A Tool for Mental Workload Evaluation and Adaptation

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ABSTRACT
This paper studies the use of mental workload patterns measured from electroencephalographic (EEG) signals in the adaptation of reading activities. Mental workload is associated with the feeling of (dis) comfort of users, based on the assumption that a higher mental workload involves a greater discomfort.

There is increasing interest in the use of physiological signals for the design of interactive systems, reinforcing the link between the application behavior and the user's emotional and mental states.

Reading processes are pervasive in visual user interfaces. Previous work has integrated EEG signals in prototypical applications, designed to analyze reading tasks, and tried to identify the most relevant features for discriminating reading and non-reading mental states. In this paper we address the possibility of adjusting the reading conditions to the user's mental state.

We start by analyzing the correlation between the mental workload and the variation of some relevant HCI textual aspects, such as text size. Then we developed applications that analyze the user's mental workload and adjust the speed of text presentation to the user's mental load. The experiments have been performed in a conventional HCI lab, with non clinical EEG equipment and setup. This is an explicit and design condition, as it targets ecological reading situations.

Categories and Subject Descriptors
H.5.2 [**Information Interfaces and Presentation**]:

Human-centered computing, Human computer interaction (HCI) → Interaction paradigms

General Terms
Design, Experimentation, Human Factors, Measurement

Keywords
Reading Adaptation, HCI, EEG Processing, Mental Workload.

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1. INTRODUCTION
The understanding of human physiological signals and its integration in computational systems increases the coupling between the application behavior and user's emotional and mental states. This trend is evident in several related areas like ubiquitous interaction [1], wearable [2] and affective computing [3] and neuroergonomy [4]. The concept of "coupled interaction" proposes a stronger adaptation between user and computational elements, transcending the classical intentional communication [5].

The use of electroencephalograms (EEG) has been widely referred in the context of BCIs [6-8] − an important example of coupled interaction systems that conveys an "alternative way of communicating with devices through brain waves" [7]. EEG signals are frequently used in BCIs because they use low cost capture devices, allow connecting users for long periods of time and are less invasive [9].

Written communication is intrinsic to humans and is therefore often used in user interfaces. It usually comes in the written form that requires reading skills. Reading in screens can be affected by aspects such as text size or contrast [10], and that is why readability can be considered a principle of interaction design as consistency or efficiency [11].

Augmented reading applications should adapt to the user's reading flow through the detection of specific user mental states. In this paper we assume that the mental workload measure is related with the user mental state, associated with the feeling of (dis) comfort of users, and assume that a higher mental workload involves a greater discomfort [12-13]. In this context, this measure can be used in augmented human reader applications, namely for controlling text presentation characteristics such as speed or contrast.

Mental workload is an EEG based measure, which was, in our case, determined every 0.5 seconds, in one second segments. It is estimated by the ratio of the spectral power in two specific EEG frequency bands, also known as rhythms: beta (13-30Hz), related to mental activity, and alpha (8-13Hz), related to the mental rest.

The paper focuses on the use of mental workload, determined in real time from the EEG signals of users, to control the speed of text presentation. When the mental workload is high, the presentation of the text should be slowed in order to reduce the discomfort of reading, when it is low, the presentation of the text must be accelerated to exploit more efficiently the available mental resources. The ultimate goal is to develop more complex applications that can adapt other text characteristics such as size, contrast or complexity to users. Other mental measures coming from neuroscience domain knowledge can also be exploited in the future.

The results of a preliminary analyzes the correlation of mental workload with the variation of relevant HCI text aspects, such as size or semantic relation, are also presented. All the experiments were performed in a conventional HCI lab, with non clinical EEG capture equipment, since we aim to address real life situations which are less controlled (comparing with clinical sets), and may imply more noise and artifact conditions.

The dissemination of portable and less obtrusive EEG capture devices, such as recent wireless and dry devices [14], will soon support the generalization of this work to more sophisticated and practical applications. Our main purpose is to design and develop usable and robust software components for integration in interactive systems that reach higher adaptation levels through this augmentation approach.

2. BRAIN SIGNALS

The hardware and software platforms used to capture and process the brain signals are briefly described in this section. Signal selection and acquisition settings were guided by two main requirements. First, the acquisition devices should be lightweight, with a limited number of channels, usable in the environment of an HCI lab. These devices, as opposed to those used in a clinical environment, do still require some level of expertise to set up an acquisition session (electrode placement and impedance adjustment) but are manageable by an experienced researcher, and are aligned with the expected evolution of less obtrusive and more portable acquisition devices.

Second, strict synchronization requirements as need by ERP (Event Related Potentials) are not used. The objective is to design reading tools that adapt to the variation of mental activity, and therefore we assume that the analysis should focus on the variation of brain waves instead of responses to discrete stimuli. The latter features (ERPs) are actually the leading source of data used in BCI (Brain Computer Interfaces) [6-8], but the former analysis is better suited for use with coming lightweight devices such as EMOTIV (http://www.emotiv.com). This focus leads to the choice of the mental workload that is determined using brain rhythms (alpha (α) and beta (β) only).

