# Discrimination of EEG Signals During the Performance of Different Mental Tasks


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## Abstract

**INTRODUCTION**

Brain-Computer Interface (BCI) has been noted as a new means of communication between the human brain and his surroundings. BCI may be regarded as an interdisciplinary field, which needs the collaboration of many engineering, medical and biomedical fields, ranging from Neurology to Biomedical Signal Processing and Pattern Recognition. For this work we have focused on the classification techniques in BCI systems.

**METHODS**

A well known data base has been chosen for this project. This data base which may be regarded as a bench mark for BCI work has been originally recorded by Keirn and Aunon. The data base consists of EEG signals recorded from seven individuals through six standard EEG channels, during the performance of five mental tasks. Our goal was to design a classifier for the discrimination of two, three, four and five different tasks.

Many methods of feature extraction were tested and several types of features such as the power densities of different frequency bands, asymmetry ratios of left and right hemisphere EEG channels, centroid frequencies, Wavelet coefficients and Principle Components of the EEG channels were investigated. These feature vectors were given to feature selection algorithms and a few of them were chosen for classification. A quadratic Bayes classifier was chosen for classification. The results were evaluated by the Leave-One-Out method.

**RESULTS & DISCUSSION**

For the two-class discrimination problem, the mean results of 97.8% Correct Classification (CC) were achieved with a combination of power density frequency features and asymmetry ratios, with a False Alarm (FA) below 3%. Wavelet coefficients and Principle Components also gave mean CC results as high as 95.2 and 94.1% respectively. Meanwhile three-, four-, and five-class discrimination of the mentioned mental tasks was performed with 92.7, 88.7 and 83.4% respectively. Although the classification results of more than two classes may seem quite poor for being used in a BCI system, but from an Information Theoretical point of view the information transfer rate of a classifier, discriminating between three, four, and five classes with the mentioned accuracies is nearly the same as a two-class discriminator, with about 98% accuracy.

**CONCLUSION**

The results of this project certify the applicability of our methods for the classification of a wide range of mental tasks. This may be regarded as a key point in the design of real-time BCI systems. It seems that further emphasis should be put on other parts of a BCI system such as the definition of proper mental tasks and user-friendly interfaces of such systems.



**I.** Keirn, Z. and Aunon, J. A new mode of communication between man and his surroundings. IEEE Trans. Biomed. Eng. Vol. 37, 1990, pp. 1209-1214.
**II.** Wolpaw, J.R, *et al* Brain-Computer Interface Technology: A Review of the First International meeting. IEEE Trans. Rehab. Eng. Vol. 8, No. 2, June 2000, pp. 164-173.


## INTRODUCTION (1)

- Brain-Computer Interface (BCI) has been noted as a new means of communication between the human brain and his surroundings[(1)]. The ultimate goal of such a system is to allow people express their thoughts by simply thinking about them.
- BCI doesn't read thoughts; but in fact discriminates between the EEG signals recorded during the performance of different mental tasks.
- In BCI systems different mental tasks make a simple alphabet through which people can communicate with their surroundings. So the key to BCI is to choose mental tasks with different EEG signatures.
- BCI is an interdisciplinary field, which needs the collaboration between many engineering, medical and biomedical fields.
- A complete BCI system consists of many different subsystems and units such as recording, noise-cancellation, feature extraction, classification and biofeedback units.

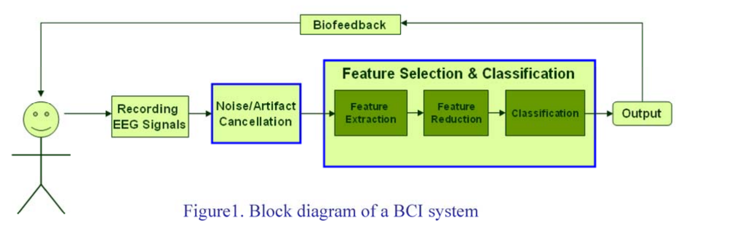


Figure1. Block diagram of a BCI system

- This work has been focused on the signal processing aspects of a BCI system, such as noise-cancellation, feature extraction and classification.

(1) J.R Wolpaw, *et al*, Brain-Computer Interface Technology: A Review of the First International meeting, *IEEE Trans. Rehab. Eng.*, Vol. 8, No. 2, June 2000, pp. 164-173.

## METHODS (2)

### 1-Database description

- A well known database has been chosen for this project. This database which may be regarded as a bench mark for BCI work has been originally recorded by Keirn and Aunon[(2)].
- The database consists of EEG signals recorded from seven individuals through six standard EEG channels, during the performance of five mental tasks. The description of this database is summarized in table 1.

