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Review:

Electroencephalogram-based brain-computer interface for the Chinese spelling system: a survey*

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Abstract: Electroencephalogram (EEG) based brain-computer interfaces allow users to communicate with the external environment by means of their EEG signals, without relying on the brain's usual output pathways such as muscles. A popular application for EEGs is the EEG-based speller, which translates EEG signals into intentions to spell particular words, thus benefiting those suffering from severe disabilities, such as amyotrophic lateral sclerosis. Although the EEG-based English speller (EEGES) has been widely studied in recent years, few studies have focused on the EEG-based Chinese speller (EEGCS). The EEGCS is more difficult to develop than the EEGES, because the English alphabet contains only 26 letters. By contrast, Chinese contains more than 11 000 logographic characters. The goal of this paper is to survey the literature on EEGCS systems. First, the taxonomy of current EEGCS systems is discussed to get the gist of the paper. Then, a common framework unifying the current EEGCS and EEGES systems is proposed, in which the concept of EEG-based choice acts as a core component. In addition, a variety of current EEGCS systems are investigated and discussed to highlight the advances, current problems, and future directions for EEGCS.

Key words: Brain-computer interface (BCI); Electroencephalography (EEG); Chinese speller; English speller
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1 Introduction

A brain-computer interface (BCI) can be viewed as a hardware and software system that allows users to communicate with their surroundings using their brain signals, without the involvement of peripheral nerves and muscles. Because a BCI creates a new non-muscular way to express a person's intentions, it is particularly beneficial for individuals suffering from severe disabilities, such as amyotrophic lateral sclerosis, not only improving their life quality, but also reducing the cost of intensive care (Coyle et al., 2003; Nicolas-Alonso and Gomez-Gil, 2012). Currently, BCI techniques are also studied in non-medical fields, such as games and entertainment (Nijholt, 2008; Blankertz et al., 2010).

Vidal (1973) proposed the first BCI system to express the phenomena of the brain's electrical signals interpreted through a human-computer interface. BCI is now just coming out of its infancy and beginning to move from the proof-of-concept and emulation stages into maturity (Allison et al., 2013). Among all the non-invasive BCIs, the electroencephalogram (EEG) based ones are favored over others, such as magnetoencephalography (MEG), functional near

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infrared spectroscopy (fNIRS), and functional magnetic resonance imaging (fMRI), because of the unique advantages of EEGs, such as high time resolution, low cost, and portable devices. As a result, there has been great interest in developing practical and feasible EEG-based systems (Mora-Cortes et al., 2014). Several early reviews were given by Nicolas-Alonso and Gomez-Gil (2012) and Shende and Jabade (2015).

One popular application of the EEG-based BCI is in spelling systems, which, according to the types of brain responses focused on, can be divided mainly into the following four categories: event-related potential (ERP) based spellers, steady state visually evoked potential (SSVEP) based spellers, motor imagery (MI) based spellers, and hybrid spellers. The four categories are described as follows:

1. ERP-based speller. The original ERP-based speller was the P300-based speller proposed by Farwell and Donchin (1988) and derived from the principle that a P300 component, although absent for a frequent but non-attended stimulus, can be evoked in response to a non-frequent stimulus (oddball) the user attended to.

Thus, diverse P300 spelling systems have been developed, in which the P300 response is evoked by visual (Kindermans et al., 2014), auditory (Höhne et al., 2011; Schreuder et al., 2011; Kaufmann et al., 2013), or tactile stimulations (Brouwer and van Erp, 2010; Kaufmann et al., 2013). However, most of the P300-based spellers exploit visual stimulations with various features, including different matrix sizes (Allison and Pineda, 2003), novel stimulus patterns (Sellers et al., 2006; Townsend et al., 2010), novel visual stimulus types (Kaufmann et al., 2011; Tangermann et al., 2011), predictive word models (Höhne et al., 2010; Ryan et al., 2010; Speier et al., 2012; Akram et al., 2014; Mora-Cortes et al., 2014), adaptive subject-specific methods (Li et al., 2008; Kindermans et al., 2011), and dynamic stopping (Verschore et al., 2012; Kindermans et al., 2013, 2014; Schreuder et al., 2013). In particular, Jin et al. (2012a) reviewed the effects of different face stimuli on the P300-based speller. They also used the visual mismatch paradigm and proposed a new strategy to reduce errors in critical functions, and such a strategy could also be used to improve the speller system (Jin et al., 2014a, 2015).

One problem associated with the P300-based speller using visual stimuli is that this paradigm uses intensified visual stimuli, which may cause discomfort, especially in the case of extensive use. Therefore, the applications for clinical or home use are limited. To address this problem, Hong et al. (2009) proposed a motion-onset paradigm of the N200-based speller. Their model, which achieves a performance comparable to that of the P300-based speller, has the advantage of low levels of contrast and discomfort. Jin et al. (2012b) reported that when both P300 and motion-onset visual-evoked potentials were well formed, such a combination could further improve the performance of the speller system.

In addition, Zhang JX et al. (2012) found that a special EEG component of the N200 (which they called the centro-parietal N200) reveals the uniqueness of Chinese characters, compared with English. Jin et al. (2014b) and Zhang Y et al. (2012) proposed the idea of using facial expression changes and also inverted faces to help decrease the fatigue in P300-based BCIs, and such an idea could also be applied to P300 spellers.

However, the main disadvantage of the ERP based spellers (including P300- and N200-based ones) is their low information transfer rates, because they require the analyzed EEG signals be averaged over several sequential trials to enhance the ERP components. To address this problem, many methods, using only a single trial signal, have been investigated (Ford et al., 1994; Delorme and Makeig, 2004; Zhu et al., 2010; Blankertz et al., 2011).

2. SSVEP-based speller. Recently, SSVEP-based BCIs have received increasing attention because they provide higher bit rates while requiring little training (Parini et al., 2009; Zhu et al., 2010). Many SSVEP-based spellers have been developed (Zhu et al., 2010; Xia et al., 2012; Liu et al., 2014; Yin et al., 2015).

Whereas ERP-based spellers analyze EEG signals in a time domain, SSVEP-based spellers analyze brain waves in the SSVEP's frequency domain, where the SSVEP has the highest peak at the stimulus flicker rate and lower peaks in the harmonics (Colwell et al., 2014).

One of the main disadvantages of SSVEPs is the limited number of items from which users can choose. Recently several researchers have addressed this issue.

Yin et al. (2015), for example, designed a dynamically optimized SSVEP spelling system with enhanced performance in terms of accuracy, speed, and the number of possible items on the user interface.

3. MI-based speller. The methods for the EEG-based spellers mentioned above, based on the P300, N200, or SSVEP, depend on external stimuli, i.e., predefined external events that generate specific EEG components. The MI-based speller, however, has been made in an internal mode, where the user performs several specific motor imageries, such as moving his/her left hand, right hand, or feet.

