OPTIMIZATION OF STEADY-STATE VISUAL RESPONSES FOR ROBUST BRAIN-COMPUTER INTERFACES

PH.D. THESIS

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ABSTRACT

The emergence of successful Brain-Computer Interfaces (BCI) that can assist the healthy and aid the disabled users, has introduced new limitless possibilities for wider use of brain technology in society. Yet, existing BCI designs are still unable to fulfill such high expectations due to restricted reliability, insufficient usability, and inadequate understanding of the underlying brain mechanisms.

This work aimed to address directly the above problems by presenting and optimizing two new multi-command BCI designs based on Steady-State Visual Evoked Potential (SSVEP) brain responses. SSVEP brain activity is elicited in precise synchrony with observed flickering visual patterns. The main goal of the work in this thesis was to optimize in new ways the information transfer rates and the reliability of multi-command SSVEP-based BCI systems. This was accomplished using two approaches: (1) Stimulus optimization to achieve maximal cortical response (frequency, size, movement, contents) for further use in BCI, and (2) Development of sensitive adaptive algorithms to extract weak target oscillations from 'noisy' EEG input signals immediately after SSVEP onset, based on the estimation of single-trial narrowband-energy changes (online) as well as on new phase-locking- and wavelet-energy variability measures (offline).

To understand in detail the properties of the SSVEP stimuli for BCI, EEG experiments were performed with very small checkerboard patterns. Challenging small-sized SSVEP stimuli were introduced to allow more flexible BCI designs through taking up as little visual estate as possible, even at the cost of reduced SSVEP signal strength. The frequency-response curve for these small SSVEP patterns was studied for 32 frequencies between 5 and 84Hz. Understanding the SSVEP frequency characteristics for small checkerboards allowed the pinpoint definition of optimal parameters and limitations of the investigated checkerboard-based SSVEP-BCI paradigm, as well as better control of inter-subject variability. The SSVEP time dynamics for 8, 14 and 28Hz stimulation and three sensor locations (occipital, parieto-temporal and frontal) was investigated in a further series of experiments, aiming to establish the time-delay limitations of the SSVEP brain response as captured by the online BCI. The knowledge acquired from these neurophysiological experiments was utilized for the optimal design of an 8-command SSVEP-based BCI system. A novel dynamic feedback paradigm was created which featured a set of eight small checkerboard patterns assembled in a very tight but simultaneously moving 2-D spatial configuration, fixed around a main object, and controlled by the user's intent. Due to this

design visual field occlusion was minimized, and long-term fatigue was reduced substantially by scaling down the demands on the visual system, and on the attention to the overall control task. BCI performance was measured and evaluated for three locations on the scalp (occipital, parieto-temporal and frontal), two of which included hairless areas for easy sensor application. In a further set of experiments, another type of SSVEP stimuli was investigated, flickering affective-face video sequences, in order to study the hypothesis that emotional-face content would be able to boost the SSVEP signals. Short happy and angry face videos were presented flickering at 5 different rates (5.6-12Hz) to eight experimental subjects, as well as three control stimuli - the blurred versions of the affective faces, and a reversing checkerboard. In an offline analysis of their basic properties, brain activity changes associated with SSVEP onset were evaluated using two measures - a new measure for phase locking value variability (PLVV) which was sensitive to inherent phase-reset changes in cortex at stimulation onset, and a more classical estimate of the wavelet energy variability. This approach using engaging SSVEP stimulus contents was further applied in a second 8-command SSVEP-BCI design which employed the same band energy evaluation measures as before for comparison. Separate BCI sessions were performed using affective face videos, their blurred versions, and checkerboards as SSVEP stimuli, and the information transfer rates were measured for each experimental condition. The BCI system was designed allow self-paced control of a multi-joint robotic arm, especially suitable for disabled and elderly users.

