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Review Paper

Spelling with non-invasive Brain–Computer Interfaces – Current and future trends

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A B S T R A C T

Brain–Computer Interfaces (BCIs) have become a large research field that include challenges mainly in neuroscience, signal processing, machine learning and user interface. A non-invasive BCI can allow the direct communication between humans and computers by analyzing electrical brain activity, recorded at the surface of the scalp with electroencephalography. The main purpose for BCIs is to enable communication for people with severe disabilities. Spelling is one of the first BCI application, it corresponds to the main communication mean for people who are unable to speak. While spelling can be the most basic application it remains a benchmark for communication applications and one challenge in the BCI community for some patients. This paper proposes a review of the current main strategies, and their limitations, for spelling words. It includes recent BCIs based on P300, steady-state visual evoked potentials and motor imagery. By considering some challenges in BCI spellers and virtual keyboards, some pragmatic issues are pointed out to eliminate false hopes about BCI for both disabled and healthy people.

Contents

1. Introduction

A Brain–Computer Interface (BCI) does not read mind (Wolpaw, 2010). It translates brain activity into computer commands. This can be achieved thanks to the detection of particular brain responses. This type of system allows people to communicate through direct measurements of brain activity, without requiring any movement (Allison et al., 2007; Birbaumer and Cohen, 2007; Kostov and Polak, 2000). The modulation of brain signals can be recorded from the scalp using electroencephalography (EEG), from cortical surface using electrocorticography (ECoG), or from neurons directly within the cortex (Wolpaw et al., 2002). BCIs may be the only hope for people with motor disabilities so severe that they cannot communicate with their families. In spite of their motor disabilities, sensory and cognitive functions are usually still enabled. For instance, people with spinal cord injuries or amyotrophic lateral sclerosis (ALS), also called Lou Gehrig's disease, are good candidates for using daily BCIs (Birbaumer and Cohen, 2007; Birbaumer et al., 1999). Although, ECoG is an efficient way to record brain activity, non-invasive BCI through EEG recording remain a major research topic as EEG provides a high time resolution in the signals and EEG recording requires relatively inexpensive equipment. In addition, non-invasive BCI could be used by healthy people as a complement to other interfaces.

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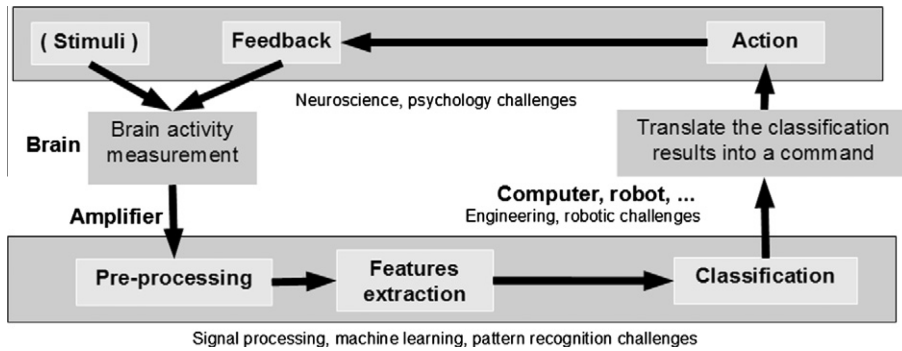

Fig. 1. Classical BCI framework.

A BCI can be decomposed into four parts (Schalk et al., 2004). First, the signal is acquired via an amplifier. Then, the signal is processed and assigned to different classes. Finally, the classes are sent to the output device components and the operating protocol links all the previous components. The signal classification component is composed of the brain signal features extraction and the translation of these signals into device commands. Fig. 1 presents the current scheme of a BCI application. It is worth mentioning that although the input signal comes from the subject to the amplifier, a BCI works as a closed loop by including feedbacks and possible external stimuli. The EEG classification strategy depends on the response to be detected. The brain responses should ideally be easily mastered by the user in order to maximize its control and its accurate and reliable translation into commands according to the user's intention. The brain responses shall therefore be detected without analyzing the EEG signal across several sessions and subjects, *i.e.* with a single trial or by averaging several trials. Among the brain responses that are currently used in non-invasive BCI, we can find event-related potentials (ERP), steady-state evoked potentials (SSVEP), motor imagery or slow cortical potentials. These responses can be provoked by external stimuli, visual or auditory (P300, SSVEP) or not (motor imagery). The expected EEG drives the classification to some specific feature extraction methods.

Although the type of BCI application as a mean of communication and control is extended every year with video games, robotic arm control, wheelchair control, etc. (Cincotti et al., 2008; Lüth et al., 2007; Millán et al., 2010), the most basic application, spelling, is still one active research area. Spelling can indeed enable the physically challenged to perform many activities. It can therefore improve their quality of life. To some extent, it can allow them more independence. This independence can be translated into social cost reduction. Besides, disabled people who can spell could work and get a more rewarding place in society. An early BCI study with locked-in patients with ALS has shown that it was possible to spell characters with self-regulated slow cortical potentials (Birbaumer et al., 2000). We focus on this paper on the current three main responses that are used for spelling in BCI: P300, SSVEP and motor imagery (event-related (de) synchronization (ERD/ERS)).

