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Cerebral and gaze data fusion for wheelchair navigation enhancement: case of distracted users

Hachem A. Lamti†*, Mohamed Moncef Ben Khelifa‡ and Vincent Hugel†

†*COnception de Systemes Mecaniques et Robotiques (COSMER) Laboratory, South University, Toulon-Var, France. E-mail: vincent.hugel@univ-tln.fr*
‡*Impact de l'Activite Physique sur la Sante (IAPS) Laboratory, South University, Toulon-Var, France. E-mail: khelifa@univ-tln.fr*

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SUMMARY
The goal of this paper is to present a new hybrid system based on the fusion of gaze data and Steady State Visual Evoked Potentials (SSVEP) not only to command a powered wheelchair, but also to account for users distraction levels (concentrated or distracted). For this purpose, a multi-layer perception neural network was set up in order to combine relevant gazing and blinking features from gaze sequence and brainwave features from occipital and parietal brain regions. The motivation behind this work is the shortages raised from the individual use of gaze-based and SSVEP-based wheelchair command techniques. The proposed framework is based on three main modules: a gaze module to select command and activate the flashing stimuli. An SSVEP module to validate the selected command. In parallel, a distraction level module estimates the intention of the user by mean of behavioral entropy and validates/inhibits the command accordingly. An experimental protocol was set up and the prototype was tested on five paraplegic subjects and compared with standard SSVEP and gaze-based systems. The results showed that the new framework performed better than conventional gaze-based and SSVEP-based systems. Navigation performance was assessed based on navigation time and obstacles collisions.

KEYWORDS: BCI, EEG, Wheelchair, SSVEP, Navigation, Gaze, Distraction, Behavioral entropy.

1. Introduction

In recent years, there has been a massive growth in the wheelchair (manual, powered) market and is estimated to 290 million euros in 2013.[1] In France, there are 8.1 million people suffering from motor disabilities due to several pathologies (among them, 1.8 million use powered or manual wheelchair) with 195,268 in possession of manual wheelchairs. Meanwhile, powered wheelchairs shares reach approximately 10% which corresponds to a market of 19,000 electric seats. At international level, 10% of worldwide population (up to 650 million people) suffer from motor disabilities[2] among them 7% need a powered wheelchair. The market increase is estimated to 8% in France and 10% worldwide.

New wheelchairs integrate adaptive technologies and options to fit the pathology, morphology, environment and to daily and professional activities of the user.[3]

Some projects[4–7] propose new techniques (self-localization, obstacle avoidance, motion scheming, etc.) to enhance wheelchair navigation experience. However, severely disabled such as Locked-In patients, Amyotrophic Lateral Sclerosis ALS and tetraplegic... find it hardly possible (in some cases impossible) to command their wheelchairs using the aforementioned solutions either because it is not adapted to their needs or because they are forced to provide some extra workloads.[8] New trends introduced more generic modalities, among them brain-based ones.

Gaze tracking techniques can be introduced as the evolution of Electro-oculography. The latter measures the differences in bioelectric potential, resulting from retinoblastoma corneal bioelectric

* Corresponding author. E-mail: lamtihachem@gmail.com

field modulated by the rotation of the eye in its orbit. This technique is the first adopted to record clinical ocular motility and the subject of several applications in the field of disability. Since then, newer approaches were proposed such as blade technique, or those based on HIRSCHBERG principle. Due to their advantages (contact-less, no skin interference, etc.), video-based techniques are widely used in gaze-based interfaces.

Yanco *et al.*[9] proposed a semi-automatic wheelchair named Wheelesly that receives commands from a Graphical User Interface. These commands are predefined by the points of view of the user. For support of the wheelchair, it must merge the order information with the state of the environment in which it navigates (example, obstacle avoidance, wall). Despite the success of this interface and the originality of its use during that period, it is not always sure this can be the perfect choice for the user who must spend much time staring at buttons with which he must control the chair that makes its control very tedious in long-term and opposes the idea that the solution must be natural relative to the user and should not ask an additional workload for navigation.

Lin *et al.*[10] proposed an improved control wheelchair solution. A calibration algorithm is used to estimate the gaze direction in real time with a relatively low-cost architecture. The tracking system uses a camera to look for capturing images of the eye movement and seeks the pupil for an image processing program. For improving the brightness of the image, charge-coupled device cameras and a small lamp were used. Thereafter, thresholding areas $Forward$, $Backward$, $Right$, $Left$ are defined. They correspond to the forward command, backward, turn right, turn left at a constant speed and preset as well as the stop command. Once the user exceeds a definite increment for each area, the command is sent to the wheelchair. This project was tested with subjects and showed good results especially for navigation time and system efficiency.

Bartolein *et al.*[11] presented a new way to ease wheelchair control for severely disabled users via gaze control and estimating the intended motion direction. They also focused on how to distinguish between relevant and non-relevant gaze behavior so they can improve safety in wheelchair navigation. The system takes into consideration people with differences into gaze behavior like, for example, asymmetries for looking left and right by training the Hidden Markov Model parameters to their individual gaze and this was done by the mean of Baum–Welch algorithm. The wheelchair motion state was designed using a Finite State Machine based on gaze states and combined to a Sip/Puff system states which are up, down and neutral.

Brain activity can be monitored via ElectroEncephalography (EEG) technology. The latter are analyzed to detect specific patterns that can be translated into commands to control softwares or hardwares. This is defined as Brain Computer Interface (BCI). BCI systems could provide severely disabled people the optimal solution adapted to their needs: Henceforth, they do not need to provide muscular activities to generate commands.[12] To operate as a source of control, specific brain features are extracted and processed: Event Related Synchronization/De-synchronization (ERD/ERS)[13] and Evoked Related Potentials (ERP)[14] constitute the most commonly adopted techniques.

ERP are electrical potential changes in visual cortex of the brain consecutive to the presentation of external stimulus.[14] In international bibliography, two ERP derivatives were proved to be very successful in wheelchair commands: Positive 300 (P300) and Steady State Visual Evoked Potentials (SSVEP).[15] The latter are continuous or harmonic frequencies obtained when the subject focuses on a flickering stimulus with a frequency higher than 4 Hz.[16] SSVEP can be elicited and detected with relatively little training. Moreover, its Information Transfer Rate (ITR) tends to surpass BCI systems as the triggering process between different states can be ensured robustly and easily by external stimuli which is not the case for other techniques such as ERD/ERS.[17,18]

As mentioned by ref. [19], SSVEP can be elicited by three frequency ranges: low (4–12 Hz), medium (12–30 Hz) and high (>30 Hz). While the first two are not recommended as they could cause epileptic seizures and visual fatigue, the generated SSVEP from the higher frequencies tend to be very weak. Yet, SSVEP commands proved its efficiency in BCI applications: in wheelchair navigation context, each detected frequency is associated with a specific direction.