D'albis et al. (2012), for example, developed an MI-based speller using an interface consisting of 27 symbols (26 letters of the English alphabet and a space symbol). Another MI-based speller is the so-called Hex-o-Spell (Blankertz et al., 2006), in which 30 different characters, arranged in six adjacent hexagons and distributed around a circle, can be selected by imagining one of two movements (moving the right hand or foot). To improve the speed, several single-trial methods for MI detection have also been studied (Ramoser et al., 2000; Blankertz et al., 2008; Khan and Sepulveda, 2012).

4. Hybrid speller. A hybrid brain-computer interaction technology has been widely used in control systems (Amiri et al., 2013a). Apart from the methods based on ERP, SSVEP, and MI, several hybrid methods are also used to develop spelling systems. Each of the hybrid methods contains at least two of the ERP, SSVEP, and MI methods. For example, Xu et al. (2013) proposed a hybrid BCI speller paradigm that integrates P300 and SSVEP signals. Yin et al. (2014) also used P300 and SSVEP input methods to develop a speedy hybrid spelling approach. Similar studies were reported by Brunner et al. (2010) and Yin et al. (2013). In addition, slow cortical potentials may be employed for developing speller systems (Birbaumer et al., 1999; Hinterberger et al., 2004). The above-mentioned methods are different from the implementations with ERP, SSVEP, and MI; therefore, we call these methods hybrid speller methods.

Although the EEG-based spellers have been widely studied in recent decades, most of them are suitable only for dealing with an alphabetic language with a limited number of letters, such as English whose words are alphabetic scripts composed of only 26 letters. By contrast, study on the EEG-based Chinese speller (EEGCS) was not reported until 2009 (Wu et al., 2009).

Till now, there are only a few references focusing on EEGCS. Unlike English, with only 26 letters, Chinese contains more than 11 000 logographic characters (Chinese characters) (Zhao, 2015). Consequently, EEGCS systems are more difficult to develop than EEG-based English speller (EEGES) ones. Nevertheless, various aspects of this issue have been addressed: both traditional Chinese characters (now used mainly in Taiwan and Hong Kong) (Minett et al., 2010, 2012) and simplified Chinese characters (now used in mainland China) (Jin et al., 2010) have been investigated; two types of phonetic symbols, Pinyin (used in mainland China) (Chen et al., 2013) and Zhuyin (used in Taiwan) (Huang et al., 2013), have been employed in EEG-based spelling systems; other aspects, such as special user interfaces (Minett et al., 2012; Huang et al., 2013), Chinese language models (Xu and Fang, 2015), and novel applications (Jin et al., 2010; Chen et al., 2013), have been addressed.

2 Taxonomy, EEG-based choice, and framework

2.1 Taxonomy of EEGCSs

Current EEGCS methods can be categorized into two classes: shape-based methods, which analyze EEG signals to select symbols that represent the form of Chinese characters, and pronunciation-based methods, or phonetic symbol based methods, which analyze EEG signals to select the symbols that represent the pronunciation of Chinese characters.

Shape-based methods can be further divided into two types: stroke-based methods, which select one stroke from each EEG-based choice, and segment-based methods, which select one segment, including one or several strokes, from each EEG-based choice.

Pronunciation-based methods can also be further grouped into two types: Pinyin-based methods, which select one symbol from the Pinyin system for each EEG-based choice, and Zhuyin-based methods, which select one symbol from the Zhuyin system for each EEG-based choice.

2.2 EEG-based choice

In general, the fundamental idea of various EEG-based spellers, either EEGCS or EEGES, is

EEG-based choice, which selects an item from a set of options by analyzing the user's EEG signals, which are evoked by exterior or interior stimuli (Fig. 1).

Each EEG-based choice usually consists of the following five successive steps (Fig. 2): preprocessing, feature extraction, feature selection, classification, and translation. In Fig. 2, the processing steps are presented on the left side of the dashed line; the results corresponding to each processing step are shown on the right side.

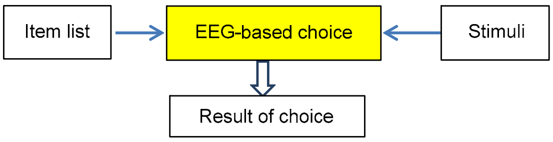

Fig. 1 The concept of EEG-based choice

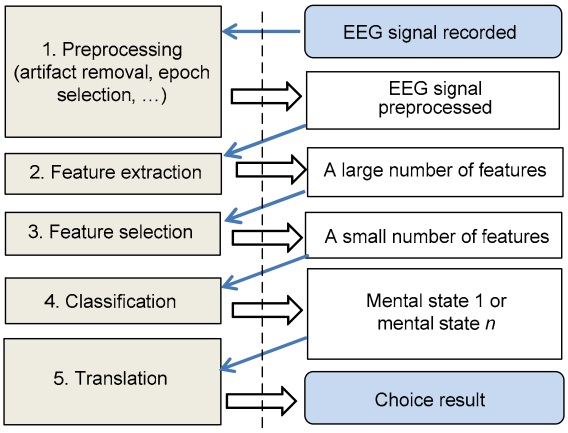

Fig. 2 Procedure of EEG-based choice

First, the recorded EEG signals are preprocessed to remove artifacts, select concerned epochs, filter unwanted frequency components, etc. Second, features are extracted from the preprocessed EEG signals. Third, because the number of features extracted is normally very large, it is difficult to suitably classify the extracted features. Feature selection is usually carried out as a critical step to identify the important features and discard the trivial ones. Fourth, based on the selected features, a classification algorithm groups the EEG signals into corresponding classes of a mental state. Finally, the mental states are translated into corresponding commands for the spelling system to further choose the target items in the user interface.

The target item, to which the user pays attention, is determined by a particular speller using the EEG-based choice, as follows:

1. P300 speller. In the P300 speller, the target item is associated with an oddball event, i.e., an event with a low probability. When a user gazes at the target item, about 300 ms after the onset of the oddball event, the P300 component in the user's EEG signal is supposed to be evoked. By detecting if the EEG signal contains the P300 component, the EEG-based choice determines if the event evoking the EEG signal is an oddball event. If so, the item associated with the oddball event is regarded as the target item, to which the user pays attention. The original P300 EEGES system (Farwell and Donchin, 1988) and many other improved ones were mentioned in Section 1. Several P300 EEGCS systems (Wu et al., 2009; Jin et al., 2010; Sun et al., 2011; Minett et al., 2012; Huang et al., 2013; Xu and Fang, 2015) will be discussed in the next section.

2. N200 speller. In the N200 speller, however, each item is associated with a motion stimulus, such as a bar moving from right to left in a small window at a specific speed. When the user gazes at the motion stimulus that is associated with the target item, the N200 is supposed to appear in the user's EEG signal. Thus, by detecting if the EEG signal contains the N200 component, the EEG-based choice determines if the item associated with the EEG signal and motion stimulus is the target. Hong et al. (2009) proposed one N200 EEGES, and Huang et al. (2013) proposed an N200 EEGCS, which will be described in the next section.

3. SSVEP speller. In the SSVEP speller, the EEG-based choice chooses a target item in a direct or indirect way. In the direct way, all items flick at the same time, but at different frequencies. If a user gazes at the target item flickering at a particular frequency f, then his/her EEG signals will, by using the Fourier analysis, contain salient frequency components at f, $2f$, ..., in the spectrum. Thus, by verifying this kind of saliency, EEG-based choice determines the target item. Details can be seen in Zhu et al. (2010) and Liu et al. (2014).