The rest of the paper is organized as follows: spellers based on the detection of the P300 wave are presented in Section 2. The main spellers based on SSVEP are described in Section 3. Then, some spellers based on the detection of motor imagery are presented in Section 4. Finally, their performance and their outcome are discussed in Section 5.

2. Spellers based on P300

The detection of event-related potentials (ERP) is one way for creating a BCI. A typical ERP based BCI is the P300 speller, which allows people to spell characters. The P300-Speller is one of the first BCI, it was first introduced in 1988 (Farwell and Donchin, 1988). The P300 wave is an ERP (Sutton et al., 1965). Its generation is possible thanks to the oddball paradigm. This paradigm provides random visual stimuli that cause a surprise effect to the subject. The classical P300-Speller layout is presented to the user on a computer screen as depicted in Fig. 2. It is composed of a 6×6 matrix, which contains all the available characters (Farwell and Donchin, 1988; Donchin et al., 2000). During the experiments, the user has to focus on the character she/he wants to spell. When the user focuses on a cell of the matrix, it is possible to detect a P300 (a positive deflection in voltage at a latency of about 300 ms relative to the stimuli onset in the EEG) time-locked to the onset of the cell intensification. To generate ERPs, the rows and columns are intensified randomly. Row/column intensifications are block randomized in a number of events equal to the number of rows and columns. The sets of intensifications are repeated N_{epoch} times for each character.

Although the P300-Speller paradigm was initially designed to spell Latin characters, a recent P300-Speller has been proposed for Chinese characters (Jin et al., 2010). Most of the improvements in the P300-Speller have been achieved at the signal processing and detection level with techniques like support vector machines (SVM) (Rakotomamonjy and Guigue, 2008) or neural networks (Cecotti and Gräser, 2010; Liang and Bougrain, 2008), Bayesian linear discriminant analysis (Cecotti et al., 2010; Hoffmann et al., 2008). In contrast, the P300-Speller graphical user interface has not been evolving much for more than two decades. Some improvements have been proposed like in Takano et al. (2009), where it was found the color of the flickering matrices should be green/blue or in Li et al. (2011) where the layout is based on the frequency of the English letters. In Townsend et al. (2010) an alternative paradigm to the classical flashes of the row/column paradigm (RCP) has been

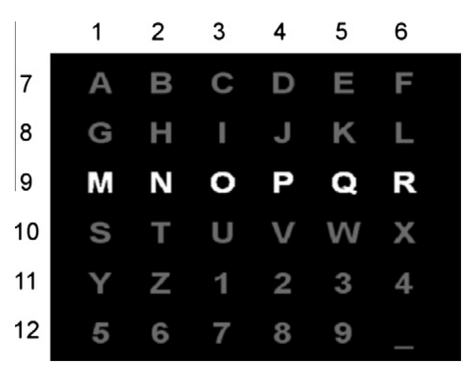

Fig. 2. Classical P300 GUI.

proposed. They have proposed the checkerboard paradigm (CBP), which is a combination of two checkerboards to avoid the confusion problems in the neighborhood of the target. In the RCP paradigm, items that are contiguous to the target (items in the same row or column) are flashed simultaneously, leading to undesired ERP. Using an 8×9 matrix of alphanumeric characters and keyboard commands, 18 participants used the CBP and RCP paradigms. With approximately 9–12 min of calibration data, they obtain a mean online accuracy of 92% for the CBP, better than the RCP with only 77%. The mean information bit rate was also significantly higher for the CBP with 23 bits per min (bpm), than for the RCP, 17 bpm. In Cecotti and Rivet (2010a), an alternative description of the RCP is proposed, which allows to flash random subsets of items in the P300 speller matrix. In this strategy, the RCP paradigm is a special case of a generic model for displaying random subsets of items. In Tangermann et al. (2010), a comparison across nine healthy subjects of four stimulus presentation modes revealed that complex highlighting effects composed of brightness enhancement, rotation, enlargement and a trichromatic grid overlay in combination with row–column spatial arrangements of simultaneously highlighted objects improved single subtrial classification performance.

In the P300-Speller, research works is being carried out in several directions. First, the P300 speller can be improved through methods that increase the reliability over time and across subjects, and the information transfer rate. For example, it can be achieved by using inter-subject information and online adaptation (Lu et al., 2009), by reducing the set of sensors (Cecotti et al., 2011; Rivet et al., 2011), by decreasing the number of repetitions (Thulasidas and Guan, 2005). For improving the reliability over time, a feedback for counting flashes and therefore increasing the stimulus meaning has been proposed (Cecotti and Rivet, 2010b) (Fig. 3). Second, with a more pessimist point of view about the possible improvement of the P300 detection, the improvement should rather come with an application oriented P300-Speller, *i.e.* with word completion, prediction, a knowledge of the vocabulary, etc., as recently proposed in Ryan et al. (2011).

