Influence of mental fatigue on P300 and SSVEP during virtual wheelchair navigation

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***Abstract*— The aim of this paper is to investigate the influence of mental fatigue on Positive 300 (P300) and Steady State Visual Evoked Potentials (SSVEP) during virtual wheelchair navigation. For this purpose, experimental protocols were setup in order to induce mental fatigue, P300 and SSVEP. Next, the correlation between mental fatigue and P300/SSVEP parameters were investigated. At the end, the best correlated features from both modalities were used as inputs for three classification techniques. Depending on the subject samples (healthy vs palsy), The best overall classification rate reached 80% for P300 modality. The results of this investigation constitute the first steps towards an anticipatory system that can assist the wheelchair driver during navigation, depending on his mental fatigue level.**

I. INTRODUCTION

Controlling a powered wheelchair can become a very hard task for elderly persons or those with heavily reduced Physical/mental abilities. Consequently, shared paradigms were introduced to enhance navigation security as it gives to the user more or less control on a need basis [1]. Such a paradigm was introduced in many studies to conceive a suitable wheelchair according to the subject pathology. Navigation enhancement was ensured either by adding new on board sensors [2], Global Positioning System (GPS)[3], or by assessing the user's performance by the mean of motor activities such as haptic feedbacks [4], or even by introducing new modalities[5]. Although these approaches showed very good results, they still centered on the wheelchair system and hold a delayed aspect; the wheelchair corrective behavior is generated after that the user commits an error during navigation.

In the present paper, the proposed shared control is rather based on human factors and holds an anticipatory aspect i.e. through human factors, the decision system triggers to the suitable navigation mode: manual, semi-autonomous and autonomous which reflect the subject physical ability to command his wheelchair. To the best of our knowledge, anticipatory human factors-based wheelchair navigation projects are not so many. In fact, experts, doctors, occupational therapist and psychologists, suggested that human factors have an important impact on navigation safety such as mental fatigue and emotions. In the current study, mental fatigue are investigated and measured through its influence on brain activity.

Performing a cognitively demanding task for an extended period of time induces a state that is labeled mental fatigue [6]. The latter is a common in everyday life and becomes clear in compromised task performance, subjective feelings of tiredness, and the accompanying unwillingness for further mental effort [7]. It shows specific perturbations on its ElectroEncephalographie (EEG) patterns, which can influence its role as a source of control. We investigate in this article two common sources of control namely: P300 and SSVEP.

The use of infrequent visual, auditory or somatosensory stimuli evokes a positive peak over the parietal cortex at about 300 ms after the stimulus presentation. This is referred as P300. Its response is elicited by the "oddball" paradigm, in which repeated stimuli are presented to the user, and there is a specific target stimuli that rarely occurs among the more common non-target stimuli. Each time the target stimulus is presented to the user, the P300 response appears in the EEG signals. A typical P300 is characterized by the following parameters:

Maximum amplitude: the maximum magnitude of the generated pick it varies depending on the sensor and the region where the P300 occurred.

Minimum amplitude: the minimum magnitude reached before that the signal stabilizes.

Latency: the time that separates the onset time of the stimulus and the appearance of the P300. Usually, this value is approximately 300 ms.

Period: the needed time for the EEG signal to stabilize after reaching its P300 maximum and minimum amplitudes.

On the other hand, Steady-state Visual Evoked Potential (SSVEP) is a brain response to visual stimulus flashing with certain pattern. It occurs when the retina is excited by a visual stimulus presented at frequencies ranging from 3,5 Hz to 75 Hz [12], where a continuous or oscillatory response is generated by the brain. SSVEP-based BCI uses flashing lights at various frequencies. Thanks to its excellent signal-to-noise ratio and relative immunity to artifacts, SSVEP has become one of the commonly used sources of control. Moreover, it has the advantages of better accuracy, high information rate and short even no training time is required [13]. A typical SSVEP signal, can be processed by the study of EEG spectral power over band wave frequencies : δ (up to 4 Hz),θ (4Hz-8Hz), α (8Hz-13Hz) β (13Hz-30Hz) and γ (30Hz-100Hz).