SSVEP-based wheelchair navigation projects are few. Ref. [19] tried to command a powered wheelchair using a high frequency SSVEP (37–40 Hz). The experiment consisted on driving the wheelchair in a room with four different layouts. They reported that the ITR could reach 72.5 bits/min with an average of 44.6 bits/min during the experience. Moreover, subjects were able to navigate effectively in the environment. Ref. [20] proposed a similar framework that integrates, besides, a safety layer to manage with obstacles collisions. The experimental evaluation showed that among

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the nine subjects that took part in the experiment, training accuracy average reached 88.2% with navigation time which ranges from 2:28 to 9:36 (min). They reported that subjects were able to command their wheelchairs safely.

Other works proposed hybrid systems. Ref. [21] tried to fuse between SSVEP and P300 in a four-choice system. They found that the hybrid system could improve performance relative to SSVEP, but it was not the case for P300 BCI. Other efforts matched between brain and other modalities such as muscular activities,[22] or even visual activity[23] and the results concluded are encouraging. However, BCI suffer from some major drawbacks which can influence its acceptability among disabled groups: In fact, due to its emergence, EEG technology did not prove its reliability to fully control a powered wheelchair especially that the number of commands which could be distinguished is very limited. In SSVEP context, the standard scheme to elicit potentials is to focus on continuously flickering stimuli. For wheelchairs users, such a system can cause visual and mental fatigue as they spend a whole day in front of the stimuli. Moreover, the number of stimuli is associated with the number of desired commands: In the context of wheelchair navigation, five stimuli to generate five directional commands each (forward, backward, left, right and stop).

The purpose of this paper is to present a new hybrid framework based on gaze/SSVEP modalities while accounting for the user's level of distraction. The motivation behind this proposal could be summarized as follows:

- Gaze-based wheelchair navigation did not show its efficiency as unintentional and sporadic fixations could not be managed successfully (this is defined as the midas touch[24]). A validation module should be added to overcome this shortage
- Gaze sequence could be used not only to select the command but to activate the corresponding stimulus, i.e., stimuli will not be flickering continuously in parallel but only the one gazed at, will be activated.
- Rather than comparing the power spectral densities of each frequency to find the predominant one, the selection phase ensured by gaze sequence will specify which frequency should be compared. This can decrease training and execution times.
- The rapidity of eyes motions can improve the performance of the navigation time, while SSVEP can ensure security as the directions will not be initiated until selected commands are validated.
- Besides the use of gaze and brain actively (to initiate wheelchair motions), they can be exploited passively (through interface feedback) in order to estimate user's distraction level and hence eliminate unintentional fixations.

The layout of this paper is as follows. In Section 2, the system overview is described as well as selection, validation and distraction modules. In Section 3, experimental setup is covered. In Section 4, the hybrid system will be compared with a standard SSVEP-based and gaze-based interfaces in terms of training accuracy, navigation time and obstacles collisions.

2. Framework Overview

The system framework is presented in Fig. 1. To initiate the wheelchair linear and angular velocities, directional commands (right, left, forward and stop) must be sent. For this purpose, the following steps are undertaken:

- The scene is projected, thanks to the front camera. The user is asked to gaze at the direction he wants the wheelchair to navigate to.
- The gaze tracker records the observation sequence $\{X_{\text{gaze}}, Y_{\text{gaze}}\}$. The latter constitute not only the inputs for the gaze features but also for brain features extraction modules.
- The gaze feature extraction module maps each sequence $\{X_{\text{gaze}}, Y_{\text{gaze}}\}$ into horizontal and vertical deviations ψ, θ as well as $\dot{\psi}, \dot{\theta}$ the horizontal and vertical deviations changes.
- Those features are then fed to a multi-layer perception (MLP) neural network machine learning which outputs one of four different classes: $forward_{\text{select}}$, $stop_{\text{select}}$, $left_{\text{select}}$ and $right_{\text{select}}$.
- At this level, the issued command from selection module is sent back to the processing unit to activate the stimulus corresponding to the selected command at coordinates $\{X_{\text{gaze}}, Y_{\text{gaze}}\}$.
- While the stimulus is flickering, brain signal is recorded, thanks to the EEG cap. After extraction, it outputs the Power Spectral Density (PSD) of the corresponding harmonics h.

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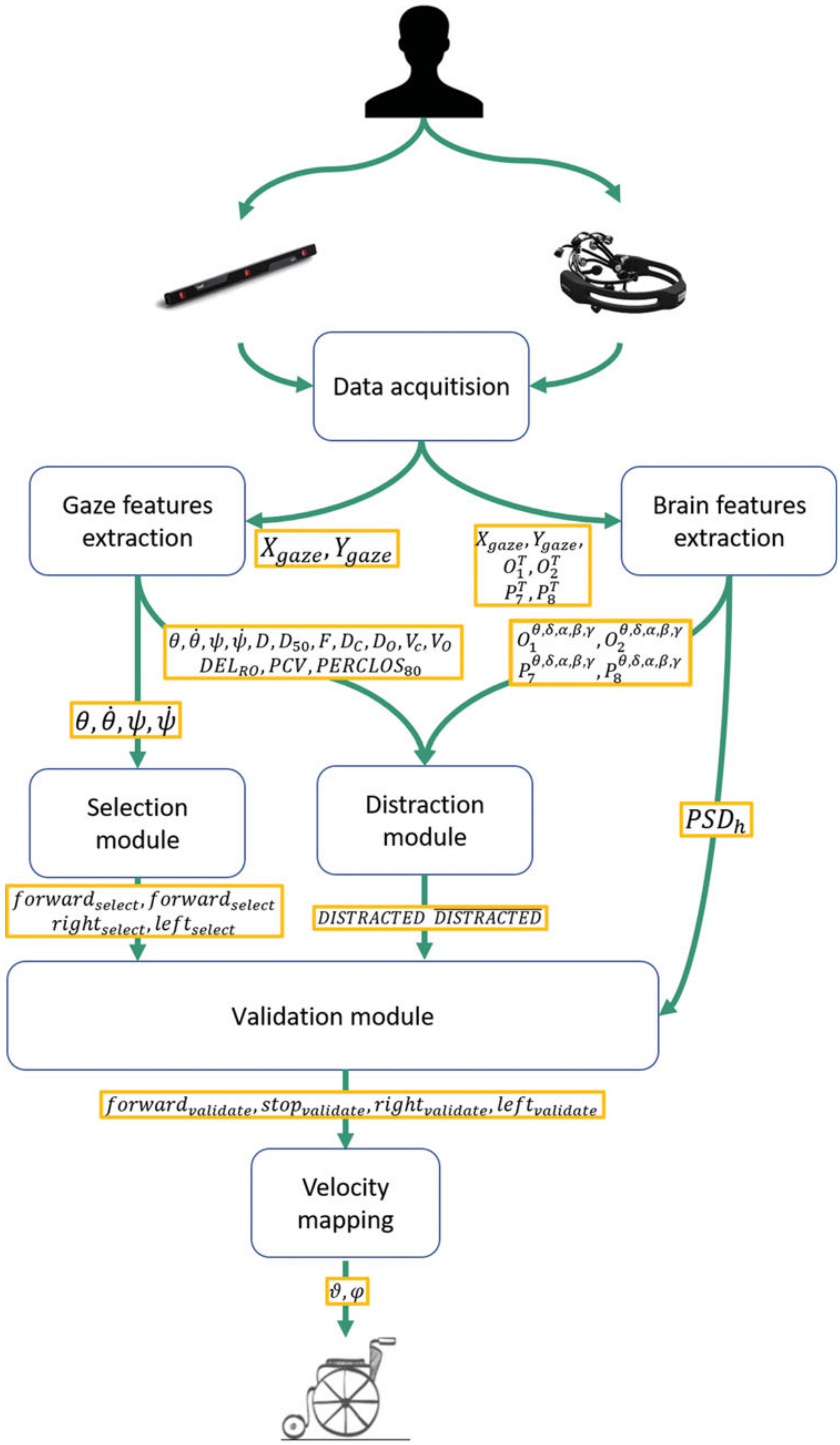