The results of the offline SSVEP signal analysis, normalized for all subjects, showed that the 5.6 – 15.3Hz small-pattern reversal stimulation evoked the strongest responses, peaking at ~12Hz, and exhibiting weaker local maxima at 5.6 Hz, 8 Hz (7.6-8.8 Hz), 12 Hz, 15.3 Hz, and 28 Hz. The shortest SSVEP onset delays were observed starting at ~0.5s for the medium-frequency 14Hz reversal. The first SSVEP maxima, which are captured by online BCI algorithms, were measured offline at 1.5-2.5s after onset. Overall, the long-term SSVEP dynamics was highly non-stationary, especially in the high-frequency range. In the online BCI evaluation experiments, an information transfer rate of 50 bits/min was achieved at occipital sensor locations (mean success rate of 98 %, mean time delay 3.4s). The BCI performance deteriorated with increasing distance from the visual cortex (down to 74% for frontal sensor locations), as also inter-subject variability increased. Notably, in this BCI design, all flickering very small stimuli conformed strictly to international guidelines for prevention of photic- and pattern-induced seizures. Furthermore, novel affective-face video contents in the flicker stimulation evoked significantly stronger SSVEP responses than their corresponding emotionally-neutral blurred versions, as well as the checkerboards. No significant differences in the occipital SSVEP responses were detected due to emotional valence (happiness vs. anger), and there were also no significant differences between the SSVEP responses of individual subjects for all experimental conditions. The frequency response curve measured for affective-face SSVEP stimuli indicated that the SSVEP activity was strongest for 10Hz flicker when averaged over all stimulus types. Although the PLVV measure was more sensitive than the wavelet energy, an adaptive combination of both phase-lock and narrow-band energy measures would be recommended in future asynchronous SSVEP-BCI implementations for best results in terms of signal sensitivity, elimination of competing brain transients in the critical SSVEP frequency bands, and lower inter-subject variability. Online SSVEP-BCI evaluation of the effect of affective face video sequences for 10 Hz flicker demonstrated that BCI delays were ~20 % shorter for affective-face stimuli than for blurred-face and neutral flicker (2.7s vs. 3.4s; success rate 99% vs. 98%). When using affective-face stimuli, a higher mean BCI information transfer rate (ITR) was achieved (64 bits/min vs. 50 bits/min for neutral stimuli). All subjects reported higher level of attention, interest and motivation for affective-face stimuli, which resulted in higher resistance to fatigue after long-term SSVEP exposure.

Taken together, these findings point to new directions in BCI research by using unobtrusively small SSVEP stimuli, emotional-face video sequences, and new analysis methods to optimize substantially the SSVEP-BCI performance and enhance the user experience. Future BCI designs using a battery of SSVEP extraction algorithms, such as the time-resolved phase synchrony and energy variability measures demonstrated here, may lead to even more robust and reliable SSVEP brain response estimates in unsupervised clinical and home settings, as well as for other challenging brain-technology tasks in service of society.

To my family, for their unconditional love.

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Parts of the BCI analysis system were implemented in a team work with Dr. Pablo Martinez.

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ABBREVIATIONS

BCI: Brain-Computer Interface

BMI: Brain-Machine Interface

CMS: Common Mode Sense (used by Biosemi EEG system)

CRT: Cathode Ray Tube

DRL: Driven Right Leg (used by Biosemi EEG system)

EEG: Electroencephalogram / electroencephalography

EMG: Electromyogram / electromyography

FC: Frontal Cortex

fMRI: Functional Magnetic Resonance Imaging

ITR: Information Transfer Rate

LCD: Liquid Crystal Display

LDA: Linear Discriminant Analysis

LED: Light-Emitting Diode

LPTC: Lateral Parieto-Temporal Cortex

MEG: Magnetoencephalogram / magnetoencephalography

OC: Occipital Cortex

PET: Positron Emission Tomography

PLV: Phase-Locking Value

PLVV: Phase-Locking Value Variability

SPLVL: Single-trial Phase-Locking Value

SSVEP: Steady-State Visual Evoked Potentials

SWT: Single-trial Wavelet Transform energy

TCP/IP: Transmission Control Protocol/Internet Protocol

VEP: Visual Evoked Potentials

WT: Wavelet Transform

WTV: Wavelet Transform (Energy) Variability

Chapter 1:

INTRODUCTION

This thesis is a multidisciplinary effort, bringing together neuroscience, information science and engineering. The work described here aims mainly to help find new ways to improve quality of life using robust and adaptive brain technology. Knowledge from three separate research areas was utilized – Brain-Computer Interfaces (BCI), Steady-State Visual Potentials (SSVEP). and affective neuroscience (emotions).