Table1. The description of the used database

- 6 EEG Channels ($C_3$, $C_4$, $P_3$, $P_4$, $O_1$ & $O_2$) + 1 EOG Channel.
- Seven subjects (6 male + 1 female)
- Five Mental Tasks:
  1) Baseline
  2) Mental Counting
  3) Mental Letter Composition
  4) Mental Multiplication
  5) Mental Rotation
- Sampling rate 250Hz

- The goal was to design classifiers for the discrimination of 2, 3, 4 and 5 of these different mental tasks.

(2) Z. Keirn & J. Aunon, A new mode of communication between man and his surroundings, *IEEE Trans. Biomed. Eng.*, Vol. 37, 1990, pp. 1209-1214.

## METHODS (continued) (3)

### 2-Noise Cancellation

- BCI systems are designed to work in daily environments which contain many noises such as the 60Hz electrical-line noise and artifacts caused by the subject.
- The 60Hz electrical-line noise was simply canceled by a software notch filter.
- The database was recorded from the subjects with open eyes, so one of the major noises of the EEG channels was the mutual effect of EOG and eye blinks (figure 2).

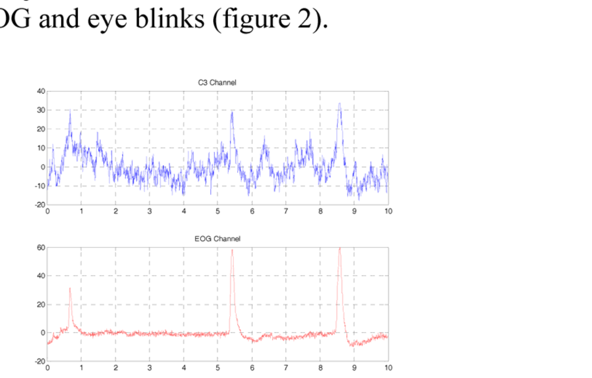

Figure2. A sample of EEG and EOG channel recorded from subject during a specific mental task

- EOG and eye blinks overlap with the EEG's spectrum, so traditional spectral filtering methods can not help.

## METHODS (continued) (4)

- In order to remove the EOG and eye blink artifacts from the EEG channels the Independent Component Analysis was used, which performs some kind of spatial filtering between the recorded channels[(3)].
- ICA extracts statistically independent and non-Gaussian sources of signals ($s_i$) from a set of recordings ($x_i$).

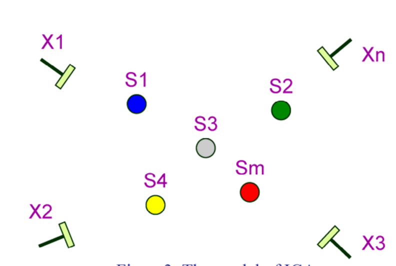


Figure3. The model of ICA

- ICA assumes that the sources have been linearly superposed with each other, and estimates the mixing matrix and its inverse (separating matrix).

Linear Model: $x_i = a_{i,1}s_1 + a_{i,2}s_2 + \ldots + a_{i,m}s_m \quad i=1,2,\ldots,n$

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & & a_{1m} \\ a_{21} & . & & . \\ & & . & . \\ a_{n1} & . & . & a_{nm} \end{bmatrix} \cdot \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_m \end{bmatrix}$$

(3) S. Makeig, T.P. Jung, D. Ghahremani, A. Bell, T.J. Sejnowski, "Blind separation of auditory event-related brain responses into independent components", *Proc. Natl. Acad. Sci. USA*, vol. 94, pp. 10979-10984, 1997.

## METHODS (continued) (5)

- Two different ICA approaches were applied to the signals in order to eliminate the effect of EOG signals from the EEG recordings:

### First Noise-Cancellation Method

- In the first method all the EEG channels were given to the ICA algorithm together, and as many sources were extracted (figure 4). Then the source having the most correlation with the EOG channel was eliminated by setting zero the coefficients of the mixing matrix, corresponding to the EOG sources.

$$\begin{bmatrix} EEG_1(t) \\ EEG_2(t) \\ \vdots \\ EEG_{N-1}(t) \\ EOG(t) \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1N} \\ a_{21} & a_{22} & & a_{2N} \\ \vdots & & & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NN} \end{bmatrix} \begin{bmatrix} s_1(t) \\ s_2(t) \\ \vdots \\ s_N(t) \end{bmatrix}$$

