EEG Signal Analysis for Silent Visual Reading Classification

I. Oliveira, O. Grigori, and N. Guimarães

***Abstract*—** This paper describes a study regarding the detection of silent visual reading mental activity through electroencephalogram (EEG) analysis and processing. Our work is in the context of human computer interaction research field, and we pretend to use EEG signals in applications to assist and analyze reading tasks.

The need of users to be constantly and tightly coupled with the applications is being highly stimulated by the design of universally-accessible interactive systems. In this context, the use of biomedical signals has become an emerging area. Visual reading has a great interest to us, since it is a frequent activity while users interact with applications. Users will stop reading whether they feel disturbed or lost, or lose their interest, or even if application visual characteristics (such as font size and color) make it difficult. The analysis of visual reading flow will allow a better understanding of users mind while interacting with applications and help to objectify some still subjective usability tests.

The work focuses on building reliable capture and preprocessing procedures, extracting relevant features and testing simple learning algorithms. The detection process uses left hemisphere EEG signals, which are referred to as being the relevant brain area for this type of tasks. The signals were processed to extract the power spectrum density of delta, theta, and alpha rhythms, known frequencies of this type of signals. We also present two real time demonstration applications of assisted reading.

***Keywords*—**Reading Detection, Electroencephalogram Signal Preprocessing, Feature Extraction, Pattern Recognition, Human Computer Interaction.

I. Introduction

Visual reading activity has always been of great concern to the human factors area, as it is highly involved in most of the cognitive processes associated with human interaction [1]. Eye tracking devices [2] already monitor human gaze, the external demonstration of reading, but the parsing of the visual reading mental flow allows a better understanding of user's mind while interacting with applications. The analysis of this flow can be used, for example, to study interface legibility, a major area of usability, in a more objective form, provided that the appropriate experiments are designed [3]. Actually in spite of usability being a critical success factor for any type of software system, its testing methods still rely substantially on totally "external" techniques such as expert reviews, direct observation or questionnaires [4][5]. An alternative is to use physiological signals to analyze more intrinsically users' mental states. But we can go on further and try also to objectively confirm some usability rules and heuristics.

The concept of coupled interaction suggests that, to achieve stronger adaptation between humans and applications, the implicit and automatic signals generated by human physical processes should be understood and used by computational systems [6]. [7] Brain computer interfaces (BCI) are one important example of this kind of systems. A BCI is defined as "a communication system that does not depend on the brains normal output pathways of peripheral nerves and muscles" [8][9]. BCI mental tasks are usually related with device manipulation (e.g. cursors), item selection (e.g. pictures) or imaginary tasks (e.g. arithmetical or geometrical operations) [10]. EEG signal has actually been widely studied for the development of this kind of interfaces [30].

Neuroergonomics is a recent research field that studies the behavior of the brain in the context of the usage of real world artifacts and situations, relating the disciplines of neurosciences and ergonomics [11]. The use of its findings in software systems design will benefit substantially usability analysis and interaction studies. The integration of the appropriate biomedical signal, such as EEG, ECG, EMG, or skin conductance, will bring into usability studies the intrinsic data that they have been analyzing from the outside [12]. The use of neurophysiologic signals, where EEG is included, has thus become a relevant source of information [29][31].

This paper presents a study about the detection of silent visual reading and non reading mental activities through EEG processing. We pretend to integrate EEG signals in applications to assist and analyze visual reading tasks. The choice of EEG signals in detriment of other neural or physiological measurements is due to its small temporal resolution and non-invasiveness [10]. EEG also reveals properties that vary with performed mental tasks and thus make it eligible for pattern recognition applications [13][14].

The paper initially focuses on building robust and reliable

Manuscript received Augoust 14, 2009. This work was partially supported by Fundação para a Ciência e Tecnologia (FCT) grant SFRH/BD/30681 /2006 and Ciência2007 Program.

I.Oliveira Author is with Universidade Lusófona de Humanidades e Tecnologia, Lisbon, Portugal and LASIGE/FCUL, University of Lisbon, Lisbon, Portugal (e-mail: ines.oliveira@ulusofona.pt).

O.Grigori Author is with LASIGE/FCUL, University of Lisbon, Lisbon, Portugal (e-mail: ogrigore@di.fc.ul.pt).