Most current P300-Spellers are still far from commercial/clinical applications and some efforts shall be made to let BCIs leave laboratories (Mak et al., 2011). The available system lacks robustness over time and across subjects. The performance does not meet users' requirements due to unadapted end-user interface, the user shall be able to control the application easily. However, there exist few exceptions mentioned in the literature like in Vaughan et al. (2006), Sellers et al. (2010), where a late stage ALS patient could use at home a P300-Speller developed by the Wolpaw lab. The French National Research Agency (ANR) through the RoBIK (Robust BCI Keyboard) project aims at developing such success to provide efficient user-dedicated BCI that will be easily used daily by a non-technician staff, *e.g.* a nurse. The intendiX solution has been proposed by g.tec in 2009. This BCI is designed to be installed and operated by caregivers or the patient's family at home. The system is based on visually evoked EEG potentials (VEP/P300). It allows the user to sequentially select characters from a keyboard-like matrix on the screen just by paying attention to the target for several seconds. Contrary to the classical P300-Speller, the matrix has a 5×10 size as depicted in Fig. 4. This BCI requires some training but most subjects can use intendiX after only 10 min with a reasonable performance. According to the g.tec company, the performance for the majority of healthy users during their first trial is estimated to a spelling rate of 5–10 characters per minute (cpm). It is worth mentioning that the intendiX system is able to detect the idling state. Therefore, the system only selects characters when the user pays attention to it. This system also allows the patient to trigger an alarm, let the computer speak the written text, print out or copy the text into an e-mail or to send commands to external devices. In addition, this BCI is proposed as a whole package (software, amplifier, caps, etc.), which provides a global solution.

Fig. 4. intendiX GUI (Gtec, 2010).

The P300 speller has often been presented as independent of the gaze and as a good choice for patients who are unable to keep a steady gaze over a target. However, for patients who are in a

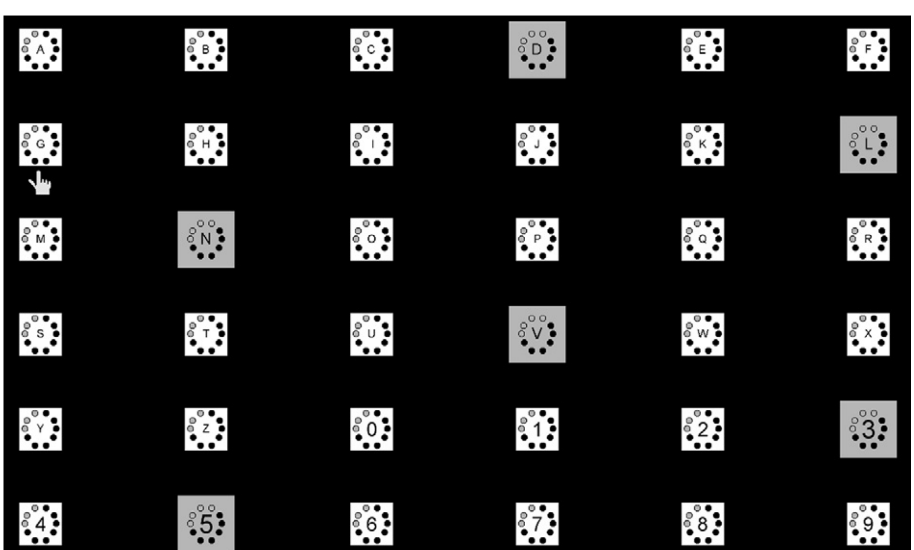

Fig. 3. P300 GUI with feedback for counting flashes and visual stimuli with subsets of items (Cecotti and Rivet, 2010b).

complete locked-in state, *i.e.* who cannot control extraocular eye muscles, it is not possible to consider a standard graphical user interface like the P300 speller. Besides, a recent studies has highlighted that the efficiency of the P300 speller depends on eye gaze (Brunner et al., 2010). In Treder et al. (2010), three visual spellers based on covert spatial attention and non-spatial feature attention are presented and tested across 13 healthy subjects. These spellers obtain a similar spelling performance during center fixation as the original P300 Speller with target fixation. In Aricò et al. (2010), an alternative P300 speller, GeoSpell (Geometric Speller), is proposed. In this speller, stimuli are delivered in a covert attention modality and thus not require eye gaze control. Alternative solutions may consider a Rapid Serial Visual Presentation (RSVP) paradigm where letters are presented randomly at the same location on the screen and a P300 is expected on the letter selected by the user as proposed by Acqualagna et al. (2010).

