Design and Customization of SSVEP-Based BCI Applications Aimed for Elderly People

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Abstract

In this chapter, we discuss the parameter setup for steady-state visually evoked potential (SSVEP)–based brain–computer interface (BCI) systems aimed for elderly people. In this respect, the reader is guided through the key features of SSVEP-based BCI applications. In detail, we discuss the appropriate choice of stimulation frequencies, classification time windows, and the number of selectable commands. Additionally, we list design choices for the graphical user interfaces geared to the needs of users of advanced age. The chapter summarizes results of our previous research, where age-related differences in BCI performance were investigated.

7.1 INTRODUCTION

Brain–computer interface (BCI) is a field of technologies that allows communication between the human brain and the computer. Brain signal data are scanned for patterns that can be interpreted as control command for external applications (Wolpaw et al. 2002).

The main BCI functions according to Wolpaw et al. include replacement, restoration, enhancement, supplement, and improvement of the central nervous system output.

For example, a BCI can be implemented as a spelling interface and has therefore the potential to become a standard tool for reestablishing communication for severely disabled people who are unable to express themselves with their traditional motor output pathway of the nervous system (Wolpaw & Wolpaw 2012).

Beside healthcare applications (see, e.g., Bamdad et al. 2015), which is the main focus of BCIs, application scenarios include computer games (Marshall et al. 2013), learning (Karkar & Mohamed 2016), and control of, for example, mobile robots (Stawicki et al. 2016).
The most common BCI approaches in modern research are the P300 event-related potential (ERP) paradigm (Spüler et al. 2012), a BCI approach using the 300-ms component of an evoked potential, event-related desynchronization/synchronization paradigm (Hsu 2013), and the steady-state visually evoked potential (SSVEP) paradigm (Zhang et al. 2015). As can be seen in Figure 7.1, research interest in BCI is constantly growing over the last years.

However, publications about SSVEP-based BCIs are in minority when compared to, for example, P300 BCIs; the PubMed database shows for the last decade 4755 results for the search term “Brain–Computer Interface Brain–Machine Interface,” but only 221 results regarding the additional phrase “SSVEP,” compared to 345 when adding the phrase “P300.”

In order to inspire research groups across the globe to explore the SSVEP paradigm, the instructions provided in this chapter provide helpful customization options for the SSVEP approach. The advantages of SSVEP-based BCIs include high information transfer rate (ITR) and little or no training time (Rupp 2014). Recent research demonstrated sufficient control of SSVEP-based BCIs for elderly users above 60 years (Volosyak et al. 2017).

### 7.2 SSVEP PARADIGM

The SSVEP paradigm exposes the user to a flickering visual stimulus at a constant frequency. Typical stimuli sources are light-emitting diodes (LEDs) or boxes rendered on a computer monitor, because this allows an implementation without any additional hardware. If the user gazes at the flickering stimuli, brainwaves are elicited with the corresponding frequency and its harmonics (Müller-Putz & Pfurtscheller 2008). These brainwaves can be recorded noninvasively from the scalp using an electroencephalogram (EEG). The BCI classifies the attended frequency and interprets it as control command using signal processing methods that handle data preprocessing, feature extraction, and feature classification.

There are several established signal processing methods for SSVEP-based BCIs: Feature extraction methods such as the Fourier-based transform methods discrete Fourier transformation and fast Fourier transformation; spatial filter methods such as principal component analysis, minimum energy combination, canonical correlation analysis, and maximum contrast combination; and wavelet transforms such as wavelet packet decomposition and continuous wavelet transform. Liu et al. (2013) provided a detailed review of these and other classification methods.

For the implementation of BCI systems, many research groups use software platforms such as OpenViBE (Renard et al. 2010) or BCI2000 (Schalk et al. 2004). These platforms allow easy creation and optimization of BCIs.
As the BCI relies on the user’s ability to control her or his eye gaze, eye-tracking systems could provide a faster control mechanism. Eye tracking devices might as well not work properly for every user. For example, the performance can be affected by light conditions and visual aids. For some users, SSVEP-based BCIs might provide a more reliable option (Stawicki et al. 2017).

7.3 CUSTOMIZATION OF SSVEP PARAMETERS

It is well known that BCI performance differs among users (see, e.g., Volosyak et al. 2011b). Sometimes, the BCI even fails to classify commands reliably. This so-called BCI inefficiency (also called BCI illiteracy or BCI deficiency) also applies to the SSVEP paradigm.

Because of several system improvements, SSVEP BCI inefficiency could be reduced over time. Table 7.1 summarizes results from three larger SSVEP BCI field studies with similar hardware and experimental setup. It can be seen that BCI inefficiency occurred less often in the more recent studies and may be caused solely by the suboptimal signal processing algorithms. In a study by Gembler et al. (2015b), even all 61 participants were able to gain control over the tested system.