This paper is divided into 3 major parts; in section 1,

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978-1-4244-7929-0/14/$26.00 ©2014 IEEE

we will expose the environmental setup and the procedure adopted to induce mental fatigue, P300 and SSVEP. In section 2, a statistical study will investigate the correlation between P300/SSVEP parameters per sensor and the fatigue level rated by subjects in each trial. In section 3, three classifications techniques were used in order to compare the viability of the two modalities.

II. Mental fatigue, P300 and SSVEP induction

A. Materials

As the experiment targets wheelchair navigation, an Invacare Storm 3G Ranger X branded wheelchair is used. Equipped with joystick, encoders were added to its wheels so the wheelchair velocity can be digitized and treated. Those can be useful to control a virtual world projected on a 180 degrees panoramic screen to help the immersion of the user in the world. EEG signals were recorded using an Emotiv Epoc headgear with 16 sensors at a sampling rate of 128Hz. The virtual world was programmed using reality factory engine used generally for video games conception. The distance between the wheelchair and the screen is 2 meters.

B. Experimental setup

The P300 virtual world consists of a hallway in which, the user has to navigate from point A to point B placed respectively at the start and at the end of the room. This being said, Three parameters were modified in each navigation scenario: luminosity (low, medium, high), number of obstacles (low, medium, high) and obstacles velocity (no velocity, low, medium, high) The combination of all cases results in 36 scenarios. the subject has to fill two missions; the first one is to be able to navigate from the starting point A to the goal point B by avoiding obstacles (either static or moving). In the second part, and in order to induce P300, each time the subject reaches the point B, a set of flickering pictures is displayed (fruits, vegetables and objects). This constitutes the time zero of the P300 waveform recording. Before starting of each scenario, an informative message is displayed with the stimulus that subject must reach to go to the next level. The onset of the target stimulus marks the beginning of the measurement of P300 latency parameter and the user has to hit it in order to activate the next scenarios. The latter are chosen randomly in a way, the learning process is inhibited as the subject don't have any idea about the modified parameter. In the other hand, for SSVEP experiment, the same hallway was used as far as the user is told navigate from point A to point B placed respectively at the start and at the end of the room. two parameters were modified in each navigation scenario: number of obstacles (low, medium, high) and obstacles velocity (no velocity, low, medium, high). The combination of all cases results in 12 scenarios. To induce SSVEP, flashing lights were placed on the hallway with a flashing frequency of 10 Hz.

C. Procedure

Ten subjects (with two suffering from cerebral palsy) took part in the experiment. they signed a consent form that explains the experiment goals and steps. After sitting comfortably in the wheelchair, they were given a set of instructions informing them of the experiment protocol and the meaning of the different scales used for self-assessment. An experimenter was also present there to answer any questions. After the sensors were placed and their signals checked, the participants performed a practice trial to familiarize themselves with the system. Next, the experimenter started the physiological signals recording. For the investigation of the correlates of the subjective ratings with the EEG signals, the EEG data was common average referenced, down-sampled to 128 Hz. Eyes artifacts were removed with Blind Source Separation technique (BSS). The signal recorded from the first five seconds of each trial was extracted as baseline. From which amplitudes (maximum and minimum) were averaged yielding to minimum and maximum reference amplitudes. Those were then subtracted from the trial amplitudes, conceding the change of amplitudes. For latency and period, those are compared to the reference mentioned by literature (300ms and 600ms). For each subject, the input measures matrix M and fatigue matrix F are initialized as follows:

$$M = \begin{pmatrix} m_{1,1} & \dots & m_{1,56} \\ \vdots & \ddots & \vdots \\ m_{36,1} & \dots & m_{36,56} \end{pmatrix} \quad (1)$$

$$F = \begin{pmatrix} f_1 \\ \vdots \\ f_{36} \end{pmatrix} \quad (2)$$

where : $m_{i,j}$ is the measure associated to the trial i and variable j defined by the combination of the parameter $par \in \{min, max, lat, per\}$ per sensor $s \in \{AF_3, AF_4, O_1, O_2, P_7, P_8$ $,F_3, F_4, T_7, T_8, FC_5, FC_6, F_7, F_8\}$ resulting in 56 possible crossings. f_i is the fatigue rating given by the subject in the i^th trial. We computed the Spearman correlated coefficients between the power changes and the subjective ratings, and computed the p-values, (p). The Spearman coefficient is calculated as follows:

$$p = 1 - \frac{6 \sum d_i^2}{n(n^2-1)} \quad (3)$$

where : d_i is defined as $d_i = x_i - y_i$ in each observation, x_i and y_i are the ranks of the raw scores $X_i = m_{i,j}$ and $Y_i = f_i$ and n is the number of samples. This was done for each subject individually and, assuming independence, the 10 resulting p-values per sensor and power were then combined to one p-value via Fishers method:

$$\chi^2 = -2 \sum_{i=1}^{k} log_e(p_i) \quad (4)$$

where : p_i is the p-value associated to the subject i. While $k = 10$ is the total number of subjects in this experiment.

For SSVEP experiment, the same procedure is applied with the introduction of flashing lights and modification of obstacles and luminosity parameters. For correlation study, brainwave signals amplitudes per sensor were used as features which results in 70 possible crossings.

III. Correlation between P300/SSVEP parameters and subjective ratings

Before proceeding to the results presentation, the subjects were gathered in two samples: the healthy sample which involves all healthy subjects, the pathological sample which contains our two palsy ones. from now on, the reported results of the applied techniques will present the average of each sample individually and the overall classification rate for the combined samples as we report the combined F-score (in percentage), based on the precision and recall measures. For P300, The results are summarized in Table I and Fig. 1 show the (average) correlations with significantly ($p < .05$) correlating electrodes highlighted.

TABLE I
THE ELECTRODES FOR WHICH THE CORRELATIONS WITH THE SCALE WERE SIGNIFICANT ($p < .05$) FOR EACH CONSIDERED PARAMETER

Parameters			
Maximum	Minimum	Latency	Period
O_1 0,01596** O_2 0,04556* T_8 0,01214**	-	-	F_3 0,03811* F_4 0,01922** FC_6 0,03136* O_1 0,01717** O_2 0,021558*

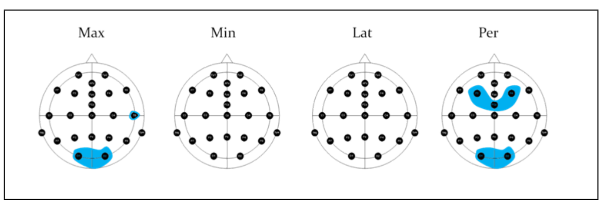

Fig. 1. Mean correlations over subjects between fatigue ratings and P300 components

For minimum and latency, no correlation was found between them and the subjective ratings ($p > .05$). This is due to the fact that the minimum is considered as response phenomena so that the signal could reach its normal state and it's not related to fatigue as well as for latency, this could be justified by the fact that latency depends on the presented stimulus which was the same in all experiments. This was also reported in many studies (see for example [14]). While other studies [15] have stated that the latency depends on the complexity of the visual stimulus presentation, this is not the case for our experiment where the same picture was used. For maximum, it can be noticed that the latter occurs especially in the occipital region, thus over visual cortices. The latter showed the strongest correlations ($p =$ .01). This is due to the fact that the presented stimuli are of visual nature. Notice also that maximum amplitude of temporal sensor T_8 correlates with subjective ratings which can be explained by the fact that temporal lobe interprets the meaning of visual stimuli and establish object recognition. In fact, the ventral part of the temporal cortices appears to be involved in high-level visual processing of complex stimuli such as faces and scenes. Anterior parts of this ventral stream for visual processing are involved in object perception and recognition[17]. In the other hand, for SSVEP, the results are reported in table II and Figure 2 show the (average) correlations with significantly ($p < .05$) with correlating electrodes highlighted.