In the indirect way, the items selected by EEG-based choices are not the final target items; instead, they act like buttons to control a cursor's movements, such as forward, backward, upward, and downward, by which the final item is selected in a way similar to the way used by a mouse cursor. A typical research of the indirect method was carried out by Yin et al. (2015), and other systems were as mentioned in Section 1. An SSVEP-based EEGCS system (Zhao, 2012) will be introduced in the next section.

4. MI speller. Like the SSVEP speller, the MI speller selects an item in an indirect way. However, different from the SSVEP speller that employs SSVEP, which is evoked by exterior stimuli, the MI speller recognizes the user's internal intention when the user performs an imagined limb movement. Motor imagery may be regarded as a mental rehearsal of a motor act without any overt motor output. However, motor imagery can modify the neuronal activity in the primary sensorimotor areas in a way that is very similar to that observable with a real executed movement (Semlitsch et al., 1986; Hoffmann et al., 2008).

By detecting these kinds of changes, which are supposed to be due to event-related desynchronization (ERD) or event-related synchronization (ERS) of the underlying neuronal groups, EEG-based choices detect the user's different intentions and mental states, by which the system controls the different directions of the cursor movement, so as to select the target letters. Details about MI-based EEGES systems can be seen in Blankertz et al. (2006). Details about MI-based EEGCS systems can be seen in Chen et al. (2013).

2.3 Framework

Based on the concept of the EEG-based choice introduced above, we propose a general framework that unifies most, if not all, of the present-day EEG-based spellers, including EEGES and EEGCS systems.

Fig. 3 shows that the framework is composed of three parts indicated by two vertical dashed lines: user interface area (left), EEG-based choice area (center), and auxiliary area (right).

In a spelling system, EEG-based choice generally consists of two phases, as shown in the EEG-based choice area (center of Fig. 3).

In the first phase, by analyzing the unique EEG components evoked by the stimuli (top-right in Fig. 3) that are associated with the features in the feature area (top-left in Fig. 3), each EEG-based choice, from the feature area, selects one character feature. Features are either strokes or segments in shape-based methods; in contrast, features are either Pinyin or Zhuyin symbols in pronunciation-based methods.

Once a series of character features has been selected, the system, by means of a dictionary, automatically produces candidate characters, each of which contains all of the selected features. Alternatively, based on a language model, the system predicts additional candidate characters that, although not containing these features, are relevant to the candidate characters already produced (Höhne et al., 2010; Ryan et al., 2010; Speier et al., 2012; Akram et al., 2014; Mora-Cortes et al., 2014).

In the second phase, the candidate characters produced in the first phase are then shown in the candidate area, which may either replace the feature area or form an independent area in the user interface, depending on the variant paradigms. Consequently, in the second phase, the user selects the target characters from the set of candidates in the candidate area, in a way similar to that in the first phase, i.e., by analyzing the EEG signals evoked by the stimuli.

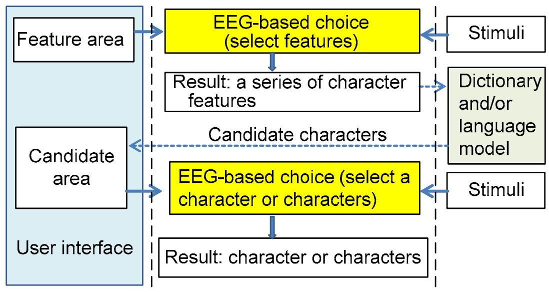

Fig. 3 Framework of the EEG-based spelling system
The framework is divided into three parts by two vertical dashed lines: user interface area (left), EEG-based choice area (center), and auxiliary area (right)

3 EEGCS

3.1 Shape-based method

The advantage of the shape-based EEGCS is that users can input a sinogram (Chinese character) even when they do not know how to pronounce it; the users need only to know the form of Chinese characters. Shape-based methods are categorized into stroke and segment-based methods (Table 1).

3.1.1 Stroke-based method

Wu et al. (2009) developed a P300 EEGCS version, which is a typical EEGCS using five basic strokes ('—', '丨', '/', '㇏', '乛'). The user interface

Table 1 Taxonomy of EEG-based Chinese speller

Method		Reference
Shape based	Stroke-based	Wu et al. (2009); Jin et al. (2010) (P300)
	Segment-based	Minett et al. (2010, 2012) (P300)
Pronunciation based	Pinyin-based	Chen et al. (2013) (MI); Xu and Fang (2015) (P300)
	Zhuyin-based	Wu et al. (2009) (P300+N200); Sun et al. (2011) (P300)

includes four regions: optional items, optional Chinese characters, selected strokes, and selected Chinese characters.

The optional items region is composed of seven items for users to select through EEG-based choices. Five items represent five strokes or optional Chinese characters, depending on different stages; the two other items, 'Bk' and 'En', provide the control functions. 'Bk' means backspace and 'En' means enter.

In the system developed by Wu et al. (2009), a user inputs a Chinese character in three steps:

Step 1: Five basic strokes are presented in the optional items region. The user selects strokes one by one through EEG-based choices until the target Chinese character, which is produced by the system according to the selected strokes, occurs in the optional Chinese character's region, along with other Chinese characters that also contain the selected strokes.

Step 2: The user selects the 'En' item through another EEG-based choice. If successful, the Chinese characters in the optional Chinese character region will be presented in the optional items region.

Step 3: The user selects the target Chinese character in the optional items region through one EEG-based choice.

During the execution of the above three steps, the items, either strokes or Chinese characters depending on the phases, flicker one by one, and the user focuses on the target item. When the target item flickers, the user pays more attention to the target item if he/she mentally counts the flickers. The P300 characteristic component of the EEG signal will be stronger. Four subjects participated in the experiments carried out by Wu et al. (2009). The EEG recordings in the experiments were performed using the Neuronscan system. Signals from four electrodes (FCZ, CZ, CPZ, and PZ) were analyzed. The reference electrode was placed on the nasal tip.

The analytical procedure used by Wu et al. (2009) was as follows: At first, the direct-current component in the signal was removed. Then, a regression algorithm was employed to cancel the influence of the electro-oculogram (EOG), followed by a fifth-order Butterworth low-pass filter with a 15 Hz cut-off frequency. Only the signals in the 200–600 ms interval after each flicker were extracted for analysis. The template matching method was used to examine whether the P300 existed or not.

The results showed that the accuracy was in the range of 38%–84%, and that the practical bit transfer rate was 1.23–8.80 bits/min (Wu et al., 2009). Although insufficient to provide a practical EEGCS, this experiment showed some interesting potentials.

Jin et al. (2010) used another stroke-based EEGCS to send messages on a cell phone. Taking the T9 stroke input system developed by Tegic Communications, Seattle, USA as a reference, they developed a user interface that included a 4×4 matrix containing five strokes, eight numbers (1–8), and three other control items. In their system, similar to the one used by Wu et al. (2009), the user inputs a Chinese character in two steps:

Step 1: After the user selects strokes through several EEG-based choices, the system presents optional Chinese characters, which are composed of the selected strokes and shown on the screen of a cell phone, where at most seven Chinese characters can be presented.