Fig. 1. The system framework. The process flow is defined by four major steps: (1) Extraction of brain and gaze features. (2) Selection of command. (3) Activation of the corresponding stimulus. (4) Processing of SSVEP signal. (4) Validation of command based on distraction state.

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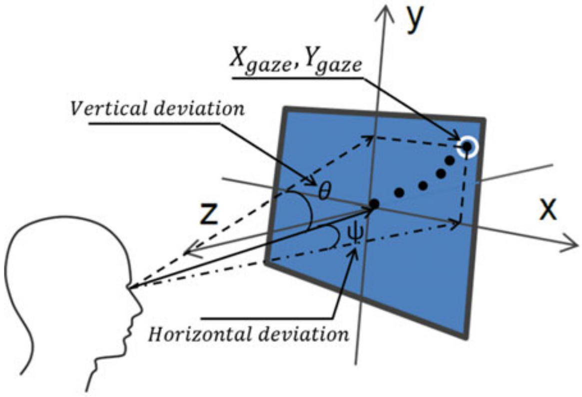

Fig. 2. Features extracted from gaze sequence: X_{gaze}, Y_{gaze}, horizontal and vertical deviations ψ, θ.

- Meanwhile, and besides gaze motion (ψ, θ, $\dot{\psi}$, $\dot{\theta}$), blinking features are also accounted for in the distraction module. The following terms will be defined in more details later: D (duration of blinking), D_{50} (duration at 50%), F (frequency), D_C, D_O (durations of closing and opening), DEL_{RO} (delay of ReOpening), PCV (Peak Closing Velocity) and PERCLOS_{80} (PERcentage of CLOSure).
- The distraction module gathers also features data from brainwave signals: δ (up to 4 Hz), θ (4 Hz–8 Hz), α (8 Hz–13 Hz), β (13 Hz–30 Hz) and γ (30 Hz–100 Hz) in the visual regions (O_1, O_2) and parietal regions (P_7, P_8) of the brain cortex.
- This module uses a second MLP fed by the behavioral entropy (BE) scores estimated from gaze, blinking and brainwave signals, to output one of the following classes: $DISTRACTED$, $\overline{DISTRACTED}$.
- According to the distraction levels and the issued commands, the validation module generates the validated command: $forward_{\text{validate}}$, $stop_{\text{validate}}$, $left_{\text{validate}}$ and $right_{\text{validate}}$.
- Finally, adequate linear and angular velocities are initiated to the wheelchair according to the issued command.

In the following, we will focus more on the main modules of this framework: selection, validation and distraction.

2.1. Selection module

According to physiological findings,[25,26] there is a strong relationship between humans gaze and locomotion: Eye and head movements anticipate users actions and indicate where the person intends to go, but it is not a general case because, when being distracted by environmental changes or searching on it, persons do not have any intention for directional changes. Based on these statements and the recorded features (ψ, θ, $\dot{\psi}$, $\dot{\theta}$ explained in Fig. 2) acquired from extraction module during experiments, a set of gaze patterns has been determined ($forward_{\text{select}}$, $stop_{\text{select}}$, $left_{\text{select}}$ and $right_{\text{select}}$):

- $forward_{\text{select}}$: indicates that the user performs a rising/constant deviation upstairs in the vertical axis.
- $left_{\text{select}}$: indicates a rising/constant deviation to the left direction with steady slope in the horizontal axis.
- $right_{\text{select}}$: indicates a rising/constant deviation to the right direction with steady slope in the horizontal axis.
- $stop_{\text{select}}$: indicates that the user performs a rising/constant deviation downstairs in the vertical axis.

It is important to mention that these features will also be assessed in the distraction module in order to decide if the user is distracted or not.

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2.2. Psd for validation module
The activated stimulus, has a flickering frequency f (in Hz). Its corresponding SSVEP response is estimated as follows:

$$y_i(t) = \sum_{h=1}^{h=H} (a_{s,h} \sin(2\pi hft) + \psi_{s,h}) + n(t) \quad (1)$$

where H is the number of harmonics, $a_{s,h}$ and $\psi_{s,h}$ are, respectively, the amplitude and the phase of the sinusoid in each electrode. n represents the noise of the signal. The latter can be caused by muscular disturbance or electrode noise. The goal is to minimize the noise in order to improve detection process. As it was stated in several studies,[20,27] a channel c can be considered as a linear combination of signals measured by electrodes. this means that at a time t, the channel c is calculated as follows:

$$c(t) = \sum_{i=1}^{i=C} w_i y_i(t) \quad (2)$$

where C is the number of channels, w_i is the optimal set that ensures minimum energy combination and minimum noise occurrence.[28,29] Thanks to its good performance which was validated in several studies, the minimum energy combination technique was implemented in this work.

In order to extract features and classify frequency, the PSD is calculated using Discrete Fourier Transform. Because *a priori* information about the selected command is already sent from the selection module, frequency estimation is based on the comparison of PSD that corresponds to the selected command (and its harmonics) with the threshold (the latter is recorded during the calibration phase). The PSD for an harmonic h and an SSVEP model S can be obtained as follows:

$$\text{PSD}_h = ||S_h c_i||^2 \quad (3)$$

The next step consists on validating the selected command once its corresponding frequency PSD exceeds the threshold and the distraction level is output as $\overline{DISTRACTED}$. Depending on those results one of the following classes is tracked: $stop_{\text{validate}}$,$forward_{\text{validate}}$, $backward_{\text{validate}}$, $left_{\text{validate}}$ and $right_{\text{validate}}$.

2.3. Distraction module
Several studies such as ref. [30] argue that distraction can take several forms: visual, auditory (phone calls), cognitive and biomechanical (tuning radio volume). Our investigation considers visual and cognitive distractions which can be assessed from gaze fixations, blinks and brainwave signals activities. They are mapped into distraction levels by the mean of BE technique. In this section, we will detail the features extracted from each modality and how we model its BE scores which are considered as inputs to the MLP machine learning.