3. Spellers based on SSVEP

In a BCI based on Steady-State Visual Evoked Potentials (SSVEP), the system reflects the user's attention to an oscillating visual stimulus (Vialatte et al., 2010). Flickering lights at different frequencies are usually used as stimuli. Their responses appear in the visual cortex and correspond to SSVEP at the same frequencies and higher harmonics (Müller-Putz et al., 2005). The amplitude and the phase that define an SSVEP response depend on the frequency, intensity and the structure of the repetitive visual pattern (Wu et al., 2008). SSVEP based BCIs have been used in many types of applications like for neuroprosthetic devices control, for the restoration of the grasp function in spinal cord injured persons (Müller-Putz and Pfurtscheller, 2008) and video games (Lalor et al., 2006). Indeed, this type of BCI performs very well and is reliable according to previous studies (Bin et al., 2009; Cecotti and Gräser, 2008; Gao et al., 2003; Friman et al., 2007). While each cell of the matrix can correspond directly to a command in the P300-Speller, the low number of commands of an SSVEP-BCI involves an adaptive strategy for creating the graphical user interface. Among the different laboratories working on SSVEP-BCI, the Institute of Automation in Bremen, Germany has proposed several efficient SSVEP-Spellers.

The SSVEP based Bremen-BCI speller has been evaluated during the CeBIT fair 2008 in Hannover, Germany and RehaCare 2008 in Düsseldorf, Germany (Allison et al., 2010; Cecotti et al., 2009; Valbuena et al., 2008; Volosyak et al., 2009). The graphical user interface of Bremen-BCI speller is presented in Fig. 5. This interface is composed of a virtual keyboard with 32 characters (letters and special symbols), which is located in the middle of the screen. The five white boxes at outer edges and upper left corner of the screen are flickering with different frequencies. These boxes correspond to the commands "left", "right", "up", "down", and "select". The subject does not need to shift his gaze too much, because the used stimuli are part of the GUI on the same LCD screen. This setup, as opposed to having an LCD for the GUI and a separate LED board for the visual stimuli, is much more convenient for the user as they do not have to shift their gaze too much.

At the command level, *i.e.* the five commands, the mean accuracy of the command detection is 92.84%, with an average information transfer rate of 22.6 bpm. In the speller level, the average information transfer rate is 17.4 bpm, equivalent to about 3.5 cpm.

In Cecotti (2010), a new SSVEP-Speller (CBCI) that does not need any calibration step is proposed. Thus, this speller is ready to work once the subject is prepared. This speller was also developed at the Institute of Automation in Bremen, Germany. The visual stimuli here are fully integrated to the graphical user interface (GUI). Contrary to some other SSVEP-BCIs, the visual stimuli and the commands are merged. This speller allows writing 27 characters: the 26 Latin characters [A–Z] and "_" for separating the words. CBCI is depicted in Fig. 6. This interface corresponds to a menu with three possible choices. When a choice is selected, then the content of this choice is split into three new choices. Three commands are dedicated to the navigation. They correspond to the three boxes that contain all the possible letters. For writing a letter, the user has to produce three commands. This number of command is fixed and independent of the letter. One command is considered for canceling the previous one. An easy access to the "undo" command must be present for enabling easily a fast correction from the user. An error can come from the user directly or indirectly. This command aims at minimizing the cost of a mistake during spelling tasks. A command is dedicated to the deletion of the last character in the written text. At any moment, the user is able to suppress the last character of the text with only one command. CBCI was tested

