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EFFECT OF FATIGUE ON SSVEP DURING VIRTUAL WHEELCHAIR NAVIGATION

[1,2]HACHEM A. LAMTI, [2]MOHAMED MONCEF BEN KHELIFA, [1]ADEL M. ALIMI1, PHILIPPE GORCE

[1]National School Of Engineers In Sfax, Tunisia, Research Group On Intelligent Machine (REGIM) Laboratory

[2]South University, Toulon-Var, France, Bio-Modélisation Et Ingénierie Des Handicaps (Handibio) Laboratory

E-mail: [1]hachem.lamti@ieee.org , adel.alimi@ieee.org, [2]khelifa@univ-tln.fr ; philippe.gorce@univ-tln.fr

ABSTRACT

The goal of this study is to investigate the influence of fatigue on Steady State Visual Evoked Potential (SSVEP) during virtual wheelchair navigation. For this purpose, an experimental environment was set based on modifiable parameters (luminosity, number of obstacles and obstacles velocities). A correlation study between SSVEP and fatigue ratings was conducted by the mean of spectral analysis. Finally, the best correlated parameters are presented for a classification using three algorithms which are MLP (Multi Layer Perceptron), LDA (Linear Discriminate Analysis) and SVM (Support Vector Machine). Those findings can help us in order to design suitable gaze/brain based wheelchair navigation.

Keywords: *SSVEP, mental fatigue, virtual navigation, wheelchair*

1. INTRODUCTION

Severely disabled people find it hardly possible to control a powered wheelchair using conventional joystick. For this purpose, shared paradigms were introduced to enhance wheelchair navigation; the basic idea is to give the user more or less control on a need basis [21]. This paradigm was integrated in many projects in order to conceive a suitable wheelchair according to the subject pathology. Vander poorten et al. [22] setup a bilateral communication channel between the wheelchair controller and the user based on haptic feedback; through the on-board sensors recordings, the local map of the wheelchair environment was rendered. Then haptic collision avoidance and haptic obstacle avoidance algorithms were introduced to help the user to maneuver successfully the wheelchair backwards inside an elevator. Urdiales et al. [23] proposed the construction of profile-based wheelchair navigation.

The prototype user profile was extracted using real traces clustered to determine the average behavior expected from the wheelchair user in order to cope with real situations. This system confirmed its efficiency on 18 volunteers affected by left and right brain stroke. Other studies, such that of Ren et al. [24], tried to introduce a map matching based on Global Positionning Systems (GPS). They also proposed an alternative to deal with difficulties faced by GPS during navigation such as poor satellite availability, by introducing a fuzzy logic-based algorithm to perform matching in sidewalks. Our previous study [25] proposed a new approach based on combining the user's gaze and mental state in order to assess wheelchair navigation performance in comparison with a standard gaze-based navigation. The results confirmed that the system performance was better using the combined modalities.

These projects focused mainly on modifying the wheelchair system either by adding new on board sensors such as GPS, cameras… either by assessing user's performance by the mean of motor activities such as haptic feedbacks which is centered on the wheelchair system and holds a delayed aspect; the correction of the navigation is generated after an error was committed which can be fatal in some cases.

In this paper, the proposed shared control is rather centered on human factors and holds an anticipatory aspect; a preventive action is taken before that the user commits an error; for example in the case where the user is highly tired, the system takes a full navigation control. To the best of our knowledge, projects dealing with human factors-based wheelchair navigation are not so many. In fact, during the exchange with doctors,

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occupational therapist and psychologists, many human factors could influence wheelchair navigation such as mental fatigue and emotions. In the current study, mental fatigue are investigated and measured through mental activity.

From clinical perspective, performing a cognitively demanding task for an extended period of time induces a state that is labeled mental fatigue [9]. 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 [10].

However, it is not well understood scientifically because it is a complex multidimensional phenomenon: It includes changes in motivational, mood, and cognitive processes [11]. Mental fatigue has been found to result in a reduced goal-directed attention [12], a decreased effectiveness in selective attention [13] and an increased difficulty in dividing attention [14]. Generally, the study of mental fatigue is gathered through its impact on brain control sources such as Event Related Synchronization/Event Related Desynchronization (ERD/ERS), Positive300 (P300), and Steady State Visual Evoked Potentials (SSVEP). Thanks to its excellent results dealing with signal-to-noise ratio and its immunity to artifacts, SSVEP is investigated in this paper.