N. Guimarães Author is with LASIGE/FCUL, University of Lisbon, Lisbon, Portugal (e-mail: guimaraesn@acm.org).

capture and preprocessing procedures, extracting relevant features and testing simple learning algorithms. The detection process uses left hemisphere EEG signals, considered a relevant area related with visual language [20]. These signals were processed to extract the power spectrum density of specific known frequencies ranges of EEG signals.

We also describe the framework that encapsulates the abstractions needed to implement the referred functionalities. This toolkit offers reusable components for preprocessing, processing, and classifying EEG signals. This framework is demonstrated through two preliminary applications, *ReadingScroller* and *ReadingTester*.

The final sections present and discuss the processing and analysis results, and reason about additional opportunities inspired by the developed work.

II. Hardware and Capture Procedure

The signal was captured using MindSet-1000, a digital system for EEG mapping with 16 channels, connected to a PC using a SCSI-interface. MindSet channels are connected to a cap, produced by Electro-Cap International. It is an EEG electrode device that is made of an elastic fabric with pure tin electrodes (sensors) attached.

Fig.1- The EEG capture montage.

The electrodes are positioned using the International 10-20 method (see Fig. 2) [13]. The signals from the electrodes are amplified in differential manner relative to the ear electrodes and are sampled with 256Hz frequency.

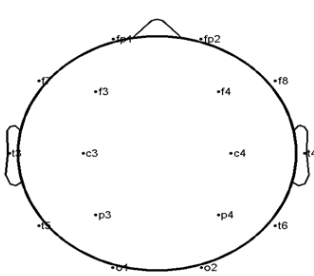

Fig. 2 – Mapping of EEG device electrodes (International 10-20 method).

A. Capture Equipment Montage

The montage of the capture equipment revealed to be complex. Working with EEG capture procedures, as other kinds of biomedical signals, demands having specific technical skills to achieve correct setup of the capture device and also to visually understand and validate the resulting signal. This requires a learning process that should not be underestimated.

All the requirements indicated by suppliers and technicians were fulfilled, and we gathered a significant set of reliable samples. Our sample capture procedure includes “grounding” the subjects.

To guarantee the reliability of captured samples the experiment was replicated using a 30 channels professional medical capture device, Neurofax EEG-1100C. This equipment was in use in a hospital, so all experiment setup was entirely prepared and tuned by expert technicians. All electrodes were also positioned using the International 10-20 method, but we restricted our processing to the same 16 electrodes used in MindSet. These signals were captured with 200Hz frequency. The results obtained with both capture devices were validated by EEG technical experts.

Setting any EEG capture equipment requires putting conductive gel and measuring the impedance in each electrode. We actually must guarantee balanced impedance in all 16 electrodes bellow 6000Ω (a threshold defined by the cap manufacturer). This assures us that the amplitude in all channels will be affected by similar impedances. To reduce impedance in an electrode it is necessary to put more gel. Impendence depends on subject-specific characteristics such as skin conductive or hair type.

B. Read and Not Read Experience

The cognitive processes regarding reading activity are a good indicator of the user concentration while interacting with an application [3]. Users will stop reading if they feel disturbed, confused, lose their interest, or even if the application visual characteristics, such as background color and text row size, difficult its legibility.

Our first experiments were based in the presentation of alternate blank and text screens containing about 40 lines of daily news text.

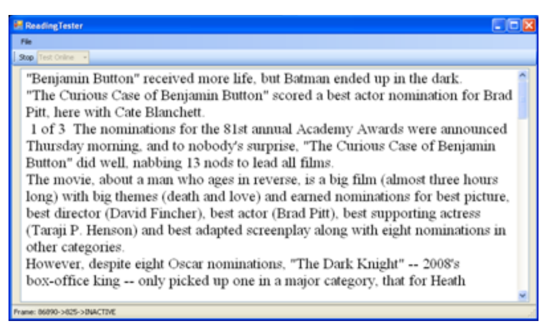

Fig. 3 - ReadingTester with a news text

Since watching a blank screen, and trying not to think in nothing special, had revealed to be very disturbing and tiring, we presented longer text, 30s, than blank screen periods, 20s. These types of periods were interlaced: one reading text sample, followed by 2 stare blank screen, and again back to read. Globally we captured 120s of both sample classes with each subject trial. All data was recorded without any previous or special training in 3 distinct subjects: all right handed, age bellow 60, two males, and one female and no relevant vision disabilities.