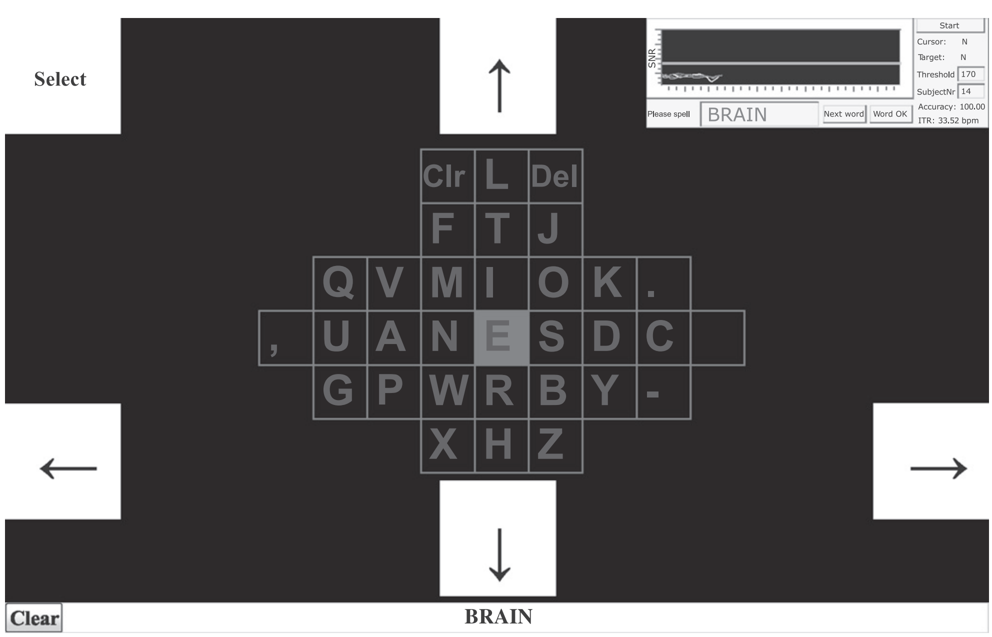

Fig. 5. Bremen-BCI GUI (Valbuena et al., 2008; Volosyak et al., 2009).

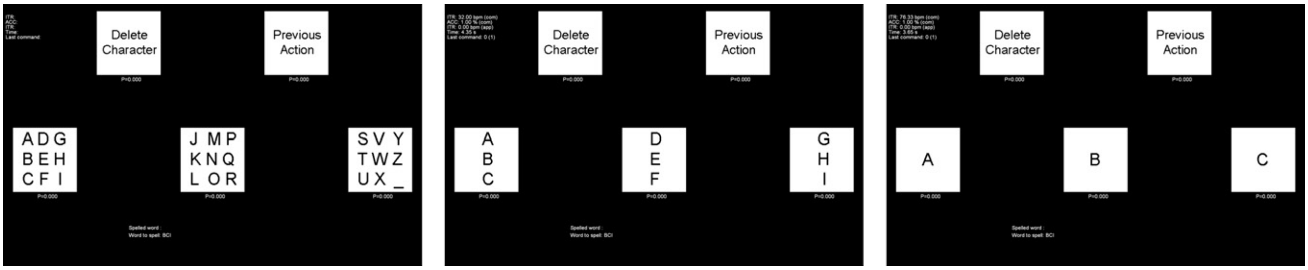

Fig. 6. CBCI GUI (Cecotti, 2010).

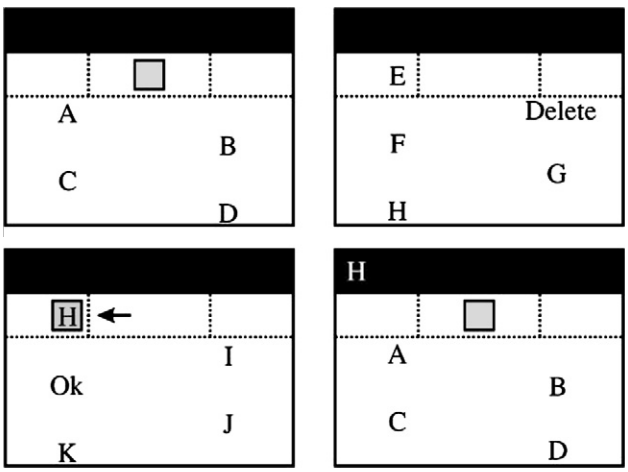

Fig. 7. Graz Virtual keyboard GUI (Scherer et al., 2004).

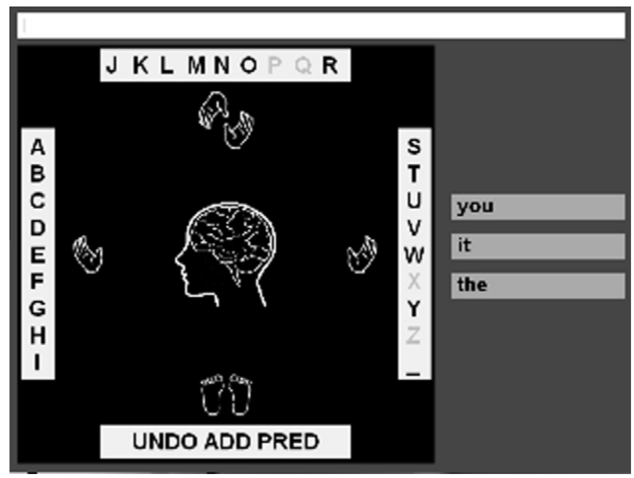

Fig. 8. AIRLab-BCI GUI (D'Albis, 2009).

on eight healthy subjects. The average accuracy and information transfer rate are 92.25% and 37.62 bpm, which is translated in the speller with an average speed of 5.51 cpm. One subject could write with an average speed of 7.34 cpm.

Contrary to the P300 speller where some adapted paradigms can provide a gaze-independent speller, SSVEP spellers are dependent and require the subject to focus on different locations. Further works shall be carried out to determine if an independent SSVEP speller is feasible and to what extent the performance would change.