Step 2: The user selects the target Chinese character by selecting its number from the list of optional Chinese characters. Eleven subjects took part in the experiments; their EEG signals were recorded by 30 electrodes in an ESI-36 system, manufactured by the Neuronscan company, alongside four electrodes recording EOG to reduce EOG artifacts from the EEG signals by means of a method proposed by Semlitsch et al. (1986).

A sixth-order Butterworth band pass filter algorithm was employed to filter the EEG to 0.1–12 Hz. Experimental results showed that the accuracy was 39%–93%, and that the average number of EEG-based choices for one Chinese character was 6–7.

One of the main goals of Jin et al. (2010) was to improve the accuracy rather than the speed. The uniqueness of their methods for processing EEG signals lies in the choice of electrodes using particle swarm optimization (PSO) algorithms, and the classification algorithm, i.e., Bayesian linear discriminate analysis (BLDA), which is an extension of the Fisher linear discriminate analysis (FLDA) (Hoffmann et al., 2008). A particle of the PSO represents a position in the electrode configuration in the search domain, and its fitness value is the error rate of the classification obtained by BLDA (Jin et al., 2010).

In contrast to Wu et al. (2009) and Jin et al. (2010) who focused on P300, Zhao (2012) proposed another stroke-based EEGCS that focuses on SSVEP. The main part of the user interface proposed by Zhao (2012) was composed of the following four parts: (1) Seven items, including six basic strokes ('—', '丨', '/', '㇏', '乛', '乙') and one control item ('Bk', meaning backspace), are arranged in a row; (2) The gray rectangle on an item can be controlled to move to the left or the right, depending on EEG analysis; (3) Three chess board squares flicker at different frequencies (left, 9.44 Hz; right, 12.14 Hz; central, 7.72 Hz); (4) The optional Chinese characters are listed above the strokes.

In Zhao's system (Zhao, 2012), the user gazes at one of the three chessboard squares. To determine at which chessboard square the user gazed, the 2000 ms segments of the signals recorded from the OZ electrode were analyzed.

The principle by which Zhao determined which square was gazed at was as follows: if the frequency amplitude of the analyzed signal at a certain frequency (at which one of the chess board squares flickered) was so manifest that it went up 1.5 times the averaged frequency amplitude over 4–30 Hz, then the chess board square that flickered at that frequency was regarded as the one at which the user gazed.

If the system determined that the left square was the one to which the user paid attention, the system controlled the gray rectangle to move to the item on the left; if the system determined that the right square was the one to which the user paid attention, the system controlled the gray rectangle to move to the item on the right; if the system determined that the central square was the one to which the user paid attention, the system selected the item covered by the gray rectangle as the target stroke.

The optional Chinese characters containing the selected strokes are listed above the strokes, and the target Chinese character can be selected in a way similar to that by which the target stroke is selected.

The limitation of this system resides in the limited number of frequencies used to evoke SSVEP. Therefore, the gray rectangle has to be moved in an inefficient way. For instance, the grey background cannot move from the first item directly to the third item. Therefore, this method is not suitable for choices of many items. Consequently, this system is only a simple prototype to show the potential for exploiting SSVEP in the design of an EEGCS system.

3.1.2 Segment-based method

Although the stroke-based method is simple and direct, it is inefficient because one EEG-based choice selects only one stroke, resulting in a low information transfer rate.

To address this issue, several segment-based EEGCS systems have been proposed. Because one segment includes one or more strokes and can be selected by one EEG-based choice, a segment-based method is much more efficient than the stroke-based methods.

Minett et al. (2010) proposed an EEGCS employing the segment-based method. The user interface in their system is a 6×6 matrix, similar to the original P300 speller used by Farwell and Donchin (1988). The difference is that the letters they use are replaced by 35 segments of traditional Chinese characters with one control item ('←') at the bottom right corner.

Thirty subjects participated in the experiments. The EEG measurements were performed using the Net Amps 200 recording system manufactured by Electrical Geodesics. Signals from five electrodes (Pz, P3, P4, P7, P8) were used for analysis. The analyzed signals were extracted from −100 ms (before stimulus onset) to 400 ms (after stimulus onset). Signals from −100 ms to 0 ms were used for baseline correction. Signals from 50 ms to 400 ms were used for classification. FLDA was used as the classification algorithm.

Minett et al. (2010) examined four types of intensifications: (1) intensify a single component by changing the foreground color, (2) intensify a single component by changing the background color, (3) intensify a row/column of components by changing the foreground color, and (4) intensify a row/column of components by changing the background color.

Minett et al. (2010) also examined different time coding of the stimuli. The stimuli were intensified for 100 ms and followed by a blank mask of either 17 ms (for all these four types) or 67 ms (for only the last two types).

The results showed that: (1) the first two types of intensification, with a 17 ms blank mask, outperformed other cases and achieved a classification accuracy greater than 80%; (2) the last type of intensification, with a 17 ms blank mask, provided the best performance, achieving a communication rate of 14.5 bits/min.

To reduce the number of EEG-based choices employed in Jin et al. (2010), and to extend 35 segments in Minett et al. (2010) to 56 segments, Minett et al. (2012) further proposed an EEGCS system with a novel segment-based method called 'first-last' (FLAST). FLAST encodes 7072 Chinese characters, and selecting each sinogram requires at most three EEG-based choices, two of which select the first and last segments of the target Chinese character, respectively. The last one selects the target Chinese character from several optional Chinese characters.

In their stimulus interface, the 56 segments and 8 control items are arranged into an 8×8 matrix. The intensification method, i.e., intensifying items in one row/column simultaneously, is similar to that proposed by Farwell and Donchin (1988). Twenty-four subjects participated in the experiment. Using the ActiveTwo EEG recording system with 32 channels (manufactured by Biosemi), signal epochs of 800 ms duration from 32 electrodes were analyzed and filtered to 0.1–40 Hz. The classification algorithm used was stepwise linear discriminant analysis (SWLDA).

Their experimental results showed that, when the input speed was set to one Chinese character per 107 s (corresponding to 0.56 Chinese characters per minute), the communication rate was 12.93 bits/min, with a segment selection mean accuracy of 82.8%. Although the desired accuracy and speed were achieved in Minett et al. (2012), an unexpected phenomenon occurred in the experiments. Because they employed an intensification approach similar to the P300 speller of Farwell and Donchin (1988), Minett et al. (2012) initially expected that a strong P300 component could be found in the EEG signal. However, no clear P300 component was found in the experiments. On the contrary, an apparent N200 component was observed. The reason was not explained by Minett et al. (2012). We assume that it may be related to the difference between the form of Chinese characters (also segments) and English letters. Our assumption can be partially supported by Zhang JX et al. (2012), but further investigation is required.

3.2 Pronunciation-based method

Pronunciation-based EEGCS systems allow users to input Chinese characters without knowledge of the forms; therefore, they are complementary to shape-based EEGCS systems.