C. *Assisted Reading Applications*

We developed two preliminary assisted reading applications that demonstrate the above experiments in real time: *ReadingScroller* and *ReadingTester*.

ReadingTester tests a “reading event script” in real time. An event script is a sequence of events with certain duration that are generated by the application (see Fig. 4).

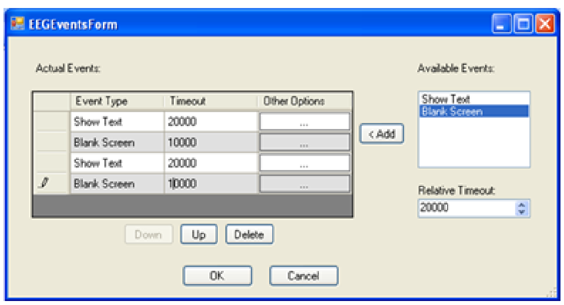

Fig. 4. Example of a reading event script.

The subject is exposed to the events, while its EEG is captured and analyzed. Only two types of events are being considered at the moment: blank screen and show text, but more can be added with insignificant effort. Fig. 3 shows the look of the application while a news text is being displayed.

When the detection process stops, the application builds a report containing performance measures. It can also record an EEG signal to a file and test events against a previously recorded file.

The idea behind *ReadingScroller* is to control a text scrolling through EEG signals: while the user is reading the scrolling should occur; if the user stops the scrolling should also stop.

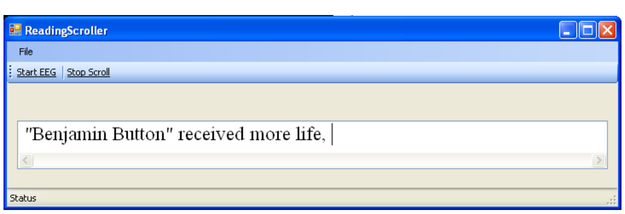

Fig. 5. ReadingScroller Application.

This interface posed us several interesting problems that have to be addressed in future. First of all, we must define what the state of not reading is while using this interface. This will probably require a one class classifier, more complicated to train and tune then a two-class one. Second, as the text is always moving it is very hard to stop reading, since the subject is always tempted to read a few words.

III. Processing and Pattern Recognition

In this section, the more relevant aspects related with feature extraction, feature selection, and classification procedures used in the reading detection, are addressed. These functionalities are encapsulated in EEGLib framework, an object oriented toolkit that can be easily integrated in applications. This framework is has two distinct layers, one implemented in C++ [24], other in MatLab [25].

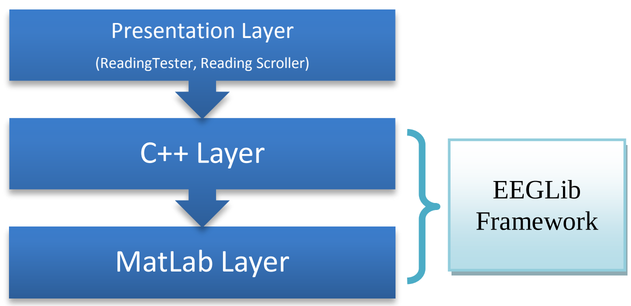

Fig. 6. EEGLib Framework main layers.

C++ layer analysis and processing operations are performed in integration with the MatLab Engine, which allows calling MatLab routines from C [25]. This integration is mediated through a single object that encapsulates the interface between both layers, called *EEGMatLabEngineInterface*.

A. *Feature Extraction*

The most common features used in EEG pattern recognition are the power spectrum density (PSD) of a set of rhythms and electrodes [15][16], coefficients from simple or multivariate autoregressive models [17][18] and Event Related Potentials [19]. The feature extraction step of the detection process determines the mean PSD in Alpha (α) – 8 to 13Hz, Theta (θ) – 4 to 8 Hz and Delta (δ) – 1 to 4 Hz – rhythms in each left hemisphere electrode. These frequency bands are very well studied EEG properties that vary spatially with performed mental tasks [13].

The mean PSD measures the amount of energy that exists in a certain rhythm and thus characterizes well its relevance in the global signal. This measure was determined in frames of 256 samples (1 sec), with an overlapping of 128 samples (0.5 sec), and was calculated using the Burg method, which had shown better results for this kind of problem, when compared with other algorithms [15]. The first 5sec and the last 3sec of each sample were discarded in order to minimize the possible artifacts caused by start-end of the recording process.