Since mental fatigue is very important, the main goal of this study is to setup a fatigue detection module that enables the wheelchair system to account for the user's mental fatigue. This information could be exploited later to control a wheelchair navigation modes; if fatigue level is low then the system considers that the user is able to drive his wheelchair by his own. Otherwise, if it detects that the user's fatigue level is medium, it presents some alternatives to the driver to enhance his navigation safety such as obstacle avoidance, motion planning… but if mental fatigue reveals to be high, the wheelchair system will switch to autonomous mode, where the wheelchair deals autonomously the whole navigation process.

Steady-state Visual Evoked Potential (SSVEP) is a brain response to visual stimulus that flashes with certain pattern. When the retina is excited by a visual stimulus presented at frequencies ranging from 3,5 Hz to 75 Hz [1], a continuous or oscillatory response is generated by the brain. The latter appears at the same or multiple frequency of the visual stimulus. SSVEP-based BCI uses lights that flash at various frequencies. These systems can be used for remotely controlled devices such as wheelchairs which can be useful for severely disabled people [2]. SSVEP provides a means to characterize preferred frequencies of neocortical dynamic processes, SSVEP is generated by stationary localized sources and distributed sources that exhibit characteristics of wave phenomena.

In Brain Computer Interface systems (BCI), many modalities were introduced such as P300, motor imagery, slow cortical response… SSVEP-based BCIs have the advantages of better accuracy, high information rate and short even no training time is required [3]. Yet it suffers from many drawbacks, such as risk of high fatigue and can induce seizure in photosensitive people.

In SSVEP-based BCI, many issues should raise such as:

- Robustness: misclassification, errors can be very annoying and in some cases very crucial especially in a wheelchair navigation context. This is why high accuracy is needed.
- Safety: flashing rate/pattern, size and color of the stimulus is very influent. It can cause an adverse effect, such as seizure, high fatigue [4]. The best chosen frequency ranges between 9 Hz and 15 Hz, with the use of white color and circular shape [5].
- Classification algorithms: most SSVEP algorithms were developed in frequency domain with the use of Welch method [6] to extract features for classification. Those algorithms are generally based on the first or even the second harmonics of the presentation frequency [7]. However, some others argue that EEG signal may contain important information about the flashing stimulus as well as the enhancement of the classification algorithm [8].

To the best of our knowledge, SSVEP was introduced as a source of control but never used to assess fatigue. This being said, the goal of this article is to study the eventual correlation between SSVEP and fatigue. Also all mentioned experiments are based on the presentation of static stimuli (flashing lights or checkerboard…) but never used in a context of virtual wheelchair navigation. The Brain Eyes WHEELchair Interface (BEWHEELI) project is the extension of former projects based on computer assisted vision [15] and motion planning [16]. It has as purpose to combine two modalities which are gaze and brain signals in order to control a powered wheelchair. This being said, the migration from joystick-based commands to brain/gaze should follow many steps.

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Furthermore, the detection of fatigue is very important in a way that, for security purposes, it could make the wheelchair switch to an autonomous mode when the user is highly tired. This article assesses the impact of fatigue on SSVEP parameters.

This article is divided into three major parts; in the first part we describe the virtual environment and hardware equipment needed for the experiment setup. In the second part, a statistical analysis is provided to investigate the correlation between subjects' ratings and the EEG signals. In the third part, the results of the different correlations and classification techniques are investigated. Finally, in the conclusion we provide the shortages of the experiment and the next steps to be taken.

2. EXPERIMENTAL ENVIRONMENT

Our experience consists on measuring the user mental fatigue while navigating in the virtual environment. This will supply a reference database in order to assign to each fatigue level class a temporal EEG data profile and thus applying different techniques offline before implementing an online fatigue detection module. Our ground-truth is the user mental fatigue rating: in fact, from a scale of 10, the given rating is classified into "low", "medium" or "high" fatigue. In this case, the association between signal features and fatigue is deduced from the correlation between the EEG activities (and especially brainwave signals) in each visualized SSVEP signal with the rate given by the subject at the end of the experiment.