The problem is that the combination of several Chinese phonetic symbols may represent the same pronunciation of many different Chinese characters. Consequently, this problem results in additional EEG-based choices to select the target Chinese character from a list of optional ones. Therefore, researchers first conducted research on the shape-based method rather than the pronunciation-based method.

However, many people prefer the pronunciation-based method due to its relationship with natural pronunciation. Therefore, in recent years, researchers have developed several pronunciation-based EEGCS systems.

Sun et al. (2011) developed a pronunciation-based method for EEGCS by detecting P300 responses. Their user interface presented a 3×4 matrix containing 11 groups of phonetic symbols (Zhuyin) with one control item. The items in the matrix were intensified in a row/column way similar to that in Farwell and Donchin (1988); i.e., the items in one row or one column were intensified simultaneously.

The procedure to select a Chinese character was as follows: Using EEG-based choices, the user first selects one item containing the target phonetic symbols. Then, the system produces nine optional Chinese characters whose phonetic symbols are in the selected item. These optional Chinese characters and three additional control items are presented in the matrix, replacing the former items. Finally, using EEG-based choices, the user selects the target Chinese character from the matrix.

Ten subjects participated in the experiment. O1 and O2 acted as reference electrodes. Using the

Braintronics system, the EEG signals from the Pz electrode were recorded at a sampling rate of 500 Hz, filtered to 0.1–15 Hz, and extracted from −100 ms (before the identification) to 500 ms (after the identification). The experiment showed that the target intensifications could evoke significantly larger P300 components in both columns and rows, compared with the non-target intensifications. Based on this kind of difference, a *t*-test in this system recognized the targets. The results showed that the average accuracy was 90%, and that the average speed approached one Chinese character per 130 s.

Huang et al. (2013) further proposed a P300- and N200-based EEGCS using phonetic symbols (Zhuyin), arranged into one matrix as in their previous research (Sun et al., 2011).

To elicit the N200 component, there was an additional small rectangle beneath each phonetic symbol, in which there was a bar moving during the coding time. However, the phonetic symbols were not as intense as those in Sun et al. (2011). During the experiment, the user gazed at the rectangular target.

The N2P3-value (the amplitude difference between P300 and N200) of the recorded EEG signals was used to determine the target symbols: the symbol at the intersection of the column with the maximum N2P3-value and the row with the maximum N2P3-value was regarded as the user's intention.

The experiment consisted of 24 trials. A1 and A2 acted as reference electrodes. The EEG signals from O1 were analyzed and filtered to 0–6 Hz. The results showed that the accuracy reached 95.8% and that the speed reached 136.6 bits/min.

Recently, Xu and Fang (2015) reported another P300-based EEGCS method using phonetic symbols, which has several characteristics: After several phonetic symbols are selected, the optional Chinese characters, whose phonetic symbols consist of the selected ones, are generated by the system and do not replace the phonetic symbols in the user interface. Instead, they are shown around the phonetic symbols. In this way, the switch between the feature (phonetic symbols) area and candidate (optional Chinese characters) area in Fig. 3 is avoided. The identifications do not flash by row/column, but by single phonetic symbol or single sonogram. The classification algorithm is the support vector machine (SVM). To increase the communication rate, a statistical language model is employed to predict the possible target Chinese characters.

Four subjects participated in the experiment. The EEG signals were recorded by a UEA-24BZ system manufactured by a Chinese company (Beijing Zhongke). The sample rate was 100 Hz. The signals from seven electrodes (Cz, Fz, Pz, P3, P4, O1, and O2) were chosen and filtered by the Chebyshev filter to 1–15 Hz. The results showed that the average speed could be 0.90 Chinese characters per minute without using the statistical language model, and could be improved to 1.13 Chinese characters per minute when the statistical language model was employed.

All the EEGCS mentioned above, including shape- and pronunciation-based methods, employ evoked EEG components such as the P300, SSVEP, and N200, which can be elicited but must depend on exterior stimuli. By contrast, Chen et al. (2013) proposed a kind of EEGCS system that employs the self-evoked EEG component, which could be elicited by the user's motor imagery without the requirement of exterior stimuli.

Considering Pinyin phonetic symbols to be also English letters, Chen et al. (2013) combined Chinese Pinyin phonetic symbols and English symbols into the same interface, and developed an asynchronous Chinese-English BCI speller based on motor imagery and a 2D cursor control strategy. The letters representing both Chinese phonetic symbols and English letters were arranged in three layers of Oct-o-Spell interfaces, along with several control items. To choose a block of items, the user had to perform three kinds of motor tasks, i.e., moving his/her left hand, right hand, or feet, to control a cursor initially located in the center of the interface until it hit the circle of the target block. Details can be seen in Chen et al. (2013). Three subjects participated in their experiments. The Fz and right earlobe were chosen as the ground electrode and reference electrode, respectively. Signals from 13 channels (FC3, FCZ, FC4, C5, C3, C1, CZ, C2, C4, C6, CP3, CPZ, and CP4) in the motor cortex area were recorded by a USB system, and filtered to 5–30 Hz. Their features were extracted by the common spatial pattern (CSP) method, and classified by the SVM algorithm. The results showed that the mean accuracy was 96.33% and that the speed was 30.86 bits/min and 5.53 letters/min.

4 Discussions

The methods for constructing EEGCS systems include shape- and pronunciation-based methods, which are mutually complementary: shape-based methods do not require users know the pronunciations of Chinese characters, whereas pronunciation-based methods do not require users know the form of Chinese characters.

Among shape-based methods, segment-based methods are more efficient than stroke-based methods, because segment-based methods can input several strokes as one segment with each EEG-based choice.

Among pronunciation-based methods, however, Pinyin- and Zhuyin-based methods are both useful and mutually complementary, because Pinyin is adopted in mainland China while Zhuyin is adopted in Taiwan.

The EEGCS systems investigated in this study are typical ones with several methods mentioned above, and with various user interfaces, stimuli, and applications. Their characteristics, such as parameters, accuracy, and speed, are summarized in Table 2.

In Table 2, we can see that, since 2009, researchers have explored various Chinese character-spelling methods, from the earlier shape-based methods including stroke- and segment-based methods, to the recent pronunciation-based methods including Pinyin- and Zhuyin-based methods.

Table 2 also shows that various kinds of EEG components, including P300, N200, SSVEP, and MI, have been used to develop EEGCS systems. Among such systems, the most frequently used method is P300. In particular, researchers have realized the necessity and possibility of employing hybrid components, such as a combination of P300 with N200 or P300 with SSVEP, to overcome the disadvantages of using a single component and thus to improve the system performance.

Different classification algorithms such as FLDA, BLDA, SVM, and template-matching methods have been employed, and the issue of electrode selection or channel selection has also been investigated (Jin et al., 2010).

Although a variety of EEGCSs have been proposed, compared with EEGES, EEGCS has been investigated to a far lower degree, and several key issues exist in the current research.