2.3.1. Visual distraction features. According to refs. [11,31–34], horizontal and vertical fixations (ψ, θ,$\dot{\psi}$ and $\dot{\theta}$) as well as blinking are good indicators to characterize visual distraction. Ref. [33] states that ocular dynamics (i.e., blinking or closing eyes) could reveal perceptive capacity degradations. Blinking is defined as closing the eyes for a duration less than 0.5 s, while the minimal duration is at roughly 150 ms. Figure 3 depicts the different blinking features detailed below:

- Blinking duration (D): This feature is calculated from the starting of the blink until the end. It is very sensitive to the detection thresholds V_C and V_O which are applied on the derivative of the signal to detect the closing and opening periods of the eyes and though the start of the blink. Due to their high influence on the blinking duration, these features are rather substituted by the duration at 50%.
- Duration at 50% (D_{50}): It is defined as the duration elapsing from the half of closing peak and the half of the opening peak. Hence, it allows to avoid the problem of the precise detection of the start and the end of the blink.
- Frequency (F): It corresponds to the total number of blinks in a time window.

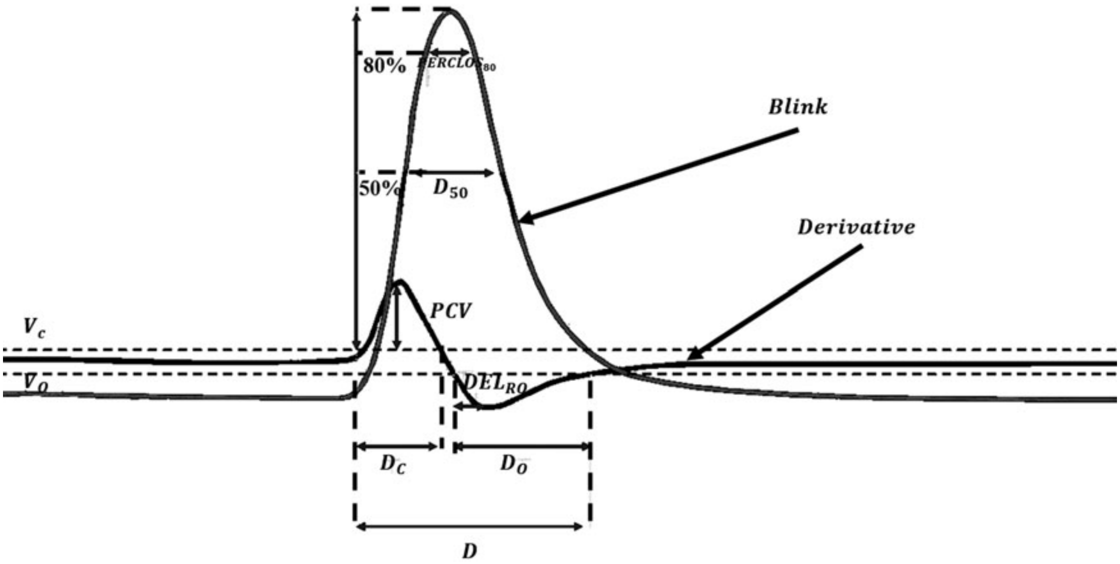

Fig. 3. An example of detected blink, its derivative and considered features.

- Closing and opening durations (D_C,D_O): They correspond to the time needed for the eyelid to close and reopen entirely.
- Delay of ReOpening ($\mathrm{DEL_{RO}}$): It is the time needed for the eyelid to reach its maximal velocity at opening phase. Thus, it is calculated from the starting time of eyes reopening to the time that corresponds to maximal V_O.
- Peak closing velocity (PCV): It is defined as the maximum velocity reached by the eyelid at the moment of eyes closure.
- PERcentage of CLOSure at 80% ($\mathrm{PERCLOS_{80}}$): This feature was proposed by ref. [35]. It is defined as the duration where the eye is closed at least 80%. Consequently, it is calculated at 80% of the maximum peak in a time window.

2.3.2. Cognitive distraction features. There has been a number of published works in the domain of cognitive states and its relation with SSVEP features such as ref. [36]. In our former study,[37] we found that the occipital region over the visual cortex showed strong correlations with the different cognitive states rated by the users during mental cognitive workload induction experiments. Besides, the parietal lobe of the brain showed good correlations with mental workloads as it is very important to integrate sensory information from different parts of the body. Based on these studies, Blind Source Separation technique[38] was used to filter EEG signals. Brainwave signals were calculated by Welch method:[39]

$$\hat{S}_f(f) = \frac{1}{\mathrm{IMH}} \sum_{i=0}^{I-1} |\sum_{z=0}^{M-1} f(z)x(z+iD)\exp(-jfz)|^2$$

where $H = \frac{1}{N}\sum_{i=0}^{N-1} f(z)^2, N$ is the length of the window $f(z)$, $x(z+iD), i = 1, 2, 3, \ldots, K, K$ uncorrelated data of a random process $x(z)$ over an interval $0 \leq z \leq I$. Our frequency intervals are between 1 Hz and 64 Hz with a window of 256 samples yielding to different frequency bands of δ (up to 4 Hz), θ (4 Hz–8 Hz), α (8 Hz–13 Hz), β (13 Hz–30 Hz) and γ (30 Hz–64 Hz). Because of the visual nature of the flickering stimuli, the brainwave signals were extracted from visual region channels O_1 and O_2 as well as parietal region P_7 and P_8. Table I summarizes the different features extracted from each band per sensor.

2.3.3. Distraction assessment from behavioral entropy. BE is a technique that exploits patterns observed in human activity within a Human Machine Interface context.[40] The main assumption of this technique is that when operators perform a practiced skill under good condition information, they are able to adopt an anticipatory control strategy, i.e., they are able to predict the consequences of their

Table I. Features extracted from EEG.

Sensor$_i$	Extracted features from each sensor$_i$	Definition
	δ_{Max}	Maximum Delta power
	δ_{Mean}	Mean Delta power
P7	δ_{Std}	Standard deviation Delta power
	θ_{Max}	Maximum Theta power
	θ_{Mean}	Mean Theta power
	θ_{Std}	Standard deviation Theta power
O1	α_{Max}	Maximum Alpha power
	α_{Mean}	Mean Alpha power
	α_{Std}	Standard deviation Alpha power
	β_{Max}	Maximum Beta power
O2	β_{Mean}	Mean Beta power
	β_{Std}	Standard deviation Beta power
	γ_{Max}	Maximum Gamma power
P8	γ_{Mean}	Mean Gamma power
	γ_{Std}	Standard deviation Gamma power

actions or inactions and consequently select the right behavior to overcome these consequences.[41] However, when operators are under workload conditions, they anticipate less and react in an exaggerated way. As anticipatory behaviors are smoother with less dramatic magnitudes and less frequent changes than reactive behaviors, BE tries to exploit these differences to estimate the level of degradation. In line with many projects,[40–42] this approach is adopted in ours where the normal condition corresponds to navigation with no distraction, while the induced condition corresponds to the distracted state.