"*The most beautiful thing we can experience is the mysterious. It is the source of all true art and all science.*" This quote from the German-born physicist Albert Einstein (1879 - 1955) relates closely to my long-term fascination with unraveling the endless mysteries of the brain, the most complex organ in the human body, in service of society, and of my fellow human beings.

1.1. The Ideal Brain-Computer Interface (BCI)

Brain-Computer Interfaces (BCI) are useful tools created with the ultimate goal of assisting the disabled, and increasing the productivity of the healthy members of society by using brain technology in daily as well as professional tasks. A BCI in operation has the simple yet very challenging job to recognize reliably from the measured brain-activity the intent of the user as requested commands and to execute the predefined tasks associated with these commands.

As explained in detail in the overview Chapter 2, there are several types of BCI. The most important BCI taxonomy is based on the way the brain activity is generated or modified consciously by the user in order to enable identification. BCIs can be based, for example, on visual potentials, motor imagery, P300 potentials, slow cortical potentials, and various mental tasks. Another useful BCI classification distinguishes between invasive and non-invasive brain signal measurements.

Regardless of the utilized paradigm and design, there are a number of basic desirable attributes (see also Table 2). An **'ideal' BCI** system should include the following target features:

1) Maximal information transfer rates (same or better than human natural capability)
2) Maximal number of available independent BCI commands
3) Minimal command delays
4) Maximal operating reliability (≥ 99%)
5) No user training necessary
6) No system training necessary
7) The inherent inter-subject / inter-session variability does not interfere with operations
8) Minimal user effort: Minimal demands to all attentional / sensory systems of the brain (user is free to perform other tasks)
9) Minimal mental fatigue after long-term operations
10) Maximal resistance to distractions, passing emotions, and neurological disorders
11) Friendly / attractive user interface
12) BCI system is mobile (no bulky equipment)
13) Emergency OFF switch is available and maximally reliable
14) Minimal preparation time ; no need for electro-gel (e.g. dry/remote electrodes)

15) Minimal operating costs.

1.2. Existing BCI Problems: Why is the Ideal BCI Difficult to Achieve?

In spite of the maturing stage of development in the Brain-Computer Interfaces research field, even the most sophisticated existing BCI designs still suffer from substantial **problems**. Almost none of the 'ideal' target features listed in Chapter 1.1 have been achieved completely and in a consistent way. Regardless of the paradigm type and implementation, non-invasive BCI systems (in general) are still short of the desired characteristics due to several important factors:

1) Imperfect signal feature extraction and classification results in restricted reliability of the BCI commands, especially for more than 2 commands
2) Low brain signal-to-noise ratios in single trials result in long time delays between user intent onset and BCI command recognition
3) Inadequate understanding of the underlying brain mechanisms resulting in undesirable high inter-subject signal variability and low number of BCI commands
4) Inherent low-sensitivity shortcomings of the electroencephalographic mode of recording
5) User training and system classifier training necessary (depending on paradigm) which results in long delays before an optimal performance can be achieved
6) Substantial attentional demands in order to evoke stronger brain activity: Users need to concentrate 100% on operating the BCI system, leaving them no room for

other useful tasks. Continuous attention results in fatigue after a few hours of operation. Minimal resistance to distractions

7) Application of EEG (electroencephalographic) electrodes needs specialized knowledge and time, as in most cases (currently) electro-gel is used, which dry up after several hours of operation. Hair needs to be washed of the electro-gel after the end of operations.
8) Equipment is bulky and expensive, usability is very limited.