The current processing procedure is restricted to the 8 left hemisphere electrodes for right-handed subjects, since this area is considered to be a relevant area relating to visual language [20][21]. A full feature vector is therefore composed by 8x3 real values.

All these functionalities are implemented in EEGLib, modeled as a C++ class, and integrated in a systematic hierarchy (see Fig. 7).

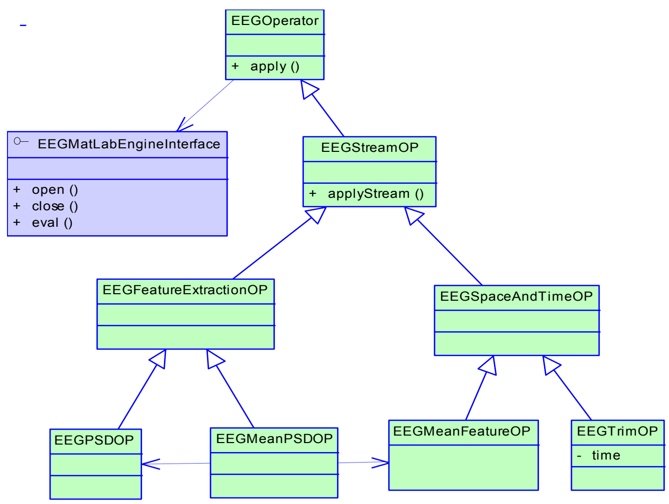

Fig. 7 – EEG Feature Extraction Data Model.

- *EEGOperator* is an abstract class that encapsulates all operations that can be applied to EEG signals, including feature extraction, selection and classification methods.

- *EEGStreamOP* class abstracts all operations applied to EEG streams.

- *EEGFeatureExtractionOP* leads the hierarchy of all operations that extract features used in classification.

- *EEGSpaceAndTimeOP*, all methods that alter stream space and time dimensions.

Streams are composed by several frames that can be overlapped. Frames are obtained from streams through windowing operations applied by iteration objects. All these concepts are also modeled as C++ classes (see Fig. 8).

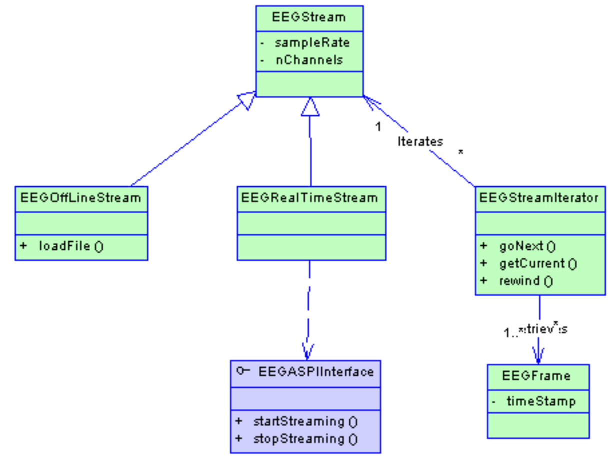

Fig. 8 – EEG Stream and Frame Data Model.

There are two main types of EEG streams:

- Offline, coming from a file.

- Real-time, captured directly from de SCSI device by using the Advanced SCSI Programming Interface (ASPI).

ASPI is a norm that allows real-time communication with Small Computer System Interface (SCSI) peripheral devices, such as MindSet. It is through *EEGASPIInterface* object that we capture and analyze EEG signals in real-time.

B. Feature Selection

We reduced the dimensionality of the feature vector by using Principal Component Analysis (PCA) [17]. PCA is a linear mathematical transformation that transforms data, a number of possibly correlated variables, in a new uncorrelated coordinate system called principal components. These coordinates are ordered by variance, allowing discarding those with less variance, which are less relevant for the classification procedure.

There is no fixed vector basis to determine the PCA, because it depends on the data itself. The main goal is to identify the most meaningful basis to express data, which willingly will filter noise and reveal hidden structure [27].

Two main concepts are behind the vector basis choice of PCA: variance and redundancy [27]. A great variance is a desirable property because it increases signal-to-noise ratio, and consequently data precision. On the other hand, expressing data more concisely and reducing the number of electrodes reduces the classification computing effort. Redundancy can be minimized by reducing the correlation of the used dimensions. Two random variables are said to be correlated if they are linearly related, which means that one can be linearly computed from the other one. In this case, one of these variables can be discarded.