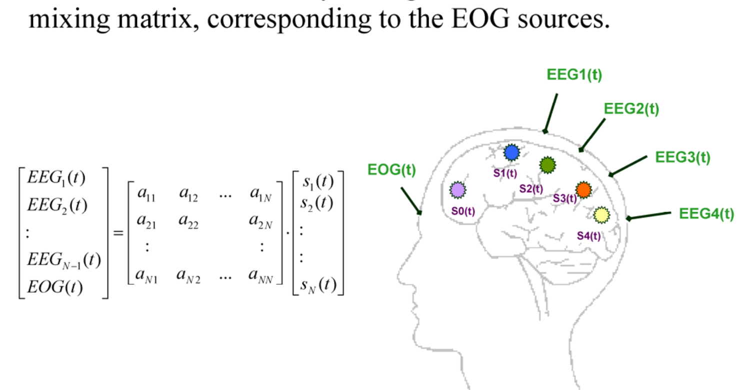


Figure4. The first model used for removing the EOG artifacts from EEG channels

## METHODS (continued) (6)

### Second Noise-Cancellation Method

- In the second method every EEG channel was given to the ICA algorithm together with the EOG channel (figure 5). Then among the two extracted sources, the one having the most correlation with the EOG channel was eliminated with a similar method as the first method.

$$\begin{bmatrix} EEG(t) \\ EOG(t) \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} s_1(t) \\ s_2(t) \end{bmatrix}$$

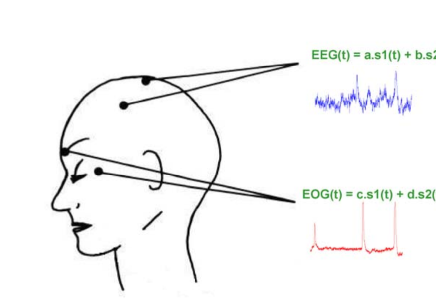


Figure 5. The second model used for removing the EOG artifacts from EEG channels

- A sample of EEG channels after the application of the second noise-cancellation method may be viewed in figure 6.

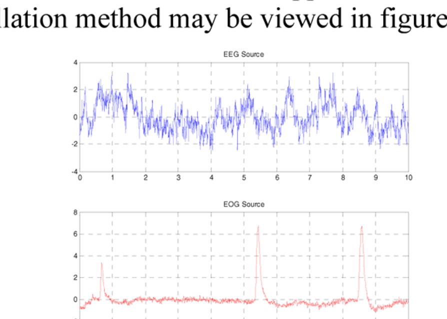

Figure6. A sample of EEG and EOG channel recorded from subject during a specific mental task(after noise-cancellation)

## METHODS (continued) (7)

### 3-Feature Extraction

- The next stage was the selection and extraction of suitable features from the de-noised database.
- Ideal features are:
  1) Close to each other for the members of each class (Small Within-Class Distance)
  2) Distanced for the members of different classes (Large Between-Class Distance)
- In order to find features having these properties, several features were extracted from the database, and then the best features or linear transforms of them were selected among the extracted features.
- The features extracted from the database are listed in table 2.

Table2. Features extracted from the EEG channels

- α-, β-, θ-, δ- band power using filter banks
- Asymmetry ratios of left/right hemisphere electrodes
- Centroid time/frequency
- Wavelet coefficients
- Principle components

- The listed features were extracted from the whole database and given to the feature selection unit in order to choose the best subset among them.

## METHODS (continued) (8)

- Two feature selection methods were adopted:
  - Forward-Sequential Feature Selection:

$$\text{Feature Extraction} \quad \begin{bmatrix} f_1 \\ f_2 \\ . \\ . \\ . \\ f_n \end{bmatrix} \xrightarrow{\text{Feature Selection (Reduction)}} \begin{bmatrix} f_1 \\ f_2 \\ . \\ f_m \end{bmatrix} \quad m << n$$

  - Optimum Linear Transform:

$$\begin{bmatrix} g_1 \\ g_2 \\ \vdots \\ g_m \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & & a_{2n} \\ \vdots & & & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \cdot \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix}$$

### 4- Classification

- The Quadratic Bayes classifier was used for classification:

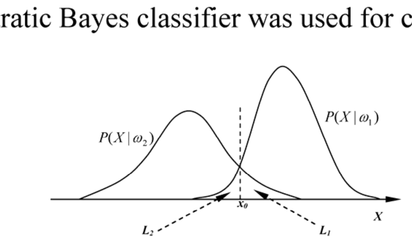


Figure7. The Quadratic Bayes classifier

$$h_{12}(\underline{X}) = \frac{1}{2}(\underline{X}-\underline{M}_1)^T \Sigma_1^{-1}(\underline{X}-\underline{M}_1) - \frac{1}{2}(\underline{X}-\underline{M}_2)^T \Sigma_2^{-1}(\underline{X}-\underline{M}_2) + \ln\frac{|\Sigma_1|}{|\Sigma_2|}$$

$$\begin{cases} h_{12}(\underline{X}) < \ln\dfrac{P(\omega_2)}{P(\omega_1)} \rightarrow \underline{X} \in \omega_1 \\ h_{12}(\underline{X}) > \ln\dfrac{P(\omega_2)}{P(\omega_1)} \rightarrow \underline{X} \in \omega_2 \end{cases}$$

## RESULTS (9)

- The classification results of different mental tasks are summarized in table 3 & 4.
- Note that these results were achieved on the database which was de-noised using the second noise cancellation method (slide #6).