1.3. Existing BCI Problems: Using SSVEP-BCI

The experimental designs and results presented in this thesis are based on the conscious control of the brain responses to rapidly changing visual stimuli. Steady-State Visual Evoked Potential (SSVEP) brain activity is elicited in precise synchrony with observed flickering visual patterns (see a review in Chapter 2.2). If two or more patterns oscillate at different frequencies on a computer screen, a user can choose which one to attend so that a corresponding BCI command is recognized. The SSVEP-BCI approach has been recognized as having a number of advantages and able to overcome many of the drawbacks of other BCI paradigms (see a review in Chapter 2.3). In spite of that promising assessment, however, the existing SSVEP-BCI systems haven't been able to realize their full potential mainly due to inherent difficulties with low SSVEP signal-to-noise ratios in the single trial measurements typical for BCI (as measured using EEG). This has prevented a much needed increase in the number of BCI commands, decrease in the size of SSVEP stimuli, and recording from suboptimal but more convenient non-occipital brain areas.

Prior to this work, existing SSVEP-BCI systems based on computer-generated stimuli (see Table 1) used mostly 2-4 large reversing checkerboard patterns in order to evoke sufficiently strong, measurable SSVEP responses (Lalor et al., 2004; Trejo et al., 2006; Oehler et al., 2008). These checkerboard stimuli covered up most of the useful visual area on the screen, substantially limiting the possible BCI applications and increasing user fatigue. In addition, the SSVEP frequencies in these studies were pre-selected in a relatively arbitrary way. The resulting BCI command delays were not studied systematically in order to understand the underlying signal dynamics, and to increase substantially the information transfer rates.

To summarize, the most important **problems in SSVEP-based BCI** systems prior to this work were:

1) Usage of too large on-screen SSVEP stimuli to evoke stronger brain responses, which obscure useful visual space (visual stimuli need to be very small)
2) Fixed usage of uniform white or large checkerboard SSVEP stimuli (other types of visual stimuli may be more appropriate)
3) Fixed flicker frequencies (optimal frequencies need to be determined for each type of SSVEP stimuli)
4) Stimuli are located far away from each other (e.g. on the edges of the screen) prompting larger eye movements (increased BCI delays, fatigues, artifacts)
5) Small number of SSVEP-BCI commands
6) FFT-based signal processing with subjective parametrization of the weights of the harmonic frequencies for each flicker
7) No insight into the mechanisms of SSVEP and BCI delays, which prevents optimization
8) Fixed data acquisition from occipital sensor locations only (no insight for BCI performance at other brain sites).

Table 1. Comparison of SSVEP-BCI approaches in this thesis and previous research

	<u>THIS THESIS</u>	**<u>PREVIOUS Research</u>**
SSVEP stimulus size (screen-based)	**very small moving checkerboards**	large stationary checkerboards, large white squares or stripes
Study of SSVEP properties?	**YES** **a) Frequency response curve** **b) SSVEP time dynamics** **c) Emotional-face contents**	NO
Sensor locations	**a) Frontal** **b) Parieto-temporal** **c) Occipital**	Occipital
SSVEP stimulus movement for spatial navigation ?	**YES**	NO
Number of SSVEP-BCI Commands (screen-based SSVEP stimuli)	**8 - 12**	2 - 4
Clustered SSVEP Stimuli (SSVEP-BCI Commands) for minimal eye movements	**YES**	NO
SSVEP-BCI ITR	64 bits / min	7 - 43 bits / min

1.4. Research Objectives Addressed in This Thesis

The work presented in this thesis aimed to address directly the existing problems described above. New approaches were necessary to remove a number of essential obstacles to the creation of practical unsupervised BCI paradigms able to work outside of the laboratory. As a result, the following research goals were pursued in this work:

