Reading Detection based on Electroencephalogram Processing

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Abstract: - This paper describes a study regarding the detection of silent visual reading and non reading mental activities through electroencephalogram (EEG) processing. Our work is in the context of human computer interaction research field, and we pretend to integrate 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 system, where the use of biomedical signals has become an emerging area.

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 is 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,

Key-Words: - Reading Detection, Electroencephalogram Signal Preprocessing, Feature Extraction, Pattern Recognition, Human Computer Interaction.

1 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 geometrical operations) [10]. EEG signal has actually been widely studied for the development of this kind of interfaces.

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 or skin conductance, will bring into usability studies the intrinsic data that they have been analyzing from the outside [12]. The use of neurophysiological signals, where EEG is included, has thus become a relevant source of information.

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 measurements (like in BCI) is due to its small temporal resolution and non-invasiveness [10]. EEG also has 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 capture and preprocessing procedures, extracting relevant features and testing simple learning algorithms. The detection process uses left hemisphere EEG signals, considered to be a relevant area related with visual language. These signals were processed to extract the power spectrum density of specific known frequencies ranges of EEG signals.
We also describe the framework that has been developed to encapsulate 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.

2 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. The channel amplification is referential to the *ear electrodes*, meaning that the signal is 32000 times amplified in relation to the signal captured in the ears lobes. MindSet channels are connected to an electro-cap – an EEG electrode application technique that is made of an elastic fabric with pure tin electrodes (sensors) attached. The electrodes are positioned using the International 10-20 method [13]. The signal was captured with 256Hz sample rate.

Fig.1- The EEG capture montage.

2.1 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, The sample captures include “grounding” the subjects, replicate the experiment using medical capture devices and validate both results by EEG technical experts.
Setting any EEG capture equipment requires putting conductive gel and measuring the impedance in each electrode. In our case, given the low cost device and software, this is done manually with a multimeter, but there are other devices that include an impedance checking application. 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.

2.2 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, difficults its legibility.
Our first experiments were based in the presentation of alternate blank and text screens containing about 40 lines of daily news text. The text was never repeated and no particular visual effort was required.

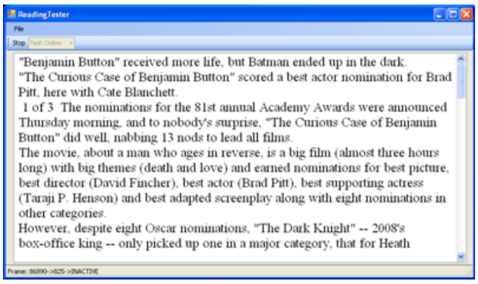

Fig. 2 - *ReadingTester* with a news text

Since staring at 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, one female, and no relevant vision disabilities.

2.3 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.

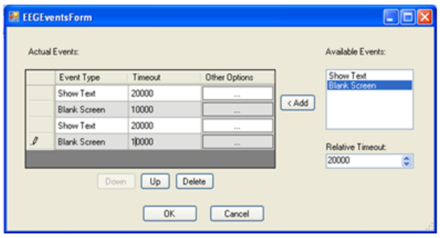

Fig. 3. Example of a reading event script.

The subject is exposed to the events, while its EEG is captured and analyzed.. Only two types of events are being considered: blank screen and show text, but more can be added with no significant effort. Fig. 2 shows the look of the application while a news text is being displayed. The application builds a report containing performance measures when the detection process stops and 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.

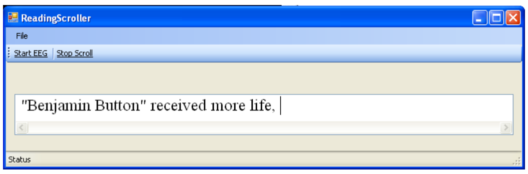

Fig. 4. *ReadingScroller* Application.

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 using this interface is. 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.

3 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 were encapsulated in EEGLib framework, an object oriented toolkit and that can be easily integrated in applications.

3.1 Feature Extraction

The most common features used in EEG pattern recognition are the power spectrum density (PSD) of a sets 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 determined 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 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 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.

All these functionalities are implemented in EEGLib, modeled as a C++ class and integrated in a systematic hierarchy (see Fig. 5).

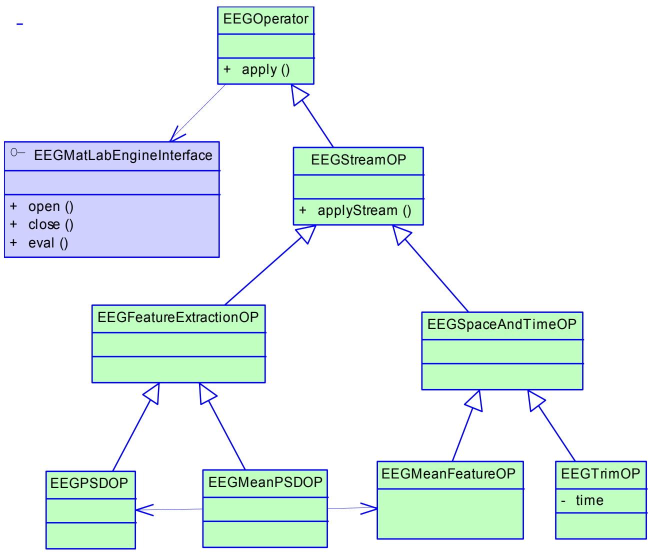

Fig. 5 – EEG Feature Extraction Data Model.

All the analysis and processing operations are performed in integration with a MatLab Engine [24]. 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

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relating visual language [20][21]. A full feature vector is therefore composed by 8x3 real values.