1. Experimental Setup

a. Hardware framework

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. As to calculate his points of gaze (POG), an ASL EyeTrac 6 eye tracker was placed in front of the user. A specific algorithm was used for system calibration and for dividing the screen into command zones. Alternatively, the Emotiv Epoc headgear is added to record brain activity.

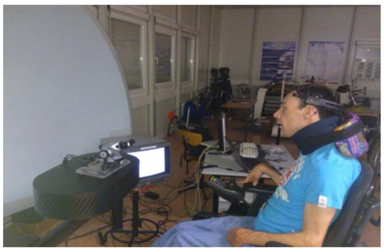

Fig. 1: Virtual World Wheelchair Navigation

b. Virtual world

The virtual world was developed using Reality Factory engine [17]. It 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, 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. The scenarios are chosen randomly in a way, the learning process is inhibited as the subject don't have any idea about the modified parameter.

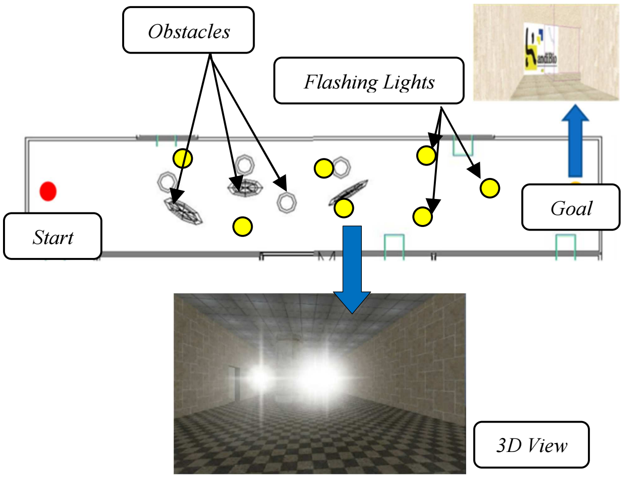

Fig. 2: The Navigation Scenario With Flashing Lights Integrated

The gaze calibration was ensured using nine-point calibration algorithm. For each iteration, a special point is projected on the screen and the user has to look on it. Meanwhile, the system estimates the corresponding points of gaze based on the feature vector defined as the distance between the central point of the corneal reflection and the central point of the pupil reflection. After success of the operation, the screen is divided into command zones. Those are respectively, left, right and idle. A min-right/max-left algorithm was implemented for

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this purpose. The idea is to ask the user to look straight ahead on the screen, from the points of gaze concentration; the maximum point position and the minimum are recorded. Then, when looking to the right the minimum point is recorded while the same operation is processed but using the maximum point position for left look. The zone separations are calculated from given points as follows:

$$X_{zone\_left} = \frac{x_{point\_center} - x_{point\_max\_left}}{2} \quad (1)$$

$$X_{zone\_right} = \frac{x_{point\_min\_right} - x_{point\_center}}{2} \quad (2)$$

Where X_{point_center} is the X coordinate of the center point of the points of gaze when the user looks straight. $X_{point\_\max\_left}$ is the X coordinate of the maximum point of the gaze concentration when the user looks left and $X_{point\_\min\_right}$ is the X coordinate of the minimum point of the gaze concentration when the user looks right. An example of the operation can be found in the Fig. 3

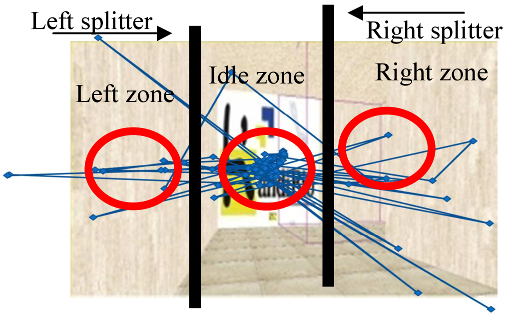

Fig. 3: Example Of Implementation Of The Min-Right/Max-Left Algorithm

It's undeniable that a wheelchair is considered as wheeled robot, this introduces some important differences. In fact, because a robot is provided with a communication protocol, it's easy to send each time the needed velocity to reach. This is not necessarily the case for a wheelchair which is considered as an analogical device. In a real wheelchair, the user has to move the joystick forward to accelerate, and backward to decelerate. In the virtual world, as it's basically a video game, to move forward or backward or to turn left or right the user has to push keyboard keys.