2.1 Signal Acquisition

All the experiments were performed in a conventional HCI lab, using a digital 16 channels system, named MindSet-1000 [15]. Each channel is connected through a pure tin sensor (electrode) to an Electro-Cap International cap made of elastic fabric. The capture was performed at 256Hz using referential electrodes placed on ear lobes.

All instructions indicated by suppliers and EEG technicians [9] were followed. These included: brushing the hair with a timber hairbrush (to reduce static), cleaning the skin with alcohol in places where the electrodes are applied, connect users to ground (to reduce electric noise) and maintain a balanced impedance and below 5kΩ across the electrodes through application of conductive gel.

Our cap assures a standard electrode disposition through a subset of the International 10-20 system norm. Under this norm, each channel is placed in a standardized position.

2.2 Signal Processing and Analysis

The signal processing sequence applied to the brain signals is shown in Figure 1. This is supported by EEGLib framework [9], an object oriented toolkit implemented by us in C++ and MatLab. This sequence is performed using one second EEG segments, overlapped by half a second. The mean amplitude (of the considered channels) is first used to identify and discard possible corrupted segments. Lower and upper thresholds are used to validate whether the amplitude meets regular characteristic EEG ranges, which usually go from 10 to 100 μV

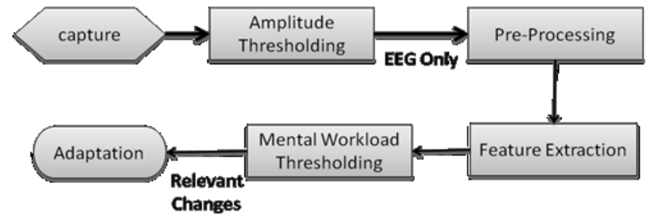

Figure 1. Signal processing and analysis sequence .

The remaining segments are then pre-processed to reduce non EEG artifacts (e.g. electrical noise). This includes a notch filter to attenuate a narrow frequency at around 50Hz. No method has been used to reduce eye and movement artifacts, since our method should be robust enough to handle these interferences.

In the next step, each segment is transformed into a vector of features, in this case a single real value which estimates the average mental workload on all channels. Mental workload is determined by the ratio of the average PSD (Power Spectrum Density) in beta and alpha rhythms. PSD measures the energy of the signal in a certain frequency. Finally, upper and lower thresholds are applied to the variation of the mean mental workload, which is determined regarding the previous estimated value.

3. WORKLOAD ANALYSIS

The feasibility of using mental workload in reading adapted tools depends on whether it is possible to successfully relate this measure to aspects that influence reading in interfaces such as text size. As the correlation estimates the probability that there is a linear relationship between two measurements, correlation analysis can be a possible approach. In this section we briefly discuss the method and present some preliminary results.

3.1 Experimental Settings

A prerecorded EEG corpus composed of 12 experimental sessions was used. Each session included a sequence of experiments, all related with silent reading on a screen, and separated by thirty (30) second resting periods. These recordings required no prior training and were performed twice on six (6) higher educated users, three (3) women and three (3) men, ages between 20 and 40, and without relevant neurological or sight known conditions.

All texts were written in the native language, never repeated for the same user and displayed such as a slide show in a 15.4'' colored LCD screen, with a 1280x800 resolution. Users sat in a chair in front of the screen, which was set in a regular desk with about 70-80 centimeters height, at a distance between 50-60 centimeters.

At the beginning of each experiment text was displayed with Arial 21px font in a black foreground over a white background. Among these experiments, we included the following:

A) Text Size Decrease. Users read a 70 words news text, one word at a time, each lasting one second. Every ten (10) seconds the size of text decreases by 3px, varying between 21px and 3px (see the simulation in Figure 2).

B) RGB Difference Background/Text Decrease. Users read a continuous news text during seventy (70) seconds. Every ten (10) seconds the RGB difference between background and text is reduced.

Figure 2.The simulation of text size variation.

C) Inconsistent Words Occurrence. Users read a sequence of 30 related words, one word at a time, each lasting one second. After the appearance of more than three (3) and less than five (5) words, the word to be displayed is replaced by another, unrelated with the topic.

3.2 Correlation Analysis and Discussion

The results of the workload correlation analysis are presented in Table 1. In experiments A and B the mental workload was correlated with the variation of the aspect considered in each experimental step, regarding the initial conditions:

$$\text{aspect\_variation}(\text{step}_i)=\text{aspect}(\text{step}_i)/\text{aspect}(\text{step}_1)$$

We considered an experimental step a recording segment where the text conditions remain constant. The same method was applied to experiment C, but regarding the occurance order of inconsistent words (1,2,3,..).

Experiment	Correlation Results	
Text Size Decrease	CORR	☑0,794
	PVAL	☑0,033
Backgroung/Text RGB Difference Decrease	CORR	☑0,722
	PVAL	0,105
Inconsistent Words Occurrence	CORR	☑-0,574
	PVAL	☑0,083

Table 1. Correlation of the mean workload with each aspect.