First of all, although various EEG components have been employed in the current EEGCS research, other components except the P300 have not been investigated as thoroughly as in the EEGES research. In fact, many methods widely used in EEGES systems can be introduced into EEGCS systems, although the corresponding paradigms might need to be redesigned with several novel ideas. On the other hand, except for the hybrid components of P300/ N200, other hybrid BCIs, such as P300/ SSVEP BCIs

Table 2 Applications in each class (optimized by PSO)

Type	Year	Number of subjects	Component	Number of electrodes	Filter (Hz)	Time interval (ms)	Classifier	Accuracy (%)	Speed	Reference
Stroke	2009	4	P300	4	–	200–600	Template	38–84	1.23–8.80 bits/min	Wu et al., 2009
	2010	11	P300	Optimized by PSO	0.1–12	0–500	BLDA	38.7–93.0	–	Jin et al., 2010
	2012	2	SSVEP	1	4–30	2000	Threshold	65–72	–	Zhao, 2012
Segment	2010	30	P300	5	0–40	−100–400	FLDA	>80	14.5 bits/min	Minett et al., 2010
	2012	24	P300	32	0.1–40	800	FLDA	63.5–82.8	12.93 bits/min	Minett et al., 2012
	2013	1	P300 +N200	1	0–6	–	N2P3	95.8	136.6 bits/min	Huang et al., 2013
Pinyin	2015	4	P300	19	1–15	0–700	SVM	–	1.13 sinograms/min	Xu and Fang, 2015
	2013	3	MI	13	5–30	–	SVM	96.33	30.86 bits/min, 5.53 letters/min	Chen et al., 2013

(Amiri et al., 2013b; Xu et al., 2013; Yin et al., 2013) developed in recent years, should have been introduced to develop EEGCS systems.

In addition, most of current EEGCS systems are tentatively exploring the feasibility of their methods with a small number of Chinese characters.

Furthermore, most of experiments were carried out with a few healthy subjects, and only a few experiments, such as those conducted by Minett et al. (2010, 2012), were performed with more than 20 subjects. Nevertheless, healthy subjects rather than disabled subjects were used.

Consequently, the values for the accuracy and speed reported in these systems may have less significance when compared with each other or with regard to disabled subjects. For this reason, we believe that two aspects are worthy of consideration in further research: (1) target user—the systems should be comfortable, and can be easily and efficiently used by disabled individuals; (2) evaluation metric—it is necessary to specify certain conditions under which evaluation of performance such as accuracy and speed could be comparable among different systems and approaches (otherwise, without common conditions, it may be difficult to quantify and provide a definitive comparison between them).

Furthermore, note that many assistant technologies, which do not depend on EEG-based choices, may be independently developed and greatly improve the system performance. For instance, natural language models can be applied to predict subsequent Chinese characters (Mora-Cortes et al., 2014; Xu and Fang, 2015). In fact, combined with a good language model, EEGCS systems can be improved in prediction, completion, and error correction, so as to be substantially improved in terms of process accuracy and speed. Mora-Cortes et al. (2014) provided a review of the advantages and challenges while implementing language models in BCI-based communication systems.

Several applications of EEGES systems, such as BCI-based web browsers (Halder et al., 2015) and Internet explorers (Bai et al., 2015), are also worthy of being introduced into EEGCS systems, and more novel applications could be developed further. Nevertheless, we believe that the key technology for EEGCS systems will still be based on EEG-based choice, which can be regarded as the core of an EEGCS system.

Finally, many novel technologies that have been efficiently employed in EEGES systems, such as channel selection for preprocessing (Colwell et al., 2014), ensemble classifiers for enhancing classification accuracy (Allison et al., 2013), and language models for improving speed (Mora-Cortes et al., 2014), are expected to be involved in EEGCS research. This leaves considerable room for the current EEGCS systems to be improved.

5 Conclusions

Contrary to the EEGES methods that have been widely studied in recent decades, research on the EEGCS began in 2009. In this paper, we reviewed most of the literature on EEGCS systems. A common framework to unify the current EEGCS and EEGES systems was proposed, followed by a presentation and discussion of the state-of-the-art work about EEGCS systems.

When developing EEGCS systems, the intrinsic difference between EEGCS and EEGES systems means that more issues should be considered compared with developing EEGES systems. On the other hand, many methods, such as other paradigms and EEG signal processing methods, which have been employed by the current EEGES systems, could be very useful for developing EEGCS systems. Thus, we believe that research on EEGCS systems is a promising field with potential for rapid development in the coming years.

References

Akram F, Han HS, Kim TS, 2014. A P300-based brain computer interface system for words typing. *Comput Biol Med*, 45:118-125. https://doi.org/10.1016/j.compbiomed.2013.12.001

Allison BZ, Pineda JA, 2003. ERPs evoked by different matrix sizes: implications for a brain computer interface (BCI) system. *IEEE Trans Neur Syst Rehabil Eng*, 11(2): 110-113. https://doi.org/10.1109/TNSRE.2003.814448

Allison BZ, Dunne S, Leeb R, et al., 2013. Towards Practical Brain-Computer Interfaces: Bridging the Gap from Research to Real-World Applications. Springer, Berlin, Germany. https://doi.org/10.1007/978-3-642-29746-5

Amiri S, Fazel-Rezai R, Asadpour V, 2013a. A review of hybrid brain-computer interface systems. *Adv Hum-Comput Interact*, 2013:187024. https://doi.org/10.1155/2013/187024

Amiri S, Rabbi A, Azinfar L, et al., 2013b. A review of P300, SSVEP, and hybrid P300/SSVEP brain-computer interface systems. In: Fazel-Rezai R (Ed.), Brain-Computer Interface Systems—Recent Progress and Future Prospects. InTechOpen, London, UK, p.195-213. https://doi.org/10.5772/50696

Bai LJ, Yu TY, Li YQ, 2015. A brain computer interface-based explorer. *J Neurosci Methods*, 244:2-7. https://doi.org/10.1016/j.jneumeth.2014.06.015

Birbaumer N, Ghanayim N, Hinterberger T, et al., 1999. A spelling device for the paralysed. *Nature*, 398(6725): 297-298. https://doi.org/10.1038/18581

Blankertz B, Dornhege G, Krauledat M, et al., 2006. The Berlin brain-computer interface presents the novel mental typewriter Hex-o-Spell. 3rd Int Brain-Computer Interface Workshop and Training Course, p.108-109.