The idea is to link both systems by simulating keyboard keys in the virtual world each time the user moves the joystick forward or backward. The same idea is applied for turning left and right based on the user's points of gaze and command zone detection.

2. Procedure

Ten subjects took part in the experiment. The results were studied depending SSVEP parameters. After sitting comfortably in the wheelchair, they were given a set of instructions to read, informing them about 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. The calibration process starts by asking the user to look at the nine points of the screen to estimate his points of gaze. After detecting the command zones, the scene is projected on the panoramic screen. The way to command the wheelchair in the environment is explained and the plan of the maze is displayed.

The user is asked to navigate from the starting point A to the ending point B where a specific visual stimulus is displayed. In each scenario, one of the two parameters (obstacles and velocity) is modified while keeping the flashing lights in each scenario. After the projection of the scene, the subject can start navigation using gaze to turn left and right and the wheelchair joystick to move backward and forward. At the end of each trial, the subject has to give his assessment on a fatigue scale (ranging from 0 to 10).

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 first five seconds of each trial was extracted as baseline. The frequency power of trials and baselines between 3 Hz and 64 Hz were then extracted using Welch's method with window of 64 samples. The baseline power was then subtracted from the trial power, yielding the change of power. The latter are averaged over the frequency bands of delta (1Hz and 3Hz), theta (4Hz and 7Hz), alpha (8Hz and 13Hz), beta (14Hz and 29Hz) and gamma (30Hz and 60Hz). For each subject, the input measures matrix M and fatigue matrix F are initialized as follows:

$$M = \begin{pmatrix} m_{1\,1} & \cdots & m_{1\,70} \\ \vdots & \ddots & \vdots \\ m_{12\,1} & \cdots & m_{12\,70} \end{pmatrix} \quad (3)$$

$$F = \begin{bmatrix} f_1 \\ \vdots \\ f_{12} \end{bmatrix} \quad (4)$$

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Where $m_{i\,j}$ is the measure associated to the trial i and variable j defined by the combination of band wave signals w ∈ {δ,θ,α,β,γ} 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 70 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:

$$p = 1 - \frac{6\sum d_i^2}{n(n^2-1)} \qquad (5)$$

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 [39], the 10 resulting p-values per sensor and power were then combined to one p-value via Fisher's method:

$$\chi^2 = -2\sum_{i=1}^{k} log_e(p_i) \qquad (6)$$

Where p_i is the p-value associated to the subject i.

While k is the total number of subjects equals to 10 in this experiment.

3. Classification

The best correlated sensors/parameters were kept for classification. And for this purpose, three classification algorithms were used namely: Support Vector Machine (SVM), Linear Discriminate Analysis (LDA) and Multi Layer Perceptron (MLP). In a supervised learning, given the feature vector as input, the output could be one of the three studied fatigue levels (Low Fatigue, Medium Fatigue, and High Fatigue).

a. Linear Discriminate Analysis (LDA)

The LDA is a linear combination of variables. They are presented in the form of:

$$\mathrm{y_{km}} = \mathrm{u_0} + \mathrm{u_1 X_{1km}} + \mathrm{u_2 X_{2km}} + \cdots + \mathrm{u_p X_{pkm}} \quad (7)$$

Where y_{km} is the value of the discriminate function for the case m on the group k as well as for X_{ikm} which is the discriminate variable X_i for the case m on the group k, and u_i are the required coefficients. This implies that the number of discriminate functions is determined by the number of considered groups.

b. Multi Layer Perceptron (MLP)

The used MLP is composed with an input layer with a size, the selected features of the input vector, a hidden layer with 20 neurons and an output layer with 3 neurons which correspond to the level of fatigue. The transfer function used is sigmoid and the database was divided into 3 sets: 70% for training, 15% for testing and 15% for validation.

c. Support Vector Machine (SVM)

SVM maps input vectors into higher dimensional space to ease classification. Then it finds a linear separation with the maximal margin in the new space. It requires the solution of the following problem:

$$\min_{w,b,\varepsilon} \frac{1}{2} w^T w + C\sum_{i=1}^{l} \varepsilon_i \quad (8)$$

$$subject\ to\ y_i(w^T\vartheta(x_i) + b) \geq 1 - \varepsilon_i,\ \text{and } \varepsilon_i \geq 0$$

Where C is the penalty parameter of the error ε_i and w is the normal vector to the hyperplane containing the training set of the instances label pairs (x_i, y_i) $i \in \{1..36\}, x_i \in R^5$ is the vector formed by the measures of the 8 parameters of the i-th trial and $y_i \in \{1,-1\}$ indicating the class to which x_i belongs, and b the offset of the hyperplane . The kernel used in this article is the Gaussian radial basis function. This could be expressed as follows:

$$K(x_i, x_j) = \vartheta(x_i)^T\,\vartheta(x_j) = e^{(-\gamma\|x_i - x_j\|^2)}\ for\ \gamma > 0 \quad (9)$$

Where $\gamma = -\frac{1}{2\sigma^2}$, σ is a free parameter called bandwidth determined exhaustively whose tuning is very critical for the good performance of the method. A search-grid cross-validation technique is used to determine C and γ [29].

3. RESULTS

1. Environmental correlation

In order to quantify the term of mental fatigue, we referred to a correlation study between mental fatigue ratings and environment parameters mainly: number of obstacles hit and duration of the trial. In fact many studies suggested the influence of fatigue

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on the navigation performance [27]. In the present experiment, the following figure presents the variation of the average of obstacles hit and durations over all participants for each trial session and explains the relationship between those parameters and fatigue scale ratings.

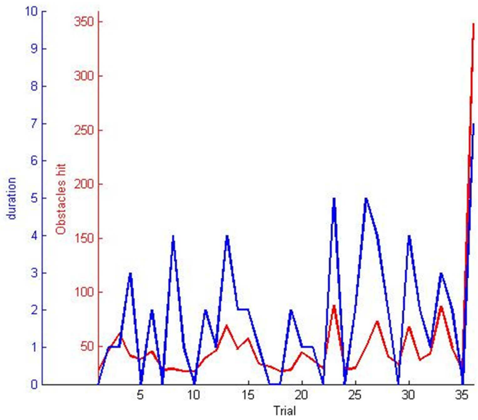

Fig. 4: (Average) Obstacles Hit And Navigation Duration Variation For The Chosen Trials

It could be noticed that number of obstacles hit and the duration of the navigation are proportional. This could be explained by the fact that if one becomes tired, he could easily hit obstacles as it affects the duration of the navigation. But other important factors could explain such a result; in some trials, obstacles are moving toward many directions with variant velocities which can make it difficult for the user to navigate with no damage. Especially in the trial 36, where the navigation time reached almost 6 minutes as well as the number of hit obstacles are 8. The same correlation study was brought to investigate the relationship between mental fatigue and environmental parameters.

Let the matrix E be the environment matrix that is formulated as follows:

$$E = \begin{pmatrix} e_{11} & e_{12} \\ \vdots & \vdots \\ e_{361} & e_{362} \end{pmatrix} \quad (10)$$

Where e_{ij} is the measure of the j th parameter ($j \in \{1,2\}$, 1= « duration » and 2= « obstacles ») in the ith trial ($i \in \{1,\cdots,36\}$).We computed the Spearman correlated coefficients between the duration, obstacles and the subjective ratings, and computed the p-values, (p) using the spearman coefficient which was explained in the equation (5).

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 $X_i = e_{ij}$ and $Y_i = f_i$ (the ith fatigue rating given in each trial). This was done for each subject. And applying equation (6), the p-values per parameter and subject were combined to one p-value that expresses, the correlation between parameter and fatigue level. The mean inter-correlations of different parameters over participants are recapitulated in the Table 1.

Table 1: Subject Inter-Correlations Between Parameters And Correlation Between Each Environmental Parameter And Fatigue

Parameter	Duration	Obstacle	Fatigue
Duration	**-**	**0.0134**	**0.024**
Obstacle	**-**	**-**	**0.019**
Fatigue	**-**	**-**	**-**

It could be observed from this table the Obstacle and duration highly correlated (p=0.0134) which is explained by the fact that an increase of the number of obstacles hit will influence the navigation time. Notice also that fatigue has a highly positive correlation with both parameters with a stronger one regarding obstacles hit (0.019). It seems that people, even when they are tired, could manage to reach the navigation goal even if the number of obstacles hit is high. This is due to the fact that in virtual navigation, in some cases, when obstacles are hit, the wheelchair gets through the wall or the pillar and doesn't stop.