Modeling: For each feature introduced earlier, we assume that the model M which predicts the operator activity at time $t+1$ from the state of the world at time t is expressed as follows:

$$\begin{aligned} M : X_t \times X_{t-1} \times \ldots \times X_0 \times A_t \times A_{t-1} \times \ldots \times A_0 &\to A_{t+1} \\ \hat{a}_{t+1} &= M(x_t, x_{t-1}, \ldots, x_0; a_t, a_{t-1}, \ldots, a_0) \end{aligned} \tag{4}$$

where x_t denotes the state of the world at time t, a_t the user activity and $\hat{a}_{t+1}$ the predicted activity based on the model. There are several choices to model M: Linear models, state-space models, but in our case we opt for a second-order Taylor series expansion. For example, if we consider that the distraction level is assessed based on horizontal angle fixation ψ, the model will be expressed as follows:

$$\begin{aligned} \hat{\psi}_t &= \psi_{t-1} + (\psi_{t-1} - \psi_{t-2}) + \frac{1}{2}((\psi_{t-1} - \psi_{t-2}) - (\psi_{t-2} - \psi_{t-3})) \\ &= \frac{5}{2}\psi_{t-1} - 2\psi_{t-2} + \frac{1}{2}\psi_{t-3} \end{aligned} \tag{5}$$

Model error: As the model is not able to predict all the user activity, an error factor is needed to be defined. We define $\bar{\psi}_t = \hat{\psi}_t$- ψ_t the prediction error. For a sequence of errors $\bar{\psi}_0, \bar{\psi}_1, \ldots, \bar{\psi}_N$ $0 \leq t \leq N$, an histogram of errors can be established for each feature. As the normalization of the histogram leads to probability mass functions $p_E(\bar{\psi}; t)$, the entropy $H(E; t)$ can be calculated:

$$H(E; t) = -\sum_{e \in E} p_E(\bar{\psi}; t) \log p_E(\bar{\psi}; t) \tag{6}$$

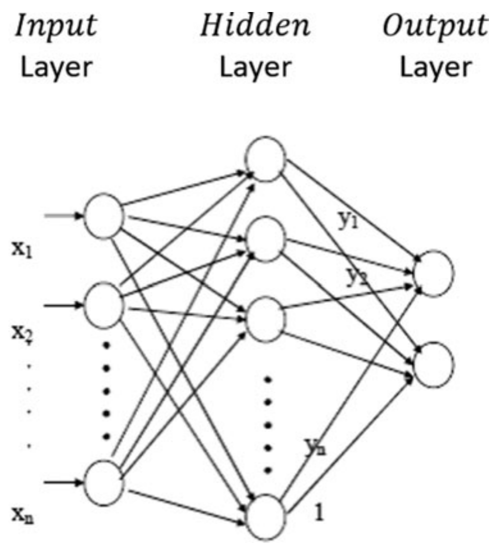

Fig. 4. The ANN MLP with its different layers: input, hidden and output.

In our case, the prediction error calculation was updated every 150 ms to ensure normally distributed data. BE provides information of the error density function under the established conditions (normal and distracted). As in the normal scenario, no perturbations were introduced, the control model is more predictable and consequently the information hold in the error density function is less than in distracted situation. These differences between information are the key idea to estimate the distraction level of the user.

2.4. Multi layer perceptron (MLP)

In this project, two Artificial Neural Network MLPs (ANN MLP) were deployed in two different levels: the first is to estimate the selected direction from the visual fixations and changes, and the second to estimate the distraction level of the user (based on BE calculated from each visual and cognitive features) to be used as a decision feature for the Validation module (the ANN MLP is illustrated in the Fig. 4).

The ANN is designed to predict the user issued command and his level of distraction in order to enhance his performance. The ANN was trained using the data collected when riding in the "No perturbation scenario" (more details are given later). Afterwards, the predicted commands (respectively the distraction level) are compared to those collected during user's run with completing distraction tasks ("Environmental search" and "Social interaction"). The adopted MLP[43] is composed by an input layer with a size, the selected features of the input vector, a hidden layer with 200 neurons (respectively 500 for distraction module) and an output layer with four neurons (respectively 2) which correspond to the selected direction $forward_{\text{select}}$, $stop_{\text{select}}$, $left_{\text{select}}$ and $right_{\text{select}}$ (respectively the state of the user (distracted or not)). The Levenberg–Marquardt method was implemented to train the MLP as it is suggested to be the most suitable for non-linear regression.[44] This method is considered as an approximation of Newton's method. Let $F(x)$ the function to be minimized with respect to the parameter vector x. If $F(x)$ reads,

$$F(x) = \sum_{i=1}^{N} e_i^2(x) \tag{7}$$

The Levenberg–Marquardt is expressed as follows:

$$\Delta x = \left[J^T(x)J(x) + \mu I\right]^{-1} J^T(x)e(x) \tag{8}$$

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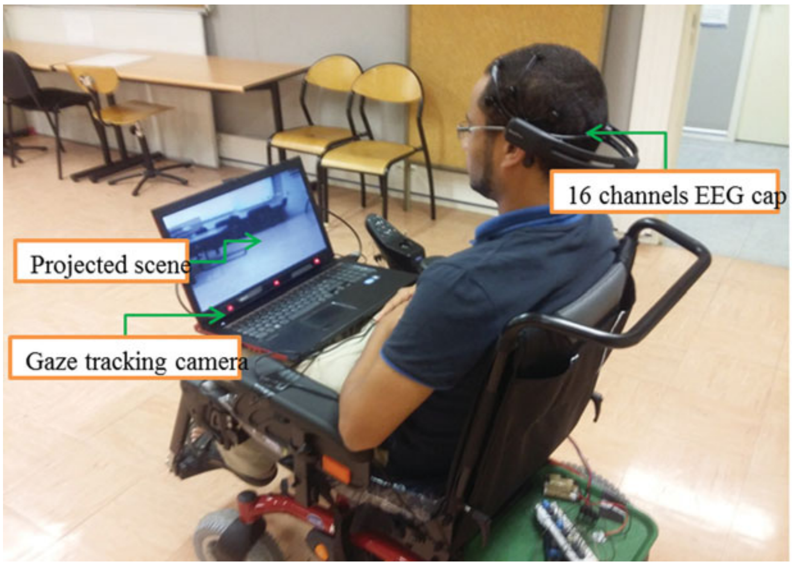

Fig. 5. A preview of the experimental setup.

where $J(x)$ is the Jacobian matrix, μ is a parameter selected experimentally and multiplied by a factor β whenever $V(x)$ is increased. Inversely, μ is divided by β whenever $V(x)$ is decreased. Depending on μ the Levenberg–Marquardt approximates the steepest descent method (case when μ is large) or the Gauss–Newton method (when μ is small). The goal is to shift quickly to toward the Gauss–Newton method as this latter converges accurately to a minimum error. After each step, μ is decreased unless the error increases. For the mapping problem, the Jacobian matrix $J(x)$ parameters are computed by modifying the back-propagation algorithm. The transfer function used is sigmoid and the cross-validation technique adopted is the test-set validation technique; the database is divided into three sets: 70% for training, 15% for testing and 15% for validation (and thus avoiding over-fitting). It is important to notice that other techniques were tested such as support vector machines (SVM) or linear discriminant analysis (LDA) but the MLP was chosen thanks to its best learning performance and faster convergence. Initially, weights were selected randomly. Then, as the obtained results are compared to the reference, weights were recurrently and continuously updated to control the network and reduce the error.