Table3. Summery of the classification results of different pairs of mental tasks

| Feature Extraction Method | Mean Correct Classification |
|---|---|
| Previously Published Results[(2)] | 84.6 % |
| Before Feature Selection | 65.3 % |
| Wavelet Coefficients | 95.2 % |
| Principle Components | 93.3 % |
| 9-Band Filter Bank | 94.1 % |
| 5-Band Filter Bank | 97.8 % |
| 5-Band Filter Bank + Optimum Linear Transform | 99.0 % |

- As it is seen in table 3, the best results were achieved with the 5-band filter bank; thus the classification of more than 2 mental tasks was performed with these features.

Table4. Summery of mean Correct Classification (%) of different mental tasks using the 5-band filter bank

| Number of Discriminated Tasks | Raw Data Set | Denoised-1 Data Set | Denoised-2 Data Set |
|---|---|---|---|
| 2 Tasks | 97.8 % | 94.9 % | 97.7 % |
| 3 Tasks | 92.7 % | 89.6 % | 92.2 % |
| 4 Tasks | 88.7 % | 83.1 % | 88.2 % |
| 5 Tasks | 83.4 % | 76.7 % | 87.8 % |

## DISCUSSION (10)

- From the results of table 4 it is apparent that the correct classification ratio decreases as the number of classes increase.
- This fact was expected by intuition, but the question which arises is:
  - "How many mental tasks should be chosen for designing a BCI system? 2 tasks with the classification precision of 97.7% of 3 tasks with the precision of 92.2%, or…?"
- Answering this question needs a criterion for comparing the results of multi-class classification problems.
- In this work the *Mean Transferred Information* criterion has been used, which is an Information Theoretical concept and was first suggested for BCI applications by Wolpaw *et al* [(1)]:
- Consider:
  - $N$ different classes, each class classified correctly with a probability $p$ (or CC %)
  - The Mean Transferred Information in such a system is:
    - $B = \log_2 N + p\log_2 p + (1-p)\log_2[\frac{1-p}{N-1}]$ (Bits/Symbol or Bits/Trial)
- This concept may graphically be depicted as in figure 8.

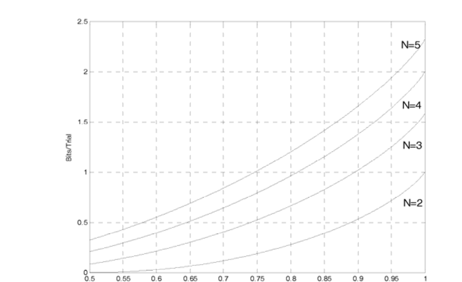


Figure8. The Mean Transferred Information in multi-class classification systems

## DISCUSSION (continued) (11)

- This criterion claims that a system which classifies 2 mental tasks with a precision of 95% transfers as much information as a classifier which classifies 3 mental tasks with 80% precision.
- If we transfer the results of table 4 on figure 8, we could compare the results of multi-class classifiers:

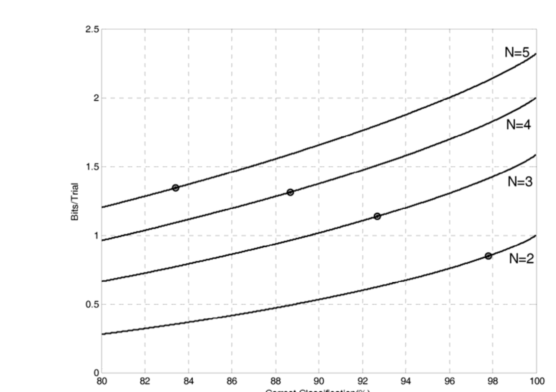


Figure9. The Mean Transferred Information in multi-mental task classification

- The results of this figure suggest that increasing the number of mental tasks may reduce the correct classification rate, but will overally, increase the *mean transferred information* in the system.

## CONCLUSION (12)

- In this work the discrimination of EEG signals during the performance of several mental tasks was investigated.
- The goal of this project was to serve as the signal processing unit of a Brain-Computer Interface system.
- EOG signals and eye blinks are the major artifacts for EEG signals. For this reason two approaches based on the Independent component analysis method were adopted which considerably canceled the artifacts' effect.
- Several types of feature extraction, feature selection, and classification methods together with a wide range of features were tested on the database; the results of which was the notable correct classification rate of 99%.
- As it was noted through out the previous slides, different mental tasks serve as an alphabet for EEG-Communication; so we generally wish to extend this alphabet by discriminating between more mental tasks. For this an Information Theoretical concept was mentioned, which suggests that systems classifying between several mental tasks may transfer more information, even though they usually decrease the correct classification rate compared with a 2-mental task discriminating system.

**Thanks for your attention!**