TABLE II
THE ELECTRODES FOR WHICH THE CORRELATIONS WITH THE SCALE WERE SIGNIFICANT ($p < .05$) FOR EACH CONSIDERED PARAMETER

Parameters				
δ	θ	α	β	γ
-	-	O_1 0,01755** O_2 0,01832** P_7 0,0354* P_8 0,032*	O_1 0,0335* O_2 0,045*	-

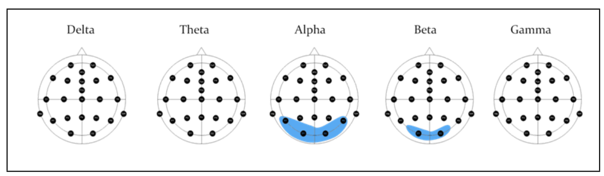

Fig. 2. Mean correlations over subjects between fatigue ratings and SSVEP components

For the band waves δ, θ and γ, no correlation was found between them and the subjective ratings ($p > .05$). This can be explained by the fact that the frequency of the flashing lights is 10Hz; as a result, response frequency is more prominent in the bands close to the stimulus frequency of presentation or to its harmonics which is not the case for the mentioned band waves. For α and β, it can be noticed that the latter occur especially in the occipital region, thus over visual cortices. The latter showed the strongest correlations ($p = .01$). This could be explained by the fact that the presented stimuli are of visual nature. Also, as the presentation frequency was fixed to 10Hz, the principal response frequency and its second harmonic are localized in the frequency bands ranging from 8Hz to 29Hz which encloses the α and β waves. This also explains the fact that α waves show the strongest correlations especially for O_1 and O_2. It could be noticed also that parietal lobe of the brain (P_7 and P_8) show a good correlation with fatigue; The parietal lobe plays important roles in integrating sensory information from various parts of the body, knowledge of numbers and their relations and in the manipulation of objects. Its function also includes visuospatial processing.

IV. CLASSIFICATION

The best correlated features were used as inputs for three classification techniques : Linear Discriminant Analysis (LDA), Multi Layer Perceptron (MLP) and Support Vector Machine (SVM). The results for healthy and palsy subjects are summarized in the following tables:

TABLE III
CLASSIFICATION RATE FOR P300 MODALITY

Technique	Classification rate		
	Healthy	Pathological	All
SVM	80%	74%	77%
LDA	82%	76%	79%
MLP	83%	77%	80%

TABLE IV
CLASSIFICATION RATE FOR SSVEP MODALITY

Technique	Classification rate		
	Healthy	Pathological	All
SVM	85%	65%	75%
LDA	88%	68%	76%
MLP	86%	64%	75%

For P300, the results show that MLP has the best classification rate with 80%. LDA (79%) presents, generally, good results as well as MLP. SVM obtained lower than MLP and LDA but the difference is neglected. In this case, two observations can be given; The number of palsy subjects is relatively low (only 2), thus there is no noticeable differences in classification rates as they are relatively low. The overall number of subjects is ten, the classification rate can be acceptable as it could be more enhanced by adding more subjects, thus enlarging the database, and providing more learning time. One of the subjects was excluded from this study due to his familiarity with video games; in fact, he was able to finish all the scenarios without being affected with fatigue which led to a very low rating scale over all experiments while for the others, the average ratings were relatively balanced. While for SSVEP, the results show that LDA has the best classification rate with 76%. MLP presents, generally, good results as well as SVM (75%). SVM and MLP were lower than LDA but the difference is not very big. The classification rate is not good enough due to many explanations; the number of subjects isn't many as it could form a good database which is also the case for the number of trials. Despite that, the classification rate could be acceptable for such conditions and may give better results if the experiment involved many subjects and many trials. There is a big difference in classification rate between healthy and pathological samples ; the latter present a very bad performance as only two subjects are not sufficient to train the used techniques as well as the number of trials per subject in case of SSVEP (12 trials) is lower than those of P300 (36 trials).

V. CONCLUSION AND PERSPECTIVES

The lack of sufficient number of palsy subjects makes it very difficult to confirm whether EEG could be reliable or not although for healthy users the results are encouraging and could be enhanced by enlarging recordings database. This being said, EEG must be compared with other physiological sensors such as Electromyography (EMG), Electrocardiography (ECG) and skin temperature; a pilot study could reveal if EEG could be integrated in a fatigue detection bloc solely, or does it require to be coupled with other sensors. Moreover, P300 and SSVEP were studied individually. The combination between them could offer more interesting results by using fusion techniques such as possibilistic or evidential theories. The combination of mental fatigue with other human factors such as emotions could be very affordable and contribute to the enhancement of wheelchair navigation.

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