Apart from the utilized classification methods and data processing algorithms, there are several other factors that influence BCI performance.

In order to develop BCIs that can reliably interpret brain patterns from as many users as possible, demographic factors need to be addressed with regard to the design of the graphical user interface (GUI) and also the user-dependent parameters.

Until now, many researchers have developed communication and healthcare applications for the SSVEP paradigm that allow users to communicate with their environment by typing sentences. Though these applications are intended to work for users of all ages, some studies reported a slightly poorer BCI performance of elderly users. In an earlier study (Gembler et al. 2015a), we compared BCI performance from users of two different age groups. All participants were asked to spell a German phrase; what we found was that the classification took longer and was less accurate for the elderly participants. These preliminary results show that age is an important demographic factor that needs to be considered during the development of BCIs.

Therefore, in the succeeding paragraphs, we want to review customization options of SSVEP-based BCIs, having in mind elderly users. In this respect, we discuss key components for the SSVEP approach such as choice of frequencies, number of stimuli and classification time windows, as well as design guidelines for the GUI.

### Table 7.1
Comparison of SSVEP BCI Performance of Our Previous BCI Field Studies

<table>
<thead>
<tr>
<th></th>
<th>Volosyak et al. 2009</th>
<th>Volosyak et al. 2011</th>
<th>Gembler et al. 2015b</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of subjects</td>
<td>37</td>
<td>86</td>
<td>61</td>
</tr>
<tr>
<td>Mean accuracy (%)</td>
<td>92.9</td>
<td>92.3</td>
<td>97.1</td>
</tr>
<tr>
<td>Literacy rate (%)</td>
<td>86.5</td>
<td>97.7</td>
<td>100</td>
</tr>
<tr>
<td>Number of stimuli</td>
<td>5</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>Time window (s)</td>
<td>2</td>
<td>2</td>
<td>0.8–8</td>
</tr>
</tbody>
</table>

Note: Subjects that were not able to gain control over the BCI (studies from 2009 and 2011) were excluded from calculation of mean values. The literacy rate describes the percentage of participants that achieved reliable control over the system.
7.3.1 Stimulation Frequencies

Stimulation frequencies are usually realized with LEDs or flickering boxes on an LCD monitor. Typically, in the latter case, the stimuli and the GUI are rendered on the same screen.

The choice of these stimulation frequencies is an important factor in BCI interface design. Two flickering targets with a frequency difference below 0.1 Hz can be reliably distinguished in the SSVEP response (Gao et al. 2003; Hwang et al. 2012; Stawicki et al. 2015). The stimulation with lower stimulation frequencies (6–12 Hz) evokes SSVEPs with larger amplitudes compared to high frequencies beyond 30 Hz (Gao et al. 2003; Zhu et al. 2010). Higher stimulation frequencies on the other hand produce less visual fatigue and show no stimulus-related seizures (Won et al. 2015).

In order to even out the imbalances in the evoked SSVEP amplitudes, each stimulus can be associated with certain individual classification thresholds. If a command is repeatedly falsely classified, without any user intention regarding this command, the threshold corresponding to the associated frequency can be increased. This might be necessary for the frequencies that elicit comparably strong SSVEP responses; for example, for a flickering at 6 Hz, the classification threshold should be set higher than for a 20-Hz target.

One should also keep in mind that the stimulation frequency elicits responses with the fundamental frequency as well as its harmonics. In order to avoid influences between frequencies, the set of stimulation frequencies should follow additional restriction rules (Volosyak et al. 2010b):

\[ f_i \neq \frac{f_j + f_k}{2}, \quad f_i \neq 2f_j - f_k, \quad f_i \neq 2f_k - f_j, \]  

(7.1)

for any stimulation frequency triple \( f_i, f_j, f_k \). It is also important to consider that the low-frequency band usually overlaps with the alpha band (7–13 Hz). Alpha wave brain activity, typically occurring when a person closes his or her eyes, might cause false classifications (Zhu et al. 2010).

7.3.2 Number of Classes

Depending on the number of simultaneously used stimulation frequencies, applications of various complexities can be realized, but identification of the target attended by the user is usually less accurate if multiple visual stimuli are used, as they may increase the probability of false classifications.

There are several methods to generate the stimuli for SSVEP-based BCIs on LCDs.

An SSVEP stimulus can be realized as a graphics object (e.g., a box on a computer screen) with the binary states drawn/not drawn, which change at a specific rate that is dependent on the monitor’s refresh rate. The number of such on/off cycles per second is then referred to as the stimulation frequency.