1) **Using very small visual patterns to minimize visual occlusion while evoking measurable SSVEP responses at different frequencies (freeing up essential screen space for application purposes) (Chapter 3, 4)**
2) **Using SSVEP patterns in close proximity to each other without brain response interference (Chapter 4)**
3) **Using a high number of commands without brain response interference (Chapter 4)**
4) **Optimal selection of SSVEP stimulation frequencies based on objectively measured EEG data (frequency response curve) (Chapter 3)**
5) **Understanding the time dynamics of the SSVEP response to small stimuli as used for BCI (time delay limitations of BCI commands) (Chapter 3)**
6) **Measuring reliable SSVEP responses from fast moving flickering/reversing visual patterns, in a novel dynamic paradigm for pattern SSVEP BCI (control of a moving object) (Chapter 4)**
7) **Achieving the highest possible BCI information transfer rates and robustness for the proposed paradigms (Chapter 4)**

8) Using sub-optimal temporal or pre-frontal sensor locations on the head for new SSVEP-BCI designs with dry electrodes (without the need for application of EEG gel) (Chapter 3, 4)

9) Effect of using emotional-face SSVEP stimuli instead of checkerboards in BCI applications (Chapter 5, 6).

These research objectives were pursued using two general directions:

1) Stimulus optimization to achieve maximal cortical response for further use in BCI (frequency, size, movement, and contents of SSVEP stimuli)

2) Development of sensitive adaptive algorithms to extract weak target SSVEP oscillations from 'noisy' EEG input signals, both offline for detailed analysis, and online for SSVEP-BCI evaluation.

Table 1 presents a concise comparison between the new approaches presented here and previous research.

In addition, the Brain-Computer Interface design and implementation described in this thesis aimed to comply fully to the 4 basic criteria for a BCI (Pfurtscheller et al., 2010b):

1) The BCI device must use directly brain signals

2) The BCI device must be capable of real-time signal processing

3) The BCI device must allow the user to modulate intentionally at least one brain signal feature through goal-directed behavior

4) The BCI device must give the user feedback information.

Overall, the research goals described above were the focus of an effort to use new knowledge in order to design, optimize experimentally and evaluate the performance of a novel eight-command SSVEP-based BCI system as described in the following chapters.

1.5. Summary of Achievements in this Thesis

The work in this thesis aimed mainly at the substantial optimization of cortical visual responses and signal processing algorithms, as well as achieving superior multi-command SSVEP-BCI information transfer rates and reliability. The following major conclusions were reached:

1) Very small checkerboard SSVEP stimuli were shown to elicit measurable and reliable single-trial brain responses
2) The SSVEP frequency response curve (5.1 Hz - 84 Hz) for small stimuli was studied, and the optimal SSVEP brain response range was determined to be 5.6 Hz – 15.3 Hz (12 Hz maximum)
3) The onset of single-trial SSVEP responses was shown to be detectable between 1.5 s and 2.5 s (using band oscillation envelope measures)
4) SSVEP dynamics (onset delays, first peaks, stationarity) were strongly dependent on the stimulation frequency. When 3 stimulation frequencies were compared (8, 14 and 28 Hz), the 14 Hz responses exhibited fastest onsets and maximal signal stability
5) The feasibility of practical SSVEP-BCI designs using dry electrodes (without electro-gel) was established by evaluating SSVEP responses from 3 distinct sensor locations (occipital, parieto-temporal and frontal). While occipital visual responses were optimal as expected, the parieto-temporal and frontal locations also allowed the detection of SSVEP responses, although with reduced strength, stationarity and reproducibility