4. Spellers based on motor imagery

Like for SSVEP-BCIs, the number of available commands limits the interface: it is not possible to assign an imagery movement to every character (only the main body limbs are usually used). A strategy must be found to combine few basic BCI commands, *e.g.* thinking of moving the left/right hand. In Scherer et al. (2004), three healthy subjects operated an asynchronously controlled three-class BCI virtual keyboard (VK) that was operated by spontaneous electroencephalogram and modulated by motor imagery. For the two successful users, the mean spelling rate was 1.99 cpm. The GUI of VK is presented in Fig. 7. It is composed of a small black upper part for the presentation of spelled letters and white area for the selection process. VK allows spelling 26 different characters and two commands: DELETE, to delete the last spelled letter and OK to confirm the spelled word. The command associated to the foot motor imagery allows scrolling the different items from the bottom to the top of the screen. The item on the topmost position could be selected by moving the feedback cursor, *i.e.* the gray square, toward the desired left or right direction by performing a left or right-hand movement imagination. Finally, VK accepts letter if cursor had exceeded subject-specific left or right threshold for a subject-specific period (continuous left-hand or right-hand motor imagery).

A predictive BCI speller based on motor imagery has been proposed at AIRLab, the Artificial Intelligence and Robotics Laboratory at the Department of Electronics and Information of the Politecnico di Milano, the Technical University of Milan, Italy (D'Albis, 2009). The GUI of this speller is presented in Fig. 8. The selection strategy is based on target expansions, like a menu, with 27 available characters, numbers, symbols. This speller possesses predictive capabilities: it allows word suggestions and disabled improbable symbols. The achieved performances are relevant. With one subject, they have obtained a high classification accuracy and the overall speller speed is estimated to 3 cpm. With two other subjects, they started with lower classification accuracies, but significant improvements have been achieved with more training sessions. These subjects reached a spelling speed of respectively 2 and 2.7 cpm (D'Albis, 2009).

The BCI research group from the Fraunhofer FIRST (IDA), Berlin, Germany has proposed the Berlin BCI (BBCI) called Hex-o-Spell that is depicted in Fig. 9 (Blankertz et al., 2006; Müller et al., 2008). This asynchronous BCI speller allows to write 29 different characters and the backspace command. The speller is controlled by two mental states: imagined right hand movement and imagined right foot movement. Six hexagonal fields are surrounding a circle. In each field, five characters or other symbols like backspace are arranged. An arrow is placed in the center of the circle for the selection of a character. When the subject imagines a right hand movement the arrow turns clockwise. With an imagined foot movement, the rotation stops and the arrow starts extending to the desired field. Once the field is selected, the six fields are arranged with the content of the selected field. The BBCI has been tested in real conditions on two volunteer and healthy subjects during the CeBIT fair 2006 in Hannover, Germany. The speed of the hex-o-spell BCI was between 2.3 and 5 cpm for one subject and between 4.6 and 7.6 cpm for the other one. This speed was measured for error-free, completed sentences, *i.e.* all typing errors that have been committed had to be corrected by using the backspace of the mental typewriter. This protocol was also used to evaluate CBCI. The original and efficient Hex-o-spell interface has also recently been tested with the visual oddball paradigm (Treder and Blankertz, 2010).

5. Discussion

5.1. Performance

In spite of the different results reported in the literature, it is not possible to have an objective comparison between the different available BCI spellers due to the inter-subject variabilities and the conditions of the experiments. For instance, the experimental conditions are very different between a dedicated magnetically shielded room for EEG recording in a laboratory and a booth at an international fair with all the surrounding noise. In addition to EEG recording conditions, a BCI speller is composed of several parts (BCI transducer, user interface, keyboard layout, word prediction, etc.) that are seldom described in the literature.

However, each BCI paradigm possesses its advantage and drawbacks. BCIs based on the detection of the P300 or SSVEP require external visual stimuli. For spelling applications, the visual stimuli are not really a disadvantage. Indeed, spellers based on motor imagery consider also a graphical user interface. With the P300 speller, each symbol is usually available on the screen, like a classical virtual keyboard. Contrary the P300 speller, an SSVEP speller must take into account several constraints based on the visual stimuli. With LEDs, it is possible to produce a large number of visual stimuli with more frequencies (Gao et al., 2003; Zhu et al., 2010). However, such solution requires an external device; the application and the visual stimuli are not located at the same place. With visual stimuli on an LCD screen, the size, the low luminosity, the vertical refresh rate of the screen are some parameters that limit the number of simultaneous visual stimuli on the screen. For this reason, it is not possible to propose to the user a virtual keyboard with a direct access to the letters. Other BCI commands must be used to navigate on the virtual keyboard. For an efficient BCI, the performance must be reliable over time and across subjects. BCIs based on motor imagery, like the Hex-o-spell, can be efficient. However, BCIs based on motor imagery or P300 requires a training session for the calibration of the system. In addition, BCIs based on motor imagery are more likely to suffer BCI illiteracy; the performance is highly dependent on the subject. On the other hand, SSVEP-BCIs do not require a training session and possess a high transfer rate (Bin et al., 2009; Cecotti, 2010).