3. Experimental Setup

3.1. Hardware framework

The experimental setup is presented in Fig. 5. An Invacare branded wheelchair was equipped with encoders to record wheelchair velocity. On board, a processing unit is placed in front of the subject to display the scene projected from the front camera. A Tobii (EyeX model)[(1)] eye tracker, with 50 Hz sampling frequency, is placed at a distance of 50 cm from the user to record gaze observation sequence. Alternatively, an Emotiv (Epoc model)[(2)] with 16 sensors and 128 Hz sampling frequency headgear was equipped to record brainwave activity according to the 10–20 standard.[45]

3.2. Participants

Five right-handed male paraplegic male subjects (mean age 30 ± 4) took part in the experiment. The paraplegia is consequent to spinal cord injury which occurred below the first thoracic vertebrae in the upper back region. Consequently, lower limbs movements are lost. Yet, subjects retain full use of their arms and hands. They were selected according to some criteria that will not interfere with the experiment results such as no caffeine, no heart disease, no lack of sleep, no alcohol and no drugs

[(1)]https://www.tobii.com
[(2)]https://www.emotiv.com

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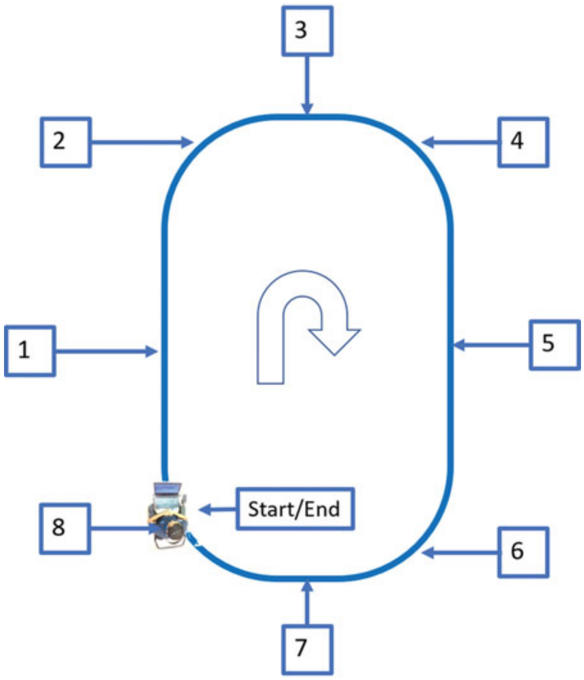

Fig. 6. The path of the first scenario with its eight portions.

that can induce stress or impact upper limbs or cognitive performance. They signed a written consent form in accordance with the declaration of Helsinki. The present study was approved by the local research ethics committee in the University of Toulon.

3.3. Procedure

In order to provide the database with sufficient training samples, three scenarios were proposed with different perturbations introduced. At this level, SSVEP-based and gaze-based interfaces are deployed individually. In fact, the former is needed to assess cognitive features and its correlation with the level of cognitive distraction, while the latter is performed to estimate the selected command and the visual distraction.

3.3.1. No perturbation scenario. In this scenario, the goal is to navigate through a circular predefined path in a clockwise direction. This means that the path is composed of eight main portions as follows (Fig. 6):

- A straight line of 3 m length where the user performs a rising/constant deviation in the vertical direction when using gaze-based interface (respectively focuses on the flickering stimulus that corresponds to the forward command of the wheelchair when using SSVEP-based interface).
- A quarter circle to the right of 1 m diameter where the user performs a rising/constant deviation to the right in the horizontal direction (respectively focuses on the flickering stimulus that corresponds to the right command of the wheelchair).
- A straight line of 1.5 m length where the user performs a rising/constant deviation in the vertical direction and rising/constant deviation in the left direction (respectively alternates between flickering stimuli that correspond to the forward and left command of the wheelchair).
- A quarter circle to the right of 1 m diameter where the user performs a rising/constant deviation to the right in the horizontal direction (respectively focuses on the flickering stimulus that corresponds to the right command of the wheelchair).
- A straight line of 3 m length where the user performs a rising/constant deviation in the vertical direction (respectively focuses on the flickering stimulus that corresponds to the forward command of the wheelchair).

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- A quarter circle to the right of 1 m diameter where the user performs a rising/constant deviation to the right in the horizontal direction (respectively focuses on the flickering stimulus that corresponds to the right command of the wheelchair).
- A straight line of 1.5 m length where the user performs a rising/constant deviation in the vertical direction and rising/constant deviation in the left direction (respectively alternates between flickering stimuli that correspond to the forward and left command of the wheelchair).
- A quarter circle to the right of 1 m diameter where the user performs a rising/constant deviation to the right in the horizontal direction (respectively focuses on the flickering stimulus that corresponds to the right command of the wheelchair).

The same path was mirrored to the left in order to collect the same data for left direction (counter clockwise). Each trial was repeated three times per modality (gaze and SSVEP) in order to gather statistically significant samples. In the next scenarios, two different perturbations were introduced in order to induce distractions.

3.3.2. Environmental search. In this scenario, the user has to follow the same path described before with a new task affected. Beforehand, many objects were added in the environment. They were placed in a way that we ensure its appearance in the field of view of the front camera as long as the end of the actual portion is not reached yet. Besides, its shapes and colors are different in order to avoid confusion of the user while searching for it. When entering a new path portion, the supervisor asks the subject to search for one of the objects placed in the environment while maintaining his first task which is the path following. The objects were selected randomly per portion, subject, trial and modality. Again, the path was mirrored to the left direction with the same task to handle. In this case, the goal is to minimize the interference of other external perturbations in order to hold the assumption that the difference between normal and perturbed scenarios is only due to the distraction of the user.

3.3.3. Social interaction. In this scenario, the same path has to be followed. However, the user has to interact with the supervisor by answering some questions while maintaining the basic control task. While the questions are not meant to be answered correctly, the idea is to stimulate the cognitive and visual workload at each mid portion term of the circuit, i.e., the question is asked when the subject reaches this particular position which constitute our time zero to start recording features data. When the user answers the question, the recording can be stopped. Same as before, this scenario was repeated three trials per subject, path and modality, and the questions were asked randomly in order to inhibit learning effect.

3.3.4. Obstacles avoidance scenario. While the aforementioned scenarios were presented in order to collect features for training database and MLP, this new one has the purpose to compare the proposed framework with the individual use of gaze-based and SSVEP-based interfaces. After sensors placement and good signal qualities checking, subjects sat comfortably in the wheelchair. The experimenter explained the goals and the steps of the three trials. After calibration session, they were asked to reach a marked goal point in a 4×5 m area where obstacles are added. The subjects are asked to execute a predefined sequence per trial as follows:

- Navigate from starting point to the first obstacle and avoid it.
- Navigate to the next obstacle (if any) and avoid it.
- Navigate to the goal point.