6) A new SSVEP-BCI system with 8 independent commands, using small checkerboard stimuli flickering in the optimal range, reached a mean information transfer rate (ITR) of 50 bits/min, with success rate of 98% and command delay of 3.4 ± 0.7 s for occipital sensor locations
7) SSVEP-BCI performance was evaluated also for parieto-temporal and frontal sensor locations, and deteriorated with increasing distance from the visual cortex (81% success rate and 4s delay for parieto-temporal sensor locations and 74% success rate and 4.3s delay for frontal electrodes)
8) No user training was necessary for this SSVEP-BCI system
9) Very close proximity (clustering) of multiple small SSVEP stimuli was used successfully for the first time in the SSVEP-BCI design
10) A moving block of multiple small SSVEP stimuli was used successfully for the first time in the SSVEP-BCI design (a novel dynamic feedback paradigm)
11) Due to the small size and close clustering of the checkerboard stimuli in the SSVEP-BCI design the visual field occlusion was substantially minimized, and long-term user fatigue was reduced
12) Flickering emotional face video sequences were shown to elicit superior SSVEP responses than checkerboard- and blurred stimuli
13) The Affective-face SSVEP frequency response curve (5 Hz - 12 Hz) was studied, and the optimal brain response for this type of SSVEP stimuli was 10 Hz
14) A new single-trial phase-locking value variability (PLVV) measure was used in the offline SSVEP analysis, and was shown to be more sensitive to SSVEP onset than a comparable band-energy based measure – wavelet-transformed energy variability (WTV)

15) A new Affective-face SSVEP-BCI design was evaluated for 10 Hz flicker and was shown to be superior to the small-checkerboard design (mean BCI delay 2.7s vs. 3.4s; mean success rate 99% vs. 98%; mean ITR 64 bits/min vs. 50 bits/min).
16) BCI users reported substantially higher motivation, attention, and less long-term fatigue when using the Affective-face SSVEP-BCI design as compared to neutral checkerboard- and blurred-face SSVEP-BCI stimuli
17) The higher reliability and stronger brain responses allowed users of the Affective-face SSVEP-BCI system to control successfully a multi-joint robotic arm with complex movements with minimal online errors. A multi-command BCI system controlling reliably a robotic arm has substantial advantages for disabled members of society.

1.6. Organization of the Thesis

This thesis (Fig. 1) focuses on an integrated approach to the optimization of SSVEP-based Brain-Computer Interfaces (Fig. 2). This was accomplished, first, by investigating the brain responses to continuous visual flicker stimulation with very small checkerboards (Chapter 3), as well as with flickering emotional face videos (Chapter 5). Second, the results were applied for designing two optimized SSVEP-BCI paradigms using the same stimuli (Chapter 4 and Chapter 6). In this work, several novel concepts were introduced and explored in order to enable new types of efficient and user-friendly Brain-Computer Interfaces.