To increase variance and reduce redundancy, PCA transformation uses eigenvectors of the covariance matrix by transforming x to u as below:

$$\begin{bmatrix} u_1 \\ \cdots \\ u_n \end{bmatrix} = \begin{bmatrix} \boldsymbol{v_1}^T \\ \cdots \\ \boldsymbol{v_n}^T \end{bmatrix} \begin{bmatrix} x_1 \\ \cdots \\ x_n \end{bmatrix} \quad (1)$$

where: u_i is the i[th] PCA components, v_i is the i[th] eigenvector of the covariance matrix, while they are ordered by decrease order, x_i is the ith input feature.

Covariance matrix is an *mxm* matrix, where *m* is the number of features that capture the covariance between all possible combinations pairs of feature dimensions [27]. Covariance between features f_1 and f_2 measures its linear relationship, generalizing the variance formula:

$$\sigma_{f_{12}}^2 = \frac{1}{n}\sum_i f_{1i} f_{2i} \quad (2)$$

When feature correlation is high, the magnitude of their covariance is also high [27].

Diagonal terms of the covariance matrix are the variances of all dimensions; off-diagonal terms, are the covariance between dimensions. To get a high variance and low redundancy it is desirable to maximize covariance matrix diagonal terms (variance) and minimize its off-diagonal terms (redundancy) [27]. An optimal covariance matrix should be diagonal, having all off-diagonal terms null (uncorrelated), and each successive dimension should be rank-ordered according to variance.

PCA diagonalizes the covariance matrix by computing its eigenvectors. It is demonstrated that any symmetric matrix (such as covariance matrix) is diagonalized by an orthogonal matrix of its eigenvectors [27]. Geometrically PCA performs a generalized rotation so that data is oriented according to a maximal variance axis.

C. Classification Method

There are many references in relation to the application of standard learning methods to EEG signals [10][11][19]. At this stage, we did not want to spend much time developing new classification algorithms. Our goal was to set up and validate all the procedure, so we chose the K-nearest neighbors' (KNN) implementation provided in SPRTOOL MATLAB Toolbox.

KNN algorithm is an instance based, lazy-learning method, since it memorizes all training data and just searches for similar samples (neighbors) when we pretend to classify a new sample [23]. Non classified samples are classified accordingly with K nearest neighbors' samples in the training set:

K is the desired number of nearest neighbors
$S=\{s_1,\ldots,s_n\}$ is the set of training samples already classified (c_i = class label of s_i)

For each unknown sample s' to be classified:
(a) For all s_i compute d_i = distance d(s', s_i)
(b) Sort in ascent order all s_i according to d_i
(c) Select the first *K* samples from the sorted list, those are the *K* closest training samples to s'. Assign a class to s' based on majority vote:

c' = argmax$_{c\in \mathrm{CLASS}}$ sum{(s_i,c) belong *S*}

KNN has been successfully used in EEG based BCI applications with low dimensional vectors [10] [28]. It is not advisable to use KNN with high dimensional vectors because its computation cost is quite high. KNN requires computing the distance of each test sample to all training samples.

KNN has the advantage of being robust to noisy training data, and EEG data is always corrupted by eye and muscle artifacts. But a significant drawback is that it is just effective if the training data is large, and EEG samples corpus are usually small due to its capture complexity.

KNN algorithm also requires determining the value of K, and to produce best results it is not clear which distance measure and which features should be used. So it is desirable to use feature selection procedures such as PCA to reduce vector dimensionality.

Both PCA and this classifier are supported through EEGLib classes (see Fig. 9).

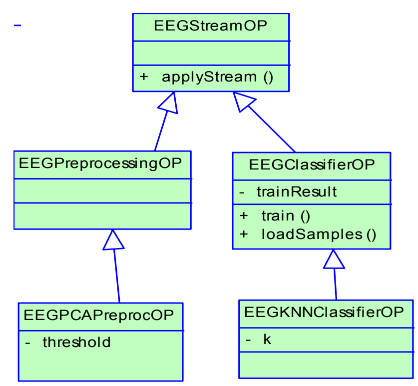

Fig. 9 – PCA and KNN Data Model.

The PCA operator allows the setting of the threshold; KNN operator has as a parameter for the number of nearest neighbors.