The results reflect that the experiment was successful to induce mental fatigue even that some bugs on the virtual reality program biased some of the results. In some other cases, the trial on itself was repeated as the subject wasn't able to avoid obstacles they hit.

2. Correlation between fatigue and subjective ratings

The results are recapitulated in Table 2 and Fig. 5 show the (average) correlations with significantly ($p < .05$) with correlating electrodes highlighted.

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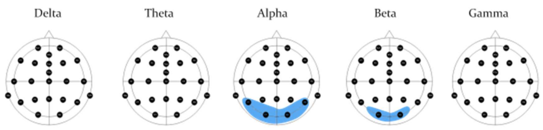

Fig. 5: The Mean Correlations Over Subjects For Fatigue Ratings With The Changes

For the band waves delta, theta and gamma, 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 Alpha and Beta, 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 Alpha and Beta waves.

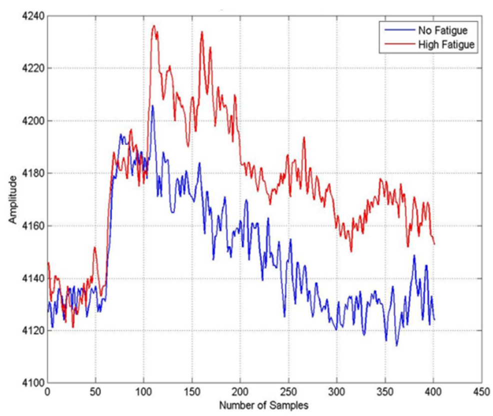

Fig. 6: Amplitude Changes Of SSVEP In The Sensor O2

The SSVEP maximum amplitude is influenced by the subject state and evolutes following many steps:

This also explains the fact that Alpha waves show the strongest correlations especially for O1 and O2. It could be noticed also that parietal lobe of the brain (P7 and P8) 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,[18] and in the manipulation of objects. Its function also includes visuospatial processing.

In the first part, the maximum amplitude increases as the user becomes more concentrated, this amplitude starts slightly to decrease as the subject becomes more and more tired. At the end, this amplitude attends its minimum as the subject is exhausted.

The results of the classification are recapitulated in the following table:

Table 3: Classification Rate Of MLP, SVM And LDA

Technique	Classification rate
SVM	75%
LDA	76%
MLP	75%

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.

4. CONCLUSION AND PERSPECTIVES

In this paper, a pilot study was conducted to assess the influence of fatigue on SSVEP over 14 EEG sensors. From the 70 overall parameters, only 5 correlate significantly with subjective ratings. Those occur essentially in the visual cortex, but found that the parietal lobe also correlates significantly in Alpha and Beta band waves while Delta, Theta and Gamma doesn't show any interesting results. As mentioned before, the goal of the current study is to seek the needed parameters to switch between manual, semi-autonomous, and autonomous wheelchair command. Another EEG component can be integrated to estimate fatigue state, is the Positive 300 (P300). In fact many studies showed the influence of fatigue on P300 (see [19] and [20]), as well as its efficiency as a BCI source of control.

For this purpose, another pilot study will be done to assess influence of fatigue on P300. Both inputs will be considered in a fusion block that plays an important role in decision making; in fact the decision issued from SSVEP can differ from the one issued from P300. The role of the fusion block is to decide whether the system has to switch to

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manual, semi-autonomous or autonomous mode depending on the user's fatigue. This can enhance the wheelchair navigation. Another approach could be established is the linking between fatigue and emotions. In fact, emotions play an important role in decision making which can affect the navigation safety and merging between fatigue and emotions can improve it further. This being said, a fuzzy logic block is being conceived to help the system merging between fatigue and emotions outputs.

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Table 2: The Electrodes For Which The Correlations With The Scale Were Significant (P < .05) For Each Considered Parameter

	Parameters						
	delta	theta	Alpha		beta		gamma
Fatigue	-	-	O_1	0,01755	O_1	0,0335	-
			O_2	0,01832	O_2	0,045	
			P_7	0,0354			
			P_8	0,032			