In the Table 1 each result is composed by two values: the correlation (CORR) and the probability of this being null or Pearson-value (PVAL). When CORR is close to 1 or -1, it is considered to be very strong, which identifies a relation; when is 0, it doesn't exist. PVAL estimates how probabilistically relevant is CORR, and desirably it should be less than 0.05 or at least 0.1. All values that meet the thresholds are marked with ☑; a grayed ☑ indicates that hresholds are barely met.

The trend shows that the mental workload, measured from users brain signals, can be correlated with these aspects, but these results cannot be yet generalized;a larger corpus is required. This is promising and helps to support the feasibility of designing and developing tools and applications using such measures to augment users' reading conditions.

4. WORKLOAD ADAPTATION TOOLS

We first developed a visualization tool, which we named *EEGWorkloadViewer* and whose overall aspect is presented in Figure 3.

This shows the variation of mental workload graphically from a prerecorded file, and allows verifying and tuning the processing sequence previously proposed. It also supports setting parameters such as all thresholds, the size of EEG segments, the channel selection and the colors used in the chart.

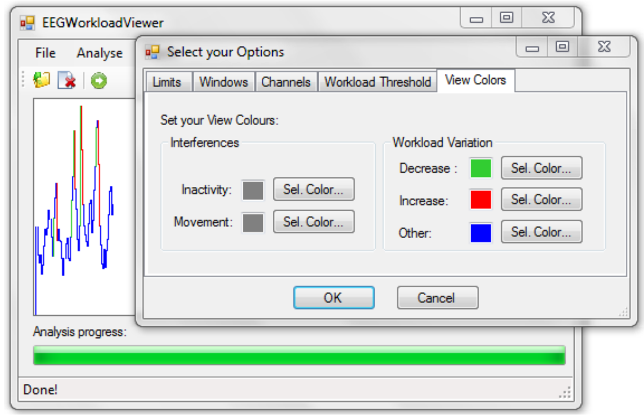

Figure 3. *EEGWorkloadViewer* application.

EEGWorkloadAdapter (see Figure 4) and *EEGWorkloadScroller* are two prototypes that adapt in real time the speed of a text presentation using the variation of mental workload. The first shows a text line by line; the latter, scrolls it horizontally.

Figure 4. *EEGWorkloadAdapter* application.

In the Figure 4, 6 channels were used: four in the frontal lobe (F3,F4, F7 and F8), two in the occipital (O1 and O2). All are common with EMOTIV device that we intend to use soon. It allows setting the parameters similarly to *EEGWorkloadViewer*, and also showing the variation of mental workload graphically.

When the variation of the mental workload (relative to previous registration) increases (above a threshold) the text presentation is slowed down to reduce the discomfort of the user; when it decreases (bellow a threshold) the text presentation is accelerated. The curves in Figure 5 show the adaptation of the velocity regarding the measured mental workload in *EEGWorkloadAdapter*.

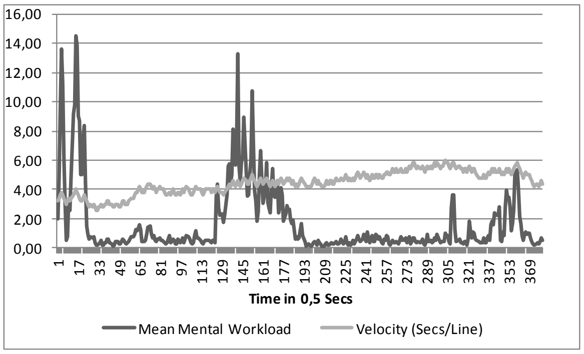

Figure 5. *EEGWorkloadAdapter* velocity adjustment and mental workload for a news text with 62 lines.

The lighter gray line shows the velocity used to change text lines; the darker, the mean mental workload. As one can see, EEG was corrupted twice by movement (around the beginning and also around 145) and in this case these segments where ignored.

Preliminary tests make us anticipate that these applications will be useful to users, but require further adjustments. Users' reading comfort in these applications must be fully assessed regarding a constant speed presentation. This requires performing more complete tests with a representative set of users.

5. CONCLUSIONS AND FUTURE WORK

This paper presented some tools that use mental workload − a measure determined from user's brain (EEG) signals, to adjust text presentation, in particular its speed.

We presented the results of a preliminary study about the correlation analysis of mental workload and the variation of aspects such as text size or RGB difference between text and background. Although these cannot be still generalized (because of the size of the corpus), they were promising towards of the existence of such relation. This helps suporting the feasibility of the proposed goal: designing and developing tools that integrate brain signal based measures to augment users reading conditions.

Based on this assumption prototype applications that adjust text presentation speed in real time using the mental workload determined from the user brain signals. One of these applications shows a text line by line, the other, scrolls it horizontally.

Preliminary tests make us anticipate that these applications will be useful to users, but require further adjustments. Users' reading comfort in these applications must be fully assessed regarding a constant speed presentation. This requires performing more complete tests with a representative set of users.

In the future we hope to design more sophisticated applications including reading interfaces that can adapt to other text characteristics such complexity, or use other mental measures coming from neuroscience domain knowledge. Additionally, these can also exploit the use of more portable and dry electrodes capture devices.

6. ACKNOWLEDGMENTS

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