IV. Results

This section describes and discusses the results regarding the supported procedures for feature extraction and selection, and classification.

A. Experiment Subject Selection

As mentioned above all data was recorded without previous training on 3 distinct subjects. All of these were right handed, with age between 30 and 50, two males, one female, Caucasian and without relevant vision disabilities. The female was the main subject having about 20 experiment trials. Men were tested once for comparison purposes.

We kept a journal about the impedance and environment conditions, subjects' degree of sleepiness and time of day. We had not met impedance requirement with male subjects: in one, the values rounded 10000Ω, the other 7000Ω. Skin conductance is influenced by factors such as the amount of hair, the usage of hair products such as gel, or race. The female subject was in fact the one with more hair and was considered having an excellent skin conductance by an EEG technician while subjected to a similar experiment in a clinical environment.

B. Classification Results

The following results were averaged in 100 trials where the number K of nearest neighbors was maintained constant. In each trial, the training and test sets were randomly selected from the reading and non-reading sample sets.

Fig. 10 shows the average classification error rate determined in all samples sets captured in the female subject, while varying the number of nearest neighbors.

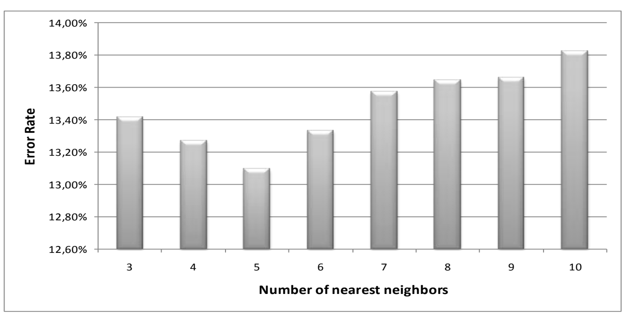

Fig. 10 - Average classification error rate.

Error rate was below 14% in this subject: two thirds of the sample sets were above this value, the remaining was bellow. This would probably be justifiable by user and environmental conditions, but this is not supported by our logging.

We chose 5-NN because it represents a minimum in the error rate, probably due to feature relevance problems. Next results are in relation to this choice.

We present the following measures in Table 1.

- Precision rate: the number of items correctly labeled as reading in relation to the total number of elements labeled as reading.

- Recall rate: the number of items correctly labeled as reading in relation to the total number of elements that actually belong to the reading class.

- False Positive rate: the number of items incorrectly labeled as reading in relation to the total number of elements that actually belong to the non reading class.

- False Negative rate: the number of items incorrectly labeled as non reading in relation to the total number of elements that actually belong to the reading class.

	Error Rate	False Pos. Rate	False Neg. Rate	Precision Rate	Recall Rate
Set 1	7,22%	6,55%	7,87%	93,55%	92,13%
Set 2	17,55%	20,64%	13,74%	77,19%	86,26%
Set 3	10,37%	12,21%	8,35%	87,19%	91,65%
Set 4	20,62%	25,42%	13,50%	69,63%	86,50%
Set 5	11,77%	13,15%	10,27%	86,36%	89,73%
Average	**13,51%**	**15,59%**	**10,75%**	**82,78%**	**89,25%**

Table 1 – Performance measures obtained in 5 sample sets with 5-KNN.

False positive rate is usually greater than false negative rate, suggesting that non reading class is more complicated to classify. As we described before non reading activity requires less concentration than reading, and can be "contaminated" by a diverse number of other mental activities. This factor also affects precision-recall relation, since precision is in general inferior to recall.

Fig. 11 shows an example of bad results obtained with a different subject that did not fulfilled impedance requirements.

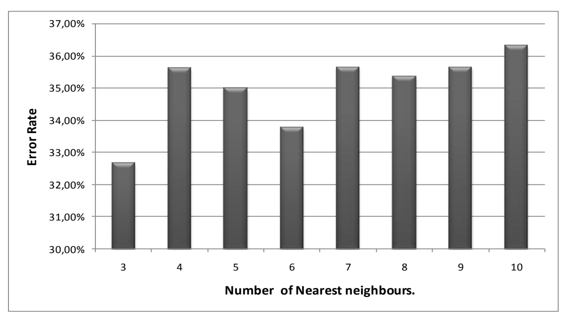

Fig. 11 – Average classification error rate in another subject: an example of bad results.