A low BCI performance can be due to a lack of attention, to the disregard of what should be written. It is possible that the user wants to produce a command but the signal processing module delivers the wrong command. In this case, the error is not voluntary and shall be corrected easily. At any moment, the user should be able to cancel the previous command with only one command. While the raw performance is an important factor, the speller's usability shall be considered as a very important aspect. If the speller is not user-friendly, the speller will not be used even with good performance.

5.2. BCI design

The usual scheme for a BCI is to record signal, pre-process the signal, detect eventual brain response and assign a command or not to the classifier output (Mason and Birch, 2003; Mason et al., 2005). In spite of SIMULINK and MATLAB (Mathworks, Boston, MA), BCI frameworks like BCI2000 and OpenViBE have been developed during the last few years (Schalk et al., 2004; Renard et al., 2010). These frameworks mostly answer the needs of neuroscientists to test well established paradigms. In such frameworks, every BCI application is usually built with the same basic components: signal acquisition, signal processing, graphical user interface. This kind of approach has been mostly focused on the signal processing part and can become an obstacle for the creation of innovative BCI paradigms. Indeed, these frameworks are limited by the granularity level they include. The finer the granularity of the framework, the greater the possibility for creating innovative models. Thus, the best granularity is obtained by directly developing a BCI application without using existing cumbersome and interventionist frameworks. While existing toolboxes or BCI frameworks may help a developer for assigning a BCI command to a particular device or software, emerging and innovative applications that should leverage BCI market require more than the connections of toolboxes or assigning a brain response to a command. Indeed, the current best spellers embed in a clever and united way the different components of a BCI (Williamson et al., 2009). In spite of the continuous request of standardized hardware and software (Brunner et al., 2011), the intendiX speller of g.tec suggests that the BCI chain shall be mastered from the EEG acquisition to the GUI, *i.e.* the final product, to propose a commercial application.

The user must be the central part during the design of BCI: from the user's ability to control some particular brain responses, the user's preference for the possibilities of the speller. This type of approach should benefit the user's experience and future applications. In fact, the involvement of users in the design process shall be enhanced. This step shall include the type of disability and consider the right modality or combination of modalities, *e.g.* auditory (Schreuder et al., 2010), haptic with the use of the somatosensory system (Brouwer and van Erp, 2010; Müller-Putz et al., 2006) (see Fig. 9).

Contrary to Fig. 1, where the different parts are represented in relation to some research interests, a global approach should be considered as presented in Fig. 10. This type of approach should better answer the main BCI purpose: optimizing the reliability of the brain signal translation into actions, which correspond to the user's intentions (Wolpaw, 2010). Further work should incorporate standardized measures inspired by Human–Computer Interaction (Van de Laar et al., 2010).

5.3. Unfinished business

By considering the Gartner's hype cycles as depicted in Fig. 11, we may wonder what is the current state of non-invasive BCI

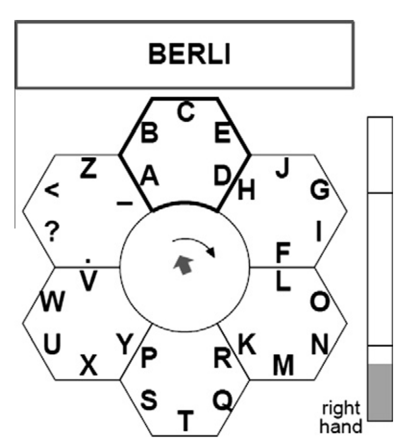

Fig. 9. Hex-o-spell GUI (Blankertz et al., 2006; Müller et al., 2008).

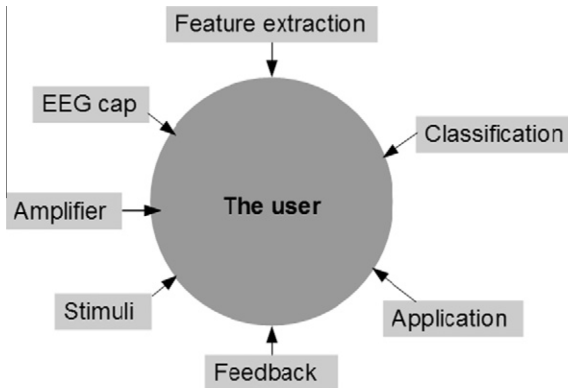

Fig. 10. A global approach centered on the user.

