tasks may above all suggests, for part of the subjects, either inappropriate investigated tasks (at least in conjunction with the used EEG features) or a week concentration of the subjects when performing the task, or even both of them. In order to exclude the second mentioned reason and give consistence to such preliminary analysis, in a future research we aim to reiterate the all steps we made in this study, but this time on similar data acquired in different days.

Acknowledgments. This work was supported by the Romanian National University Research Council under Grant ID 1552.

References

1. Wheeler, R. E., Davidson, R. J., Tomarken, A. J.: Frontal Brain Asymmetry and Emotional Reactivity: A Biological Substrate of Affective Style, Psychophysiol. 30 (1), 82–89 (1993)
2. Bulla-Hellwig, M., Volmer, J., Götzen, A., Skreczek, W., Hartje, W: Hemispheric Asymmetry of Arterial Blood Flow Velocity Changes During Verbal and Visuospatial Tasks, Neuropsychologia 34 (10), 987–991 (1996)
3. Ray, M.K, Mackay, C.E, Harmer, C.J., Crow, T.J.: Bilateral Generic Working Memory Circuit Requires Left-Lateralized Addition for Verbal Processing. Cerebral Cortex 18 (6), 1421–1428 (2008)
4. Doyle, J.C., Ornstein, R., Galin , D.: Lateral Specialization of Cognitive Mode: II EEG frequency analysis, Psychophysiol. 11, 567–578 (1974)
5. Costafreda, S.G., Fu, C.H.Y., Lee, L., Everitt, B., Brammer, M.J., David, A.S.: A Systematic Review and Quantitative Appraisal of fMRI Studies of Verbal Fluency: Role of the Left Inferior Frontal Gyrus, Hum. Brain Mapp. 27 (10), 799–810 (2006)
6. Fernández, T., Harmony, T., Rodríguez, M., Bernal, J., Silva, J., Reyes, A., Marosi, E.: EEG Activation Patterns During the Performance of Tasks Involving Different Components of Mental Calculation. Electroenceph. Clin. Neuro-physiol. 94, 175–182 (1995)
7. Henning, S., Merboldt, K.D., Frahm, J: Task- and EEG-Correlated Analyses of BOLD MRI Responses to Eyes Opening and Closing. Brain Res. 1073-1074 (2006)
8. Neuper, C., Scherer, R., Reiner, M., Pfurtscheller, G.: Imagery of Motor Actions: Differential Effects of Kinesthetic and Visual–Motor Mode of Imagery in Single-Trial EEG, Cognitive Brain Resarch 25 (3), 668–677 (2005)
9. Palaniappan, R., Huan, N.J.: Effects of Hidden Unit Sizes and Autoregressive Features in Mental Task Classification, World Acad. of Sci., Eng. and Tech. 12 (2005)
10. Keirn, Z. A., Aunon, J. I.: A New Mode of Communication Between Man and His Surroundings, IEEE Trans. Biomed. Eng. 37 (12), 1209–1214 (1990)