C. Applying PCA

The application of PCA to select features was also tested in iterations of 100 trials. Fig. 12. displays the average error rate in relation to the number of features used in the detection procedure.

The error rate variation is initially mild, but as we expected it starts to increase after using 13 features. This means that relevancy of the removed components to the detection procedures starts to be significant. We obviously chose 13 features and determined some detection performance measures (see Table 2.)

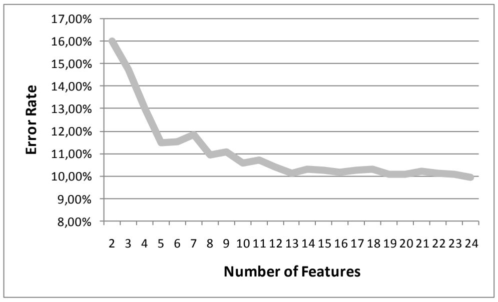

Fig. 12 – PCA application with 5-KNN.

	Error Rate	False Pos. Rate	False Neg. Rate	Precision Rate	Recall Rate
Set 1	4,80%	8,04%	2,25%	97,75%	91,96%
Set 2	13,44%	23,96%	4,97%	95,03%	76,04%
Set 3	9,12%	13,39%	5,58%	94,42%	86,61%
Set 4	16,74%	29,39%	6,76%	93,24%	70,61%
Set 5	6,54%	9,65%	3,99%	96,01%	90,35%
Average	**10,13%**	**16,89%**	**4,71%**	**95,29%**	**83,11%**

Table 2 – Performance measures obtained after PCA application (selection of 13 features).

The comparison between Tables 1 and 2 shows that the error rate with PCA decreased from 1 to 3% in all sample sets, essentially caused by significant decrease in false negative rate. As consequence, precision had also dropped, but recall had increased.

V. Conclusions and Future Work

This paper described a study about the detection of reading and non reading mental activities through EEG processing. We have demonstrated that this method has potential to be used in usability research and coupled interaction design.

The paper also presented the main issues regarding the construction of robust and reliable capture and preprocessing procedures, extracting relevant features and testing some simple learning algorithms. These functionalities were included in a framework that offers reusable components for preprocessing, processing and classifying EEG signals, and currently support applications like *ReadingScroller* and *ReadingTester*. This work inspired relevant additional opportunities.

A. Generalization and user differences

The tests mentioned above were made with a restricted number of subjects. The focus has been the development and optimization of the framework and tools. More subjects and samples are needed, in order to increase the results' robustness. Some degree of diversity related with user differences is expected, such as skin conductance, hair type or sleepiness, as well as contextual constraints, such as environmental differences. We would like to compensate these aspects by defining and designing adequate calibration procedures that adapt to the individual user profiles and conditions.

B. Feature Selection

Before applying PCA, the feature selection is being performed according to referenced domain source information [20], which indicates that visual reading cognitive processes are more intense in left hemisphere for right-handed people.

With PCA, we go further by applying a global mathematical transformation, but this does not consider the spatial distribution of the signals nor its specificities regarding functional neurosciences knowledge. Functional neurosciences try to map cognitive processes into skull areas. These processes cause certain activity patterns (rhythms) in specific electrodes related with those areas.

A further step in feature selection should rely on this kind of information analysis. In order to do that we are going to use dissimilarity measures in each of the features streams. This analysis should be performed independently of a specific classification method, in order to validate the selection itself, by determining whether main differences are situated in electrodes and rhythms related with visual language processing.

Acknowledgment

This work was partially supported by Fundação para a Ciência e Tecnologia (FCT) grant SFRH/BD/30681 /2006 and Ciência2007 Program. We also thank Dr. Carla Bentes and the Santa Maria Hospital neuro-sciences team for helping with their EEG expertise.

References

[1] B. Shneiderman, *Design the User Interface*, Addison Wesley- 3rd edition, 1997.

[2] D.C. Richardson, M.J. Spivey, "Eye-Tracking: Research Areas and Applications", in *Encyclopedia of Biomaterials and Bimedical Engineering*, Informa Healthcare, 2004.

[3] I. Oliveira, R. Lopes, N. M. Guimarães. "Development of a Biosignals Framework for Usability Analysis (Poster)", present at ACM SAC´09 HCI Track, 2009.

[4] J. Rubin, *Handbook of Usability Testing: How to Plan, Design, and Conduct Effective Tests*, John Wiley & Sons, 1994.