3.2 Feature Selection and Classification

We reduced the dimensionality of the feature vector by using Principal Component Analysis (PCA) [17]. This is a linear mathematical transformation that transforms data in a new uncorrelated coordinate system – the principal components. These coordinates are ordered by variance, allowing discarding the coordinates with less variance, which is less relevant for the classification procedure. There is no fixed vector basis to determine the PCA, because those depend on the data itself. This transformation uses eigen values of the covariance matrix by transforming *x* em *u* as below:

$$\begin{bmatrix} u_1 \\ \cdots \\ u_n \end{bmatrix} = \begin{bmatrix} v_1 \\ \cdots \\ v_n \end{bmatrix} \begin{bmatrix} x_1 \\ \cdots \\ x_n \end{bmatrix} \qquad (1)$$

u_1 is the first PCA, u_2 is the second, and so on. v_i is the ith eigen value of the covariance matrix, while they are ordered by decrease order.

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 [23][24].

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 [25]. Non classified samples are classified accordingly with k nearest neighbors' samples in the training set:

> k is the desired number of nearest neighbors
> S={s1, ... ,sn} is the set of training samples already classified (ci = classification of si)
>
> For each sample s' to be classified:
> (a) For all si compute di =distance d(s', si)
> (b) Sort all si according to di values
> (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' = $\text{argmax}_{c\in\text{CLASS}}$ sum{(si,c) belong S}

KNN has been successfully used in EEG based BCI Interfaces with low dimensional vectors [10]. Both PCA and this classifier are supported through EEGLib classes (see Fig. 6). The PCA operator allows the setting of the threshold; KNN operator has as a parameter for the number of nearest neighbors.

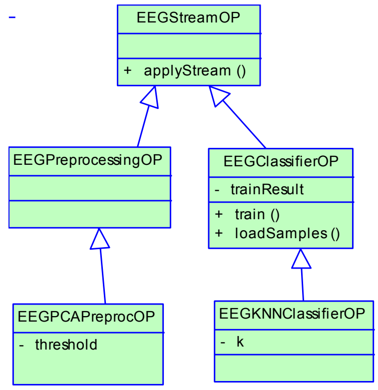

Fig. 6 – PCA and KNN Data Model.

4 Results

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

4.1 Experiment Subject Selection

As mentioned above all data was recorded without no previous training in 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 10000**Ω**, with 7000**Ω**. 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.

4. 2 Classification Results

The following results were averaged in 100 trials where the number 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. 7 shows the average classification error rate determined in all samples sets captured in the female subject, while varying the number of nearest neighbors.

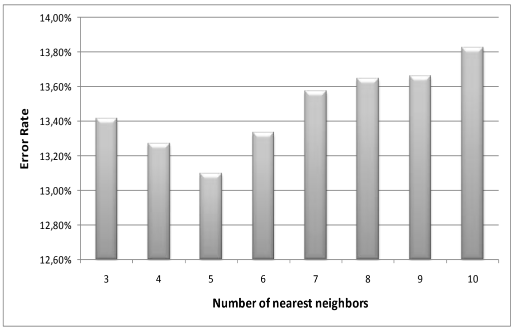

Fig. 7 - Average classification error rate.

Error rate was below 14% in this subject: two thirds of the sample sets were above this value, the remaining were 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.

	False Pos. Rate	False Neg. Rate	Precision Rate	Recall Rate
Set 1	6,55%	7,87%	93,55%	92,13%
Set 2	20,64%	13,74%	77,19%	86,26%
Set 3	12,21%	8,35%	87,19%	91,65%
Set 4	25,42%	13,50%	69,63%	86,50%
Set 5	13,15%	10,27%	86,36%	89,73%
Average	**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 that recall.

Fig. 8 shows an example of bad results obtained with a different subject that did not fulfilled impedance requirements.

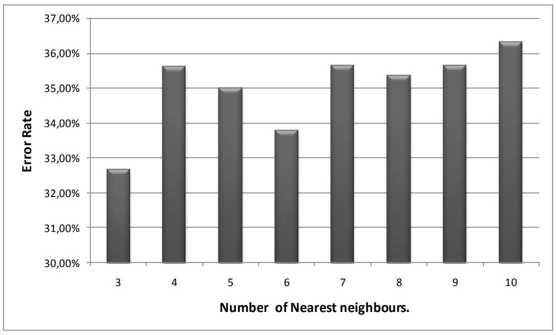

Fig. 8 – Average classification error rate in another subject: an example of bad results.

4.3 Applying PCA

The application of PCA to select features was also tested in iterations of 100 trials. Fig. 9. displays the average error rate in relation to the number of features used in the detection procedure.

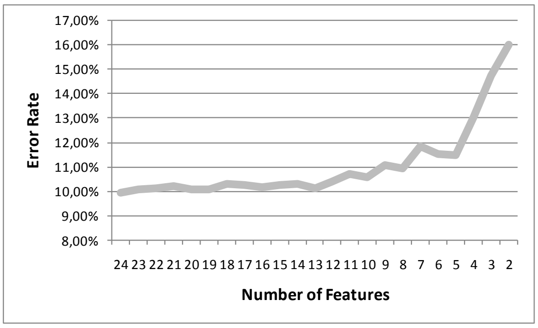

Fig. 9 – PCA application with 5-KNN.

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.)

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

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

5 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 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.

5.1 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.

5.2 Feature Selection

Before applying PCA, the feature selection is being performed according to referenced domain 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.

Feature selection should rely on this kind of information. 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.

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