However, this sequence changes from one trial to another where an obstacle is added sequentially ranging from 1 to 3 obstacles in the third trial. An example of a navigation scenario can be illustrated in Fig. 7.

The rest period between trials is 15 min. This marks the end of the experience with the SSVEP-based modality. The same experience is undertaken after a week (assuming that this duration is sufficient to inhibit learning effects) with the gaze-based modality to finish with the hybrid system a week later. All subjects went through the same sequence of trials.

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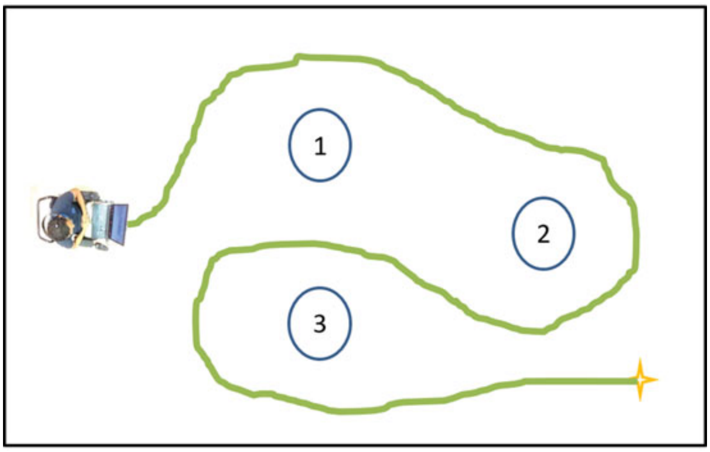

Fig. 7. An example of navigation path for the third trial with three obstacles.

4. Results and Discussions

4.1. Behavioral entropy scores

The different BE scores for visual and cognitive distractions were averaged over the corresponding features for all subjects per scenario (Normal, Discussion and Search). Figure 8 depicts the different comparisons between scenarios. It could be noticed that BE scores increased from Normal to Discussion and Search. This confirms that the distractions introduced in the scenarios were efficient to induce the needed effects especially for Search scenario where the scores reached its maximum. However, we can notice the differences between the impact of Discussion and Search scenarios on visual and cognitive BE scores. While the former had a more impact on cognitive distraction and less effect on visual, it was inverted when analyzing Search scenario. This could be explained by the fact that when users are searching in the environment, they solicit more their ocular capacities which in turn impacts the visual fixations and blinks features. Jointly, occipital region of the visual cortex are solicited which explains the increase in the BE cognitive score. In the Discussion scenario, ocular activity was not solicited as the subjects focus mainly on wheelchair navigation. On the other hand, when they are thinking about the answers to the questions, their visual and parietal regions are activated which was reflected on the BE cognitive scores. This would explain, why the differences between BE cognitive scores are less evident than BE visual scores between Discussion and Search scenarios.

4.2. Systems performances comparison

The comparison between the three modalities is based on four major criteria: training, runs accuracies, navigation time and obstacles collisions. The first criterion, is gathered with reference to the recorded video from the integrated camera of the subject looking at different directions during navigation trials. For the second criterion, navigation time is the duration recorded when the subject starts piloting his wheelchair until he reached the goal point. For the last criterion, it is defined as the sum of the number of times the wheelchair hit an obstacle. Tables II–V summarize the obtained results for the five subjects.

The training accuracy revealed that the average for SSVEP modality reached 96.68% versus 96.64% for gaze modality and 99.28% for the hybrid system. All systems showed good classification rates but the hybrid system performs better thanks to the *a priori* information about the selected command. Consequently, execution time decreased and classification rate is enhanced. This fact was also confirmed when collecting the run accuracy which decreased to 96.59% (96.8% for gaze and 98.8% hybrid) for the first trial, 96.3% (97% and 97.26%) for the second and 95.13% (95.96% and 98.36%) for the third trial. This is due to the stressful situations the user had to cope with, especially that the number of obstacles is incrementally increasing and, proportionally, the space provided for navigation is narrowed. Yet, even for the hardest trial, the classification rate for the hybrid system

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Table II. Training accuracy comparison.

	Training (in %)		
Subject	SSVEP	gaze	gaze/SSVEP
S1	95.45	96.23	98.5
S2	100	96.5	97.9
S3	96.5	97	100
S4	98	98	100
S5	93.48	95.5	100
Average	96.68	96.64	99.28

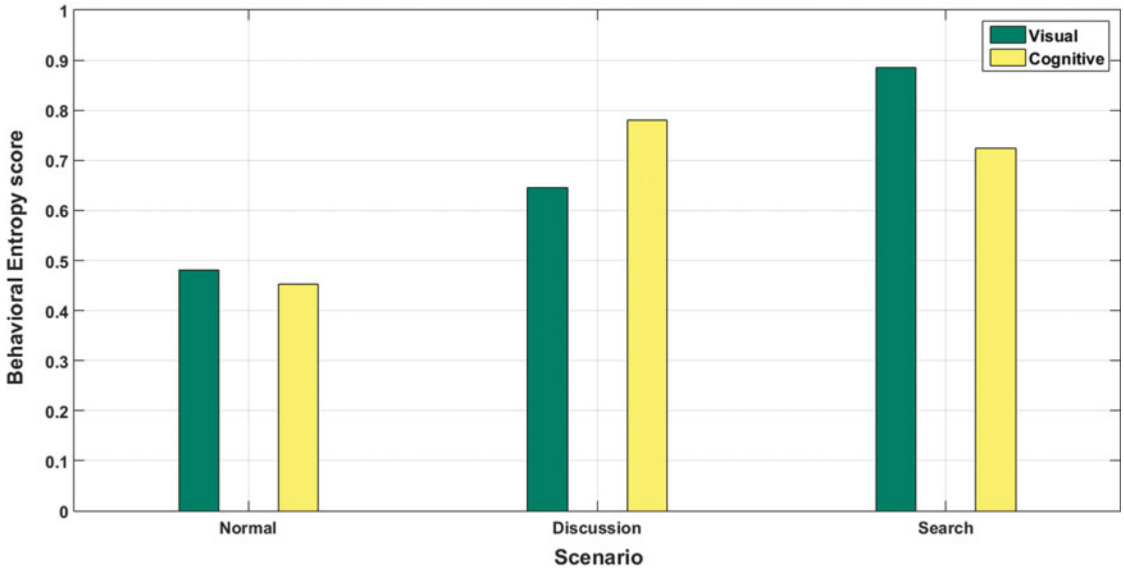

Fig. 8. Average BE scores results over all subjects per scenario and distraction type (visual or cognitive).

was maintained as high as for the training classification rate which was not the case neither for the SSVEP nor gaze-based navigation.