The frequency approximation method as proposed by Wang et al. (2010) is suitable to implement a high amount of targets on a computer monitor.

In this frame-based stimulus approximation method, a varying number of frames is used in each cycle. The stimulus signal at frequency \( f \) can be generated by

\[ \text{stim}(f,i) = \text{square}(2\pi f(i/r)), \]  

(7.2)

where \( r \) is the monitor refresh rate and \( \text{square}(2\pi f(i/r)) \) generates the square wave with frequency \( f \) and frame index \( i \).

Recently, we investigated the possibilities and limitations regarding the number of targets that can be realized using this method (Gembler et al. 2016). Though some participants achieved remarkable results, the classification accuracy generally dropped with a higher number of targets, for some users to such a degree that reliable control was not possible (see Table 7.2). With increasing target number, the distance between targets and the target size needed to be lowered. The closer proximity...
of the target boxes influenced the classification accuracy as adjacent boxes were often falsely classified for multitarget BCIs. Some participants also expressed discomfort when using these systems.

The aspect of user friendliness has also to be considered, especially when designing a GUI for elderly people. Though generally slower, BCIs with a small number of stimuli have their advantages. Such BCIs offer more freedom in frequency selection and are less fatiguing for the visual channel of the user. If fewer targets are used, the stimulation frequencies can be selected as divisors of the vertical refresh rate of the monitor, ensuring a constant number of frames in each cycle (Volosyak et al. 2009a). Table 7.3 provides such frequencies for the most common monitor refresh rates.

Several studies reported that SSVEP also correlates with the duty cycle, which describes the percentage of the on-phase of the stimulation cycle (Shyu et al. 2013; Wu 2009). In both cited studies, the standard approach (a duty cycle of 0.5) did not yield the strongest SSVEP responses. Hence, the determination of the optimal duty cycle could be relevant, particularly for high frequencies because of their generally lower amplitudes of SSVEP responses.

### 7.3.3 Time Windows

The length of the time period between consecutive command classifications is another factor that has a high impact on the BCI performance. The classification accuracy benefits from a larger amount of collected EEG data to interpret the user intention.

Volosyak et al. (2010a) analyzed the impact of the time window used for EEG data classification in a performance comparison on eight different time segment lengths over 10 participants. Their results, displayed in Table 7.4, confirmed a close relation between the time window length and accuracy. It was also observed that some users need to gaze at the stimulation target for a comparably long period of time, before a selection was classified.

In another study (Gembler et al. 2015a), we investigated age-associated differences in SSVEP-based BCI control and found that command classifications were performed faster and more accurate for users of the younger group (see Figure 7.2). Each of the two tested age groups consisted of five participants, ranging from 19 to 27 years and 66 to 70 years. Though for some elderly users the system was slow, it interpreted the user intention reliably. Appropriate time window lengths can enable poor performers to gain accuracy and control over the BCI.

For optimal performance, the time window can be customized individually for each user. This can also be done during an automated training session as demonstrated in Gembler et al. (2015b).

### Table 7.2

<table>
<thead>
<tr>
<th>Subject #</th>
<th>15 Targets</th>
<th>28 Targets</th>
<th>60 Targets</th>
<th>84 Targets</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Acc (%)</td>
<td>ITR (bpm)</td>
<td>Acc (%)</td>
<td>ITR (bpm)</td>
</tr>
<tr>
<td>1</td>
<td>83.33</td>
<td>31.00</td>
<td>100</td>
<td>39.37</td>
</tr>
<tr>
<td>2</td>
<td>100</td>
<td>130.15</td>
<td>100</td>
<td>120.30</td>
</tr>
<tr>
<td>3</td>
<td>93.75</td>
<td>29.65</td>
<td>80.00</td>
<td>22.35</td>
</tr>
<tr>
<td>4</td>
<td>93.75</td>
<td>40.25</td>
<td>84.85</td>
<td>52.02</td>
</tr>
<tr>
<td>5</td>
<td>100</td>
<td>83.63</td>
<td>90.32</td>
<td>59.30</td>
</tr>
<tr>
<td>6</td>
<td>44.12</td>
<td>7.09</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>7</td>
<td>83.33</td>
<td>61.79</td>
<td>82.35</td>
<td>70.92</td>
</tr>
</tbody>
</table>


Note: Seven healthy participants controlled stimulation matrices with different amount of targets. The dash indicates that no control over the system was achieved.
Additionaly, adaptive methods based on the online performance can be implemented to update the time windows (da Cruz et al. 2015; Volosyak et al. 2011a). Figure 7.3 shows an illustration of an adaptive time window extension method.

### 7.4 DESIGN OF THE GUI

There are several ways to design a GUI tailored to the needs of elderly users. A low number of targets reduces the cognitive and visual load, which might result in enhanced BCI performance. In several studies, four target systems have proven to yield high classification accuracies and 100% literacy rates (see also Table 7.1). For example, in the mentioned field study with 61 participants, conducted in our laboratory, the system reliably interpreted brain signals for all participants (Gembler et al. 2015b). In the following, we provide details of a four-target BCI system, the three-step spelling application (Gembler et al. 2015a).
Four commands were represented on the computer screen by flickering boxes of default sizes 175 × 175 pixels (see Figure 7.4).

Three boxes were arranged horizontally in the upper part of the screen containing the letters “A–I,” “J–R,” and “S–_,” respectively. The additional fourth box, containing the command “Löschen” (German for delete), was located on the right side of the screen.

A box for the output text was located at the center of the screen. The content of the three boxes containing the alphabet changed to more specific sets according to the first selection. At least three steps were necessary to choose a single character. The steps necessary to select the letter “E” are illustrated in Figure 7.5. Between the first and the second step and between the second and the third step, the far right box (initially “Löschen”) contained the command “zurück” (German for back), which took the user to the previous step.

To increase the overall user friendliness of the GUI, additional feedback mechanisms were implemented. The size of the boxes varied in relation to the SSVEP amplitude during the experiment (Volosyak et al. 2009b). Each box was outlined by a frame, which determined the maximum size of a box before the command classification. This additional real-time visual feedback about the SSVEP signals exposes to the user what command is about to be executed.

<table>
<thead>
<tr>
<th>Time Segment (s)</th>
<th>Mean Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.00</td>
<td>93.49</td>
</tr>
<tr>
<td>3.00</td>
<td>92.77</td>
</tr>
<tr>
<td>2.00</td>
<td>90.33</td>
</tr>
<tr>
<td>1.50</td>
<td>84.61</td>
</tr>
<tr>
<td>1.00</td>
<td>80.01</td>
</tr>
<tr>
<td>0.75</td>
<td>73.45</td>
</tr>
<tr>
<td>0.50</td>
<td>58.66</td>
</tr>
<tr>
<td>0.25</td>
<td>27.29</td>
</tr>
</tbody>
</table>

Further, in order to reduce the information load of the visual channel, every command classification was followed by an audio feedback with the name of the selected command or the letter spelled. In addition, after each performed classification, the visual stimulation paused for approximately a second to give the user time to shift his or her gaze to the next letter. Though the inclusion of this gaze shifting period reduces the system speed, it serves several purposes. It reduces false classifications caused by movement artifacts during the gaze shifting period.

**FIGURE 7.3** Changes in the classification time window after performed classifications. (Modified from Stawicki, P., Gembler, F., & Volosyak, I. (2016). Driving a semiautonomous mobile robotic car controlled by an SSVEP-based BCI. *Computational Intelligence and Neuroscience, 2016*, 5.) Command classifications were performed with time windows of different predefined lengths. In case no command classification was executed (gray), the window slid until it could be extended to the next predefined value. For example, if no classification could be made using 8 blocks of EEG data (the smallest predefined time window length), the window slid until a classification was made or until it could be extended to the next predefined time window length, 10 blocks of EEG data. After each performed classification (green), additional time for gaze shifting was included (red). During this gaze shifting period, the classifier output was rejected.

**FIGURE 7.4** Graphical user interface of the three-step spelling application. The task was to spell the German pangram “ZWEI BOXKÄMPFER JAGEN EVA QUER DURCH SYLT.”
Further, it assures that the collected EEG data are independent of the previously attended visual stimulus. This is especially helpful to prevent the subsequent classification of identical commands.

### 7.5 SUMMARY

In order to customize SSVEP-based BCIs for elderly users, several issues need to be considered. If a user interface is optimized in respect to speed only, it might lack classification accuracy and hence user friendliness. False classifications can be annoying in daily use; several participants prefer a slower BCI over a faster but less precise system (Gembler et al. 2014). Especially for elderly people, a BCI customized for high classification accuracy might be the more suitable choice. This usually means a lower number of stimuli and larger classification time windows should be used.

The topic of frequency selection still needs to be investigated further. Age-associated differences regarding optimal frequency selection need to be tested. Frequencies just below the alpha wave tend to evoke the strongest SSVEP response and yielded good performance in several studies. Some users, however, might find higher frequencies more user friendly for daily use. However, higher frequencies are generally harder to detect. Determination of frequency-specific duty cycles might enhance the SSVEP signal strength.

When designing the GUI for elderly users, the general emphasis should be put on interface simplicity, clarity of design, and intuitive control rather than speed; the visual and cognitive load should be minimized as short-term memory and episodic memory decrease when we age.

### REFERENCES