[5] J. Nielsen, *Usability Engineering*, Morgan Kaufmann, 1994.

[6] G. J. Doherty, M. Massink, "Continuous Interaction and Human Control", *Proceedings of 18th European Conference on Human Decision Making and Manual Control*, 1999.

[7] E.N. Bruce, *Biomedical Signal Processing and Signal Modeling*, John Wiley & Sons, 2001.

[8] J. R. Wolpaw, et al., "Brain–Computer Interface Technology: A Review of the First International Meeting", *IEEE Transactions on Rehabilitation Engineering*, Vol. 8, 2000.

[9] J.R. Millán. "Adaptative Brain Interfaces", *Communications of the ACM*, 2003.

[10] G. Molina, *Direct Brain-Computer Communi-cation through scalp recorded EEG signals*. PhD Thesis, École Polytechnique Fédérale de Lausane, 2004.

[11] R. Parasuraman, M. Rizzo, *Neuroergonomics: The Brain at Work*, Oxford University Press, 2006.

[12] R.D. Beer, et al., "The Usability Lab of the Future", *Proceedings of IFIP INTERACT03: Human Computer Interaction 2003*, 2003.

[13] B.J. Fisch. *Fisch and Spehlmann's EEG Primer: Basic Principles of Digital and Analog EEG*, Elesevier, 1999.

[14] E. Niedermeyer, L. Silva, *The Normal EEG of the Waking Adult, Electroencephalography: Basic Principles, Clinical Applications and Related Fields*, Lippincott Williams & Wilkins, 1999.

[15] Z.A. Keirn, J. I. Aunon, "A New Mode of Communication between Man and His Surroundings", *IEEE Transactions on Biomedical Engineering*, Vol. 37, 1990.

[16] V. Bostanov, "BCI Competion 2003 – Data Sets Ib and Iib: Feature Extraction Form Event-Related Potentials With Continuos Wavelet Transform and the t-Value Scalogram", *Transations on Biomedical Engineering*, Vol. 51, 2004.

[17] C. W. Anderson, E. A. Stolz e S. Shamsunder, Multivariate autoregressive models for classification of spontaneous EEG during mental tasks, IEEE Transactions on Biomedical Engineering, Vol. 45, 1998.

[18] P. Sykacek, S. J. Roberts e M. Stokes. "Adaptive BCI Based on Variational Bayesian Kalman Filtering: An Empirical Evaluation", *IEEE Transactions on Biomedical Engineering*, Vol.51, 2004.

[19] S. Sanei, J.A. Chambers. *EEG Signal Processing*, John Wiley & Sons, 2007.

[20] E. Bizas, G. Simos, C.J. Stam, S. Arvanitis, D. Terzakis, S. Micheloyannis, "EEG Correlates of Cerebral Engagement in Reading Tasks", *Brain Topography*, Vol. 12, 1999.

[21] R.J. Steinberg. *Cognitive Psychology*, Thomson Wadsworth, 2003.

[22] T.M. Mitchell, *Machine Learning*, McGraw-Hill. 1997.

[23] Stephen Prata, *C++ Primer Plus*, SAMS, 2005.

[24] MathWorks. http://www.mathworks.com , 2009.

[25] Statistical Pattern Recognition Toolbox, http://cmp.felk.cvut.cz/cmp/software/stprtool/index.html, 2009.

[26] Jonathon Shlens, "A Tutorial on Principal Component, Center for Neural Science", New York University, 2009.

[27] F.Lotte, M. Congedo, A. Lecuyer1, F. Lamarche, B. Arnaldi, "A Review of Classication Algorithms for EEG-based Brain-Computer Interfaces", *TOPICAL REVIEW*, IRISA / INRIA Rennes, Campus universitaire de Beaulieu.

[28] D. Rubio, M.I. Troparevsky, "Time Dependent Source Models for EEG", *WSEAS Transactions on Mathematics*, 2005.

[29] V. Khare, J. Santhosh, S. Anand, M. Bhatia , "Controlling a wheelchair using EEG Signal", *WSEAS Transactions on Biology and Biomedecine*, 2009.

[30] J. R. Chávez, C. A. Cruz, "Pattern Recognition Applied to Mouse Pointer Controlled by Ocular Movements", *WSEAS Transactions on Systems*, 2009.