For the navigation performance, which was assessed through obstacles collisions and navigation time. For the former, the number of collisions increases depending on the trial. With more obstacles, more collisions occur. However, the difference between systems regarding obstacles hit becomes more and more evident from the first trial 6(6 and 2), second 14(19 and 3) and the third 18(19 and 8). Even though a better performance is noticed in the third trial, the difference is still evident. In fact, the SSVEP interface is based on stimuli flickering continuously for a long period which can influence the subject concentration and decrease his performance to avoid obstacles. Ocular motions are very fast which can engender very sensitive system yielding to more errors to occur while for the hybrid system, only one stimulus is flickering (where the user is gazing). For the navigation time, the duration of the navigation depends on trial difficulty. While the duration ranges from 2:28 to 5:02 (1:45 to 4:00 and 2:10 to 5:10) for the first trial, this range increases considerably for the second 3:00 to 13:12 (2:30 to 8:20 and 2:30 to 7:00) and for the third 5:12 to 15:48 (3:00 to 7:50 and 4:12 to 9:25) with an evident advantage assigned to the gaze-based system. Same as obstacles collisions, the differences between SSVEP, gaze and hybrid system is evident and increases depending on the trial. This fact is also justified by the simultaneous use of gaze and SSVEP: Eyes movements are very rapid and can provide a very reactive system with satisfying execution time but biased performance.[23] The use of SSVEP to validate the selected command increases the performance at the expense of the rapidity. This trade-off is very important because in wheelchair navigation context security is granted with the highest priority. However, slow systems are also rejected by users.

Except for subject S2, who found it difficult to navigate using the hybrid system, the other subjects were able to navigate successfully even better than using the standard SSVEP- or gaze-based system.

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Table III. Run accuracy comparison.

	Run (in %)								
	SSVEP			Gaze			Gaze/SSVEP		
Subject	T_1	T_2	T_3	T_1	T_2	T_3	T_1	T_2	T_3
S1	95.5	95	94	96	96	93.5	100	98	98.5
S2	100	100	97.36	98	97.5	98	98	95.5	96.4
S3	95.47	95.5	94.3	95	95	94	100	97	98.9
S4	98	97.5	97	99	100	98	98	98.9	99
S5	94	93.5	93	96	96.5	96.3	98	98	99
Average	96.59	96.3	95.13	96.8	97	95.96	98.8	97.26	98.36

Table IV. Obstacles collisions.

	Collisions								
	SSVEP			Gaze			Gaze/SSVEP		
Subject	T_1	T_2	T_3	T_1	T_2	T_3	T_1	T_2	T_3
S1	0	2	2	0	2	2	0	0	1
S2	0	1	2	0	2	2	1	3	4
S3	2	3	6	1	6	6	0	0	1
S4	1	3	3	0	5	4	0	0	0
S5	3	5	5	5	4	5	1	0	2
Total	6	14	18	6	19	19	2	3	8
Average	1.2	2.8	1.2	2	3.8	3.8	0.4	0.6	1.6

Table V. Navigation times during runs.

	Time (min)								
	SSVEP			Gaze			Gaze/SSVEP		
Subject	T_1	T_2	T_3	T_1	T_2	T_3	T_1	T_2	T_3
S1	2:28	3:00	5:12	1:45	2:30	3:00	2:10	2:30	4:30
S2	3:05	3:02	6:30	3:00	5:00	7:50	5:10	7:00	9:25
S3	3:15	5:05	10:15	4:00	8:20	7:30	2:10	3:46	4:12
S4	2:56	6:10	6:15	3:50	5:45	6:00	2:19	3:10	3:59
S5	5:02	13:12	15:48	3:00	5:00	6:00	3:10	5:48	6:00
Average	3:35	6:09	9:00	3:11	5:21	6:06	3:00	4:54	6:02

However, they also expressed some dissatisfaction to use the hybrid system, especially that they are condemned to look at the projected scene from the front camera which lacks some "natural" aspects for navigation. This means also that the field of view is cropped by the camera specifications and the subject is limited to it. In future investigations, the screen could be replaced with small led ahead of the user.

Subject S5, seems to have difficulties to drive his wheelchair with all modalities despite he succeeded to achieve successfully all scenarios. He expressed his discomfort with the flickering stimuli even if their number has decreased in the hybrid system. This also could raise a lot of issues regarding the applicability of the concept of SSVEP. For this purpose, more subjects will be gathered in future schemes to assess an overall tendency among users groups.

Another shortage in this experimental setup, the assumption of one week between the two tests can be not sufficient as to inhibit learning effect. This assumption should be accounted for in the next schemes as to verify if longer duration could affect subjects performances. However, the results of this first step are encouraging and the tests on severer disabled subjects could be undertaken.

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The use of ANN MLP was motivated by the experimental results when compared with SVM and LDA, however many other algorithms could be candidates to bring better results such as Convolutional Neural Networks—Deep learning. In fact, many studies confirmed that the latter outperformed ANN MLP not only in training but also in real time experiments.[46–48] The authors investigate the implementation of such a technique to test its efficiency.

To be noticed, psychological study was also carried in this experiment using a Self-assessment manikins and a Nasa-TLX workload scales to assess emotional and workload feedbacks. They revealed that subjects were stressed (in some cases, highly stressed) even when using the hybrid system. Moreover, visual and mental fatigue were also noticed for SSVEP and less for hybrid system. This fact is consecutive to the use of flickering stimuli which can be the main issue before disabled users can accept the proposed solution. This specific point was also reported in our previous works[37,49,50] where emotion and mental fatigue were induced in simulated environments. Consequently, behavior entropy assumption could be biased by this fact as we consider that he differences between normal and distracted scenarios are only due to the distraction level of the user. Yet, we can claim that other external perturbations were overlapping with distraction.

5. Conclusions and Perspectives

In this paper, a hybrid system based on the combination between SSVEP and gaze sequence is presented. The motivation behind this proposal is the complementarity between visual and cerebral modalities. While for the former eyes motions offer rapidity, SSVEP can provide the security for the system. An experimental platform was set up and hybrid system was compared to a standard SSVEP- and gaze-based navigation systems. The results were assessed based on system accuracy and navigation performance. It was found that hybrid system is more efficient than SSVEP and gaze in learning statistics and navigation performances. During experimental setup, obstacles were placed in specific locations and distances. However, in real-life situations, those conditions can vary drastically and influence the navigation performance (hallway crossing, chairs and tables avoiding, etc.). Another point could be addressed is the moving obstacles: humans, other wheelchairs and animals... can add more complexity to the problem as their motions and speed are unpredictable. The performance of this model should be assessed in future schemes. It should be stated also that, as the project is still in its infancy and the goal of this paper is only to prove the concept, on-board sensors are being mounted on the wheelchair to enhance security. In dangerous situations, such as facing obstacles while the system is asking the user to watch the flickering screen, the wheelchair can manage to autonomously assist the driver to overcome this situation. Decision layer will be supplied with inputs coming for the user and the sensors.

It is important to state that even if this project can bring some elements to enhance navigation and offer some technological novelties, many presented solutions were rejected by subjects due to their dissatisfaction regarding semi-autonomous systems: subjects are more comfortable with manual system rather than assisted. This trade-off between technological assistance and subjects satisfaction is to be considered. The latter can be assessed by mental state and mental workload impact on EEG signals.

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