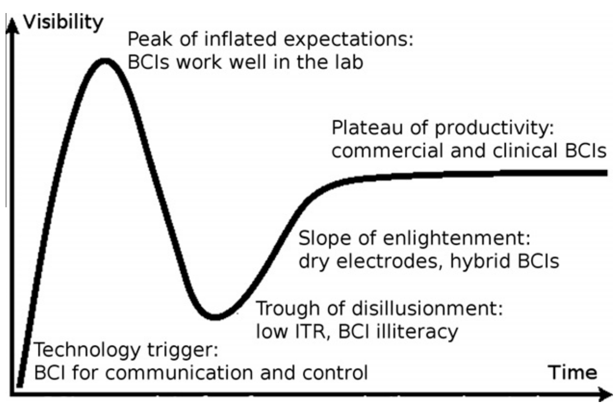

Fig. 11. Gartner hype cycles.

(Gartner, 1995). We are relatively far from the plateau of productivity. The only commercial speller is the intendiX speller of g.tec. Depending on the considered consumer target, we are between the thought of disillusionment, *i.e.* BCIs fail to meet expectations and promises, and the slope of enlightenment, *i.e.* research groups and some companies continue to understand the benefits and practical application of BCI technology. Unfortunately, BCIs often remain at the stage of disillusionment for completely locked-in patients. The multidisciplinary aspect of BCI is one of the reasons for the low increase of commercial BCI. In fact, the advances in sensors, neuroscience and machine learning do not progress at the same pace in relation to their outcome in BCI. The brain signals that are currently used have been studied for more than 30 years, *e.g.* the P300 ERP. While SVM and neural networks can provide the base of efficient classifiers, some brain signals can often be discriminated with a simple Fisher linear discriminant analysis (LDA) (Krusienski et al., 2006). These observations suggest that other research directions shall be explored. Finally, the main bottleneck for commercial non-invasive BCI applications is the sensor aspect.

The real problem for bringing BCI outside of laboratories is how to bring electroencephalography outside of laboratories. This challenge can be compared to the early days of personal computer (PC) in the early 1970s. Several issues can be listed: the cost of the amplifier, the electrodes, the time needed to place the system, the resistance to the noise. This statement is valid for every type of consumer target. For healthy people, a long preparation, the abrasive gel in the hair and on the scalp are serious drawbacks. Even with a performance equal to what is offered on a computer keyboard, few people are ready to wash their hair each time they wish to use Word or a LaTeX editor. For disabled people, the time needed for the preparation and the time where the system can stay operational can be an obstacle as a nurse cannot be present all the time near the patient. At the second workshop of the European project TOBI (Tools for Brain–computer Interaction) in December 2010, the preparation time and the sensors were hot topics even for the case of patients with severe disabilities.

For all these reasons, commercial non-invasive BCI will remain very limited to the public if efficient dry electrodes will not be available for a fast preparation (Sullivan et al., 2008; Gargiulo et al., 2010). The type of electrode should ideally be placed anywhere on the scalp and not be limited to locations where there is no hair. Companies like Emotiv Systems (http://www.emotiv.com), NeuroSky (http://www.neurosky.com) or Starlab (http://enobio.starlab.es/) propose currently portable solutions for recording EEG signals. The BCI design and therefore the choice of the brain response might be first chosen in relation to available devices for recording EEG.

6. Conclusion

The same way that word processing was one of the first reasons for personal computers (PC), communication through spelling was one of the first applications in BCI. After more than two decades of active research, the promises of BCI have not really been fulfilled. Spelling still remains a challenge for patients with strong disabilities and the ITR cannot challenge other devices for healthy persons. It therefore stays as one of the main challenge in BCI applications. Writing a simple message, an e-mail,... remains a difficult task to achieve for people with severe disabilities. Given the current potential market of BCI users and in relation to the current BCI performance, it is difficult to stay optimistic for the development of viable commercial software. The simultaneous development of eye-tracker systems like the Eye-Com EC7T eye tracking system (Eye-Com Corporation, http://eyecomcorp.com/) or the Tobii glasses (Tobii, http://www.tobii.com) could definitively limit the future of BCI for spelling applications.

Whereas recent BCI competitions have allowed comparisons of different machine learning methods, these benchmarks are limited to one aspect of a BCI. The graphical user interface should actually benefit the same attention as the signal processing part (Allison, 2009). This is particularly the case with SSVEP spellers that have constraints due to the number of available flashes on the screen: the ITR based on the BCI commands has to be translated without loss into the ITR based on the character. The presented spellers in this paper are only based on one type of brain activity. The next generation of BCIs will combine the detection of several brain responses, as hybrid BCIs (Pfurtscheller et al., 2010). Such solutions could provide faster and more robust spellers. They could solve to some extent the BCI illiteracy. This problem can be determinant for the choice of a specific BCI. Recent work has been conducted to address this problem: for P300 (Guger et al., 2003, 2009), SSVEP (Allison et al., 2010), and sensorimotor rhythms (Vidaurre and Blankertz, 2009). Instead of considering a brain response and trying to optimize the system in relation to a person, the user shall be the heart of the BCI and then the best brain responses, or the best existing BCI, shall be chosen to optimize the user's control.

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