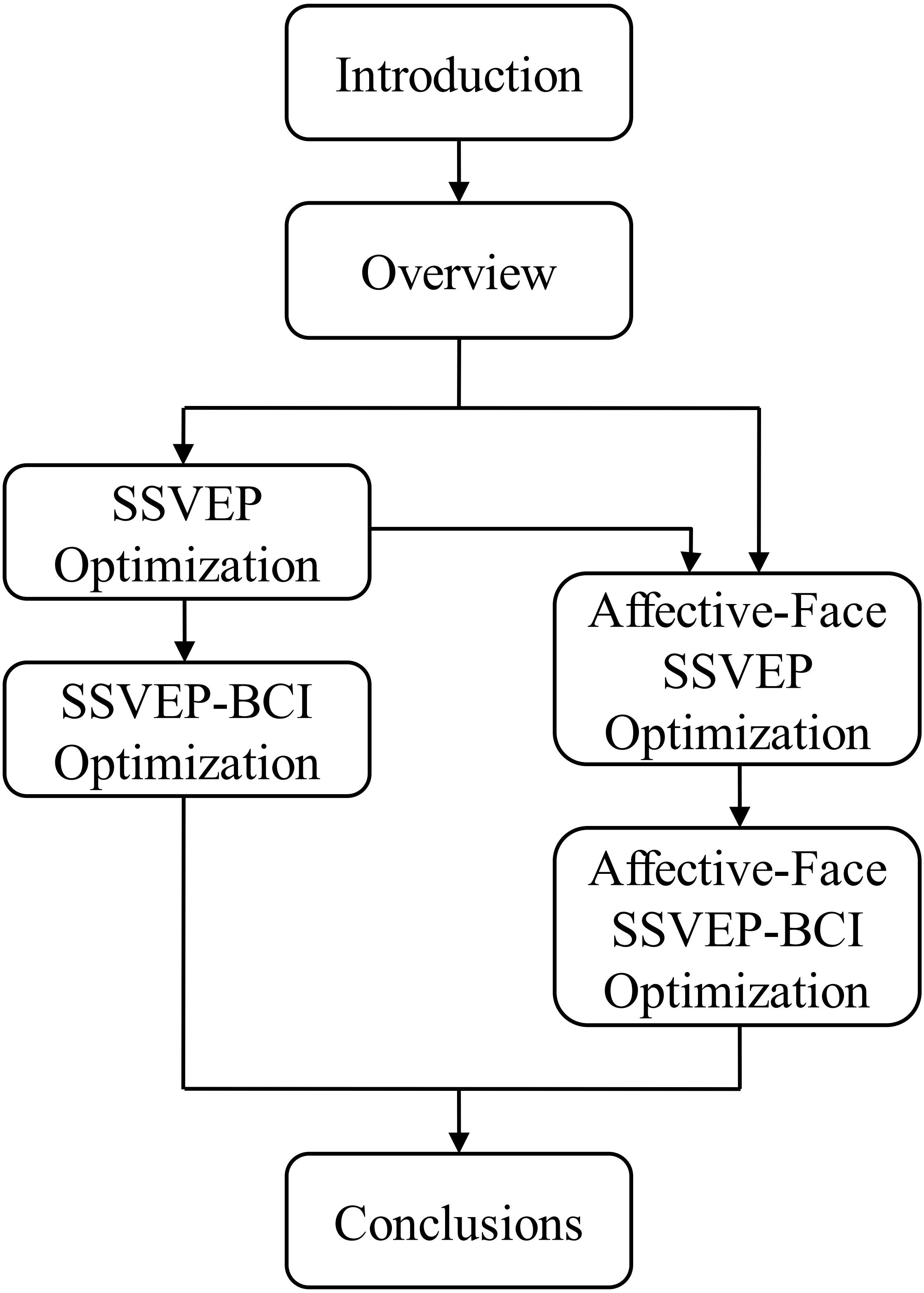


Fig. 1. Diagram of the organization of this thesis

Chapter 2:

OVERVIEW OF PREVIOUS RESEARCH

2.1. Brain-Computer Interfaces (BCIs)

2.1.1. Why are Brain-Computer Interfaces necessary?

Today's advances in technology and signal processing algorithms are giving brain researchers a new edge, allowing us to go one crucial step further, from understanding brain functions, to actually using this knowledge to change the world. Brainwave-based technologies such as Brain-Computer Interfaces (BCI), when made sufficiently user-friendly, reliable, and affordable, will help mankind not only to conquer crippling disabilities through neuroprosthetics and rehabilitation, but also to improve precision of control for vehicles and robots in hostile environments such as space, to let people live in intelligent e-homes, to integrate new electronic body enhancements whenever necessary, and to play and communicate in novel ways.

2.1.2. Brain-Computer Interfaces – Definition, Application and Requirements

A Brain-Computer Interface (BCI) is any brain-to-machine communication system, which is able to interpret and execute voluntary brain commands, with no dependence on the normal executive pathways of the body such as muscles and peripheral nerves (Wolpaw et al., 2000).