Blankertz B, Tomioka R, Lemm S, et al., 2008. Optimizing spatial filters for robust EEG single-trial analysis. *IEEE Signal Process Mag*, 25(1):41-56. https://doi.org/10.1109/MSP.2008.4408441

Blankertz B, Tangermann M, Vidaurre C, et al., 2010. The Berlin brain-computer interface: non-medical uses of BCI technology. *Front Neurosci*, 4:198. https://doi.org/10.3389/fnins.2010.00198

Blankertz B, Lemm S, Treder M, et al., 2011. Single-trial analysis and classification of ERP components—a tutorial. *Neuroimage*, 56(2):814-825. https://doi.org/10.1016/j.neuroimage.2010.06.048

Brouwer AM, van Erp JB, 2010. A tactile P300 brain-computer interface. *Front Neurosci*, 4:19. https://doi.org/10.3389/fnins.2010.00019

Brunner P, Joshi S, Briskin S, et al., 2010. Does the 'P300' speller depend on eye gaze? *J Neur Eng*, 7(5):056013. https://doi.org/10.1088/1741-2560/7/5/056013

Chen CH, Yang J, Huang YB, et al., 2013. A cursor control based Chinese-English BCI speller. 20th Int Conf on Neural Information Processing, p.403-410. https://doi.org/10.1007/978-3-642-42054-2_50

Colwell KA, Ryan DB, Throckmorton CS, et al., 2014. Channel selection methods for the P300 speller. *J Neurosci Methods*, 232:6-15. https://doi.org/10.1016/j.jneumeth.2014.04.009

Coyle S, Ward T, Markham C, 2003. Brain-computer interfaces: a review. *Interdiscip Sci Rev*, 28(2):112-118. https://doi.org/10.1179/030801803225005102

D'albis T, Blatt R, Tedesco R, et al., 2012. A predictive speller controlled by a brain-computer interface based on motor imagery. *ACM Trans Comput-Hum Interact*, 19(3):20. https://doi.org/10.1145/2362364.2362368

Delorme A, Makeig S, 2004. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *J Neurosci Methods*, 134(1):9-21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Farwell LA, Donchin E, 1988. Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalogr Clin Neurophysiol*, 70(6):510-523. https://doi.org/10.1016/0013-4694(88)90149-6

Ford JM, White P, Lim KO, et al., 1994. Schizophrenics have fewer and smaller P300s: a single-trial analysis. *Biol Psychiatry*, 35(2):96-103. https://doi.org/10.1016/0006-3223(94)91198-3

Halder S, Pinegger A, Käthner I, et al., 2015. Brain-controlled applications using dynamic P300 speller matrices. *Artif Intell Med*, 63(1):7-17. https://doi.org/10.1016/j.artmed.2014.12.001

Hinterberger T, Schmidt S, Neumann N, et al., 2004. Brain-computer communication and slow cortical potentials. *IEEE Trans Biomed Eng*, 51(6):1011-1018. https://doi.org/10.1109/TBME.2004.827067

Hoffmann U, Vesin JM, Ebrahimi T, et al., 2008. An efficient P300-based brain-computer interface for disabled subjects. *J Neurosci Methods*, 167(1):115-125. https://doi.org/10.1016/j.jneumeth.2007.03.005

Höhne J, Schreuder M, Blankertz B, et al., 2010. Two-dimensional auditory P300 speller with predictive text system. Annual Int Conf of the IEEE Engineering in Medicine and Biology Society, p.4185-4188. https://doi.org/10.1109/IEMBS.2010.5627379

Höhne J, Schreuder M, Blankertz B, et al., 2011. A novel 9-class auditory ERP paradigm driving a predictive text entry system. *Front Neurosci*, 5:99. https://doi.org/10.3389/fnins.2011.00099

Hong B, Guo F, Liu T, et al., 2009. N200-speller using motion-onset visual response. *Clin Neurophysiol*, 120(9):1658-1666. https://doi.org/10.1016/j.clinph.2009.06.026

Huang TW, Tai YH, Tian YJ, et al., 2013. The fastest BCI for writing Chinese characters using brain waves. 4th Global Congress on Intelligent Systems, p.346-349. https://doi.org/10.1109/GCIS.2013.62

Jin J, Allison BZ, Brunner C, et al., 2010. P300 Chinese input system based on Bayesian LDA. *Biomed Eng/Biomed Tech*, 55(1):5-18. https://doi.org/10.1515/bmt.2010.003

Jin J, Allison BZ, Kaufmann T, et al., 2012a. The changing face of P300 BCIs: a comparison of stimulus changes in a P300 BCI involving faces, emotion, and movement. *PLOS ONE*, 7(11):e49688. https://doi.org/10.1371/journal.pone.0049688

Jin J, Allison BZ, Wang XY, et al., 2012b. A combined brain-computer interface based on P300 potentials and motion-onset visual evoked potentials. *J Neurosci Methods*, 205(2):265-276. https://doi.org/10.1016/j.jneumeth.2012.01.004

Jin J, Allison BZ, Zhang Y, et al., 2014a. An ERP-based BCI using an oddball paradigm with different faces and reduced errors in critical functions. *Int J Neur Syst*, 24(8): 1450027. https://doi.org/10.1142/S0129065714500270

Jin J, Daly I, Zhang Y, et al., 2014b. An optimized ERP brain-computer interface based on facial expression changes. *J Neur Eng*, 11(3):036004. https://doi.org/10.1088/1741-2560/11/3/036004

Jin J, Sellers EW, Zhou SJ, et al., 2015. A P300 brain-computer interface based on a modification of the mismatch negativity paradigm. *Int J Neur Syst*, 25(3): 1550011. https://doi.org/10.1142/S0129065715500112

Kaufmann T, Schulz SM, Grünzinger C, et al., 2011. Flashing characters with famous faces improves ERP-based brain-computer interface performance. *J Neur Eng*, 8(5): 056016. https://doi.org/10.1088/1741-2560/8/5/056016

Kaufmann T, Holz EM, Kübler A, 2013. Comparison of tactile, auditory, and visual modality for brain-computer interface use: a case study with a patient in the locked-in state. *Front Neurosci*, 7:129. https://doi.org/10.3389/fnins.2013.00129

Khan YU, Sepulveda F, 2012. EEG single-trial classification of different motor imagery tasks using measures of dispersion and power in frequency bands. *Int J Biomed Eng Technol*, 8(4):343-356. https://doi.org/10.1504/IJBET.2012.046960

Kindermans PJ, Verstraeten D, Buteneers P, et al., 2011. How do you like your P300 speller: adaptive, accurate and simple? 5th Int Conf on Brain-Computer Interface, p.1-4.

Kindermans PJ, Verschore H, Schrauwen B, 2013. A unified probabilistic approach to improve spelling in an event-related potential-based brain-computer interface. *IEEE Trans Biomed Eng*, 60(10):2696-2705. https://doi.org/10.1109/TBME.2013.2262524

Kindermans PJ, Tangermann M, Muller KR, et al., 2014. Integrating dynamic stopping, transfer learning and language models in an adaptive zero-training ERP speller. *J Neur Eng*, 11(3):35005. https://doi.org/10.1088/1741-2560/11/3/035005

Li YQ, Guan CT, Li HQ, et al., 2008. A self-training semi-supervised SVM algorithm and its application in an EEG-based brain computer interface speller system. *Patt Recogn Lett*, 29(9):1285-1294. https://doi.org/10.1016/j.patrec.2008.01.030

Liu Q, Chen K, Ai QS, et al., 2014. Review: recent development of signal processing algorithms for SSVEP-based brain computer interfaces. *J Med Biol Eng*, 34(4):299-309. https://doi.org/10.5405/jmbe.1522

Minett JW, Peng G, Zhou L, et al., 2010. An assistive communication brain-computer interface for Chinese text input. 4th IEEE Int Conf on Bioinformatics and Biomedical Engineering, p.1-4. https://doi.org/10.1109/ICBBE.2010.5515559

Minett JW, Zheng HY, Fong MCM, et al., 2012. A Chinese text input brain-computer interface based on the P300 speller. *Int J Hum-Comput Interact*, 28(7):472-483. https://doi.org/10.1080/10447318.2011.622970

Mora-Cortes A, Manyakov NV, Chumerin N, et al., 2014. Language model applications to spelling with brain-computer interfaces. *Sensors*, 14(4):5967-5993. https://doi.org/10.3390/s140405967

Nicolas-Alonso LF, Gomez-Gil J, 2012. Brain computer interfaces: a review. *Sensors*, 12(2):1211-1279. https://doi.org/10.3390/s120201211

Nijholt A, 2008. BCI for games: a ‘state of the art’ survey. 7th Int Conf on Entertainment Computing, p.225-228. https://doi.org/10.1007/978-3-540-89222-9_29

Parini S, Maggi L, Turconi AC, et al., 2009. A robust and self-paced BCI system based on a four class SSVEP paradigm: algorithms and protocols for a high-transfer-rate direct brain communication. *Comput Intell Neurosci*, 2009:864564. https://doi.org/10.1155/2009/864564

Ramoser H, Muller-Gerking J, Pfurtscheller G, 2000. Optimal spatial filtering of single trial EEG during imagined hand movement. *IEEE Trans Rehabil Eng*, 8(4):441-446. https://doi.org/10.1109/86.895946

Ryan DB, Frye GE, Townsend G, et al., 2010. Predictive spelling with a P300-based brain-computer interface: increasing the rate of communication. *Int J Hum-Comput Interact*, 27(1):69-84. https://doi.org/10.1080/10447318.2011.535754

Schreuder M, Rost T, Tangermann M, 2011. Listen, you are writing! Speeding up online spelling with a dynamic auditory BCI. *Front Neurosci*, 5:112. https://doi.org/10.3389/fnins.2011.00112

Schreuder M, Höhne J, Blankertz B, et al., 2013. Optimizing event-related potential based brain-computer interfaces: a systematic evaluation of dynamic stopping methods. *J Neur Eng*, 10(3):036025. https://doi.org/10.1088/1741-2560/10/3/036025

Sellers EW, Krusienski DJ, McFarland DJ, et al., 2006. A P300 event-related potential brain-computer interface (BCI): the effects of matrix size and inter stimulus interval on performance. *Biol Psychol*, 73(3):242-252. https://doi.org/10.1016/j.biopsycho.2006.04.007

Semlitsch HV, Anderer P, Schuster P, et al., 1986. A solution for reliable and valid reduction of ocular artifacts, applied to the P300 ERP. *Psychophysiology*, 23(6):695-703. https://doi.org/10.1111/j.1469-8986.1986.tb00696.x

Shende PM, Jabade VS, 2015. Literature review of brain computer interface (BCI) using electroencephalogram signal. Int Conf on Pervasive Computing, p.1-5. https://doi.org/10.1109/PERVASIVE.2015.7087109

Speier W, Arnold C, Lu J, et al., 2012. Natural language processing with dynamic classification improves P300 speller accuracy and bit rate. *J Neur Eng*, 9(1):016004. https://doi.org/10.1088/1741-2560/9/1/016004

Sun KT, Huang TW, Chen MC, 2011. Design of Chinese spelling system based on ERP. IEEE 11th Int Conf on Bioinformatics and Bioengineering, p.310-313. https://doi.org/10.1109/BIBE.2011.57

Tangermann M, Schreuder M, Dähne S, et al., 2011. Optimized stimulation events for a visual ERP BCI. *Int J Bioelectromagn*, 13(3):119-120.

Townsend G, LaPallo BK, Boulay CB, et al., 2010. A novel P300-based brain-computer interface stimulus presentation paradigm: moving beyond rows and columns. *Clin Neurophysiol*, 121(7):1109-1120. https://doi.org/10.1016/j.clinph.2010.01.030

Verschore H, Kindermans PJ, Verstraeten D, et al., 2012. Dynamic stopping improves the speed and accuracy of a P300 speller. 22nd Int Conf on Artificial Neural Networks and Machine Learning, p.661-668. https://doi.org/10.1007/978-3-642-33269-2_83

Vidal JJ, 1973. Toward direct brain-computer communication. *Ann Rev Biophys Bioeng*, 2:157-180. https://doi.org/10.1146/annurev.bb.02.060173.001105

Wu B, Su Y, Zhang JH, et al., 2009. A virtual Chinese keyboard BCI system based on P300 potentials. *Acta Electron Sin*, 37(8):1733-1738, 1745 (in Chinese). https://doi.org/10.3321/j.issn:0372-2112.2009.08.019

Xia B, Yang H, Zhang QM, et al., 2012. Control 2-dimensional movement using a three-class motor imagery based brain-computer interface. Annual Int Conf of the IEEE Engineering in Medicine and Biology Society. https://doi.org/10.1109/EMBC.2012.6346305

Xu MP, Qi HZ, Wan BK, et al., 2013. A hybrid BCI speller paradigm combining P300 potential and the SSVEP blocking feature. *J Neur Eng*, 10(2):026001. https://doi.org/10.1088/1741-2560/10/2/026001

Xu X, Fang HJ, 2015. A P300-based BCI system for online Chinese input. *J Huaqiao Univ* (*Nat Sci*), 36(3):269-274 (in Chinese). https://doi.org/10.11830/ISSN.1000-5013.2015.03.0269

Yin EW, Zhou ZT, Jiang J, et al., 2013. A novel hybrid BCI speller based on the incorporation of SSVEP into the P300 paradigm. *J Neur Eng*, 10(2):026012. https://doi.org/10.1088/1741-2560/10/2/026012

Yin EW, Zhou ZT, Jiang J, et al., 2014. A speedy hybrid BCI spelling approach combining P300 and SSVEP. *IEEE Trans Biomed Eng*, 61(2):473-483. https://doi.org/10.1109/TBME.2013.2281976

Yin EW, Zhou ZT, Jiang J, et al., 2015. A dynamically optimized SSVEP brain-computer interface (BCI) speller. *IEEE Trans Biomed Eng*, 62(6):1447-1456. https://doi.org/10.1109/TBME.2014.2320948

Zhang JX, Fang Z, Du YC, et al., 2012. Centro-parietal N200: an event-related potential component specific to Chinese visual word recognition. *Chin Sci Bull*, 57(13):1516-1532. https://doi.org/10.1007/s11434-011-4932-y

Zhang Y, Zhao QB, Jin J, et al., 2012. A novel BCI based on ERP components sensitive to configural processing of human faces. *J Neur Eng*, 9(2):026018. https://doi.org/10.1088/1741-2560/9/2/026018

Zhao G, 2015. The contemporary Chinese dictionary. *Int J Lexicography*, 28(1):107-123. https://doi.org/10.1093/ijl/ecu030

Zhao JB, 2012. Steady-State Visual Evoked Potential: the Attentional Mechanism and the Application in Brain Computer Interface. PhD Thesis, Zhejiang University, Hangzhou, China (in Chinese).

Zhu DH, Bieger J, Molina GG, et al., 2010. A survey of stimulation methods used in SSVEP-based BCIs. *Comput Intell Neurosci*, 2010:702357. https://doi.org/10.1155/2010/702357