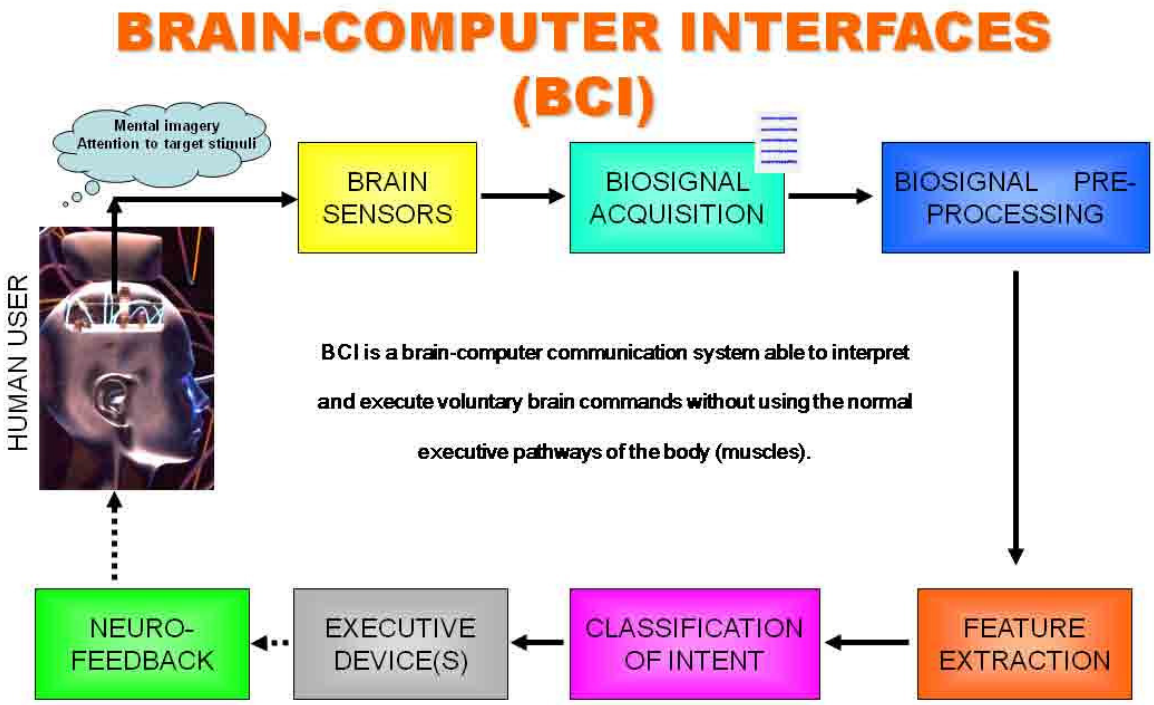


Fig.2. Basic block diagram of a Brain-Computer Interface (BCI) system (Bakardjian, 2004)

BCI technology has the potential to find wide acceptance in society. Possible practical applications of BCI are:

1) Mobility assistance for the elderly and disabled; recreation (brain control of wheelchairs, robots and vehicles for self-reliance and self-service)

2) Remote control of devices (hazardous environments - space, fire; telerobotics)

3) Communications, creative work (email, documents)

4) Virtual reality creations (multi-player games, role play, navigation)

5) Neuroprosthesis and rehabilitation (replace or restore function of limbs)

6) Remote monitor of attention in pilots or drivers (Vaughan et al., 2003)

7) Brain-based art creation (Vaughan et al., 2003)

8) Neural enhancements control in a healthy human body such as additional artificial limbs, memory chip implants (there may be ethical issues)

BCI is a particularly challenging task from the point of view of biosignal processing, because often single-trial analysis use dense electrode arrays to compensate for low signal-to-noise ratios due to the unavailability of inter-trial statistics. In addition to the single trials, online BCI systems need to overcome a further limitation in spatial resolution, with only a few electrodes available in order to make such devices easier to handle. From the point of view of the necessary requirements, an optimal BCI system should exhibit the following characteristics:

1) Maximal number of commands (maximal choice / degrees of freedom)

2) Maximal accuracy of command recognition (high noise and artifact resistance)

3) Maximal speed of command transfer (stimulus rate, information content)

4) Maximal comfort for users (sensors, environment, ease of control = low mental load)

5) Maximal tolerance to fatigue and shifting emotional states

6) Maximal tolerance to distractions (external stimuli, passing thoughts, memories)

7) Maximal tolerance to neurological disorders

8) Maximal tolerance to inter-subject variability

9) Minimal training (both for user and machine)

10) Minimal cost of operation

11) Maximal robustness: ON/OFF/IDLE commands; recycle or cancel commands

12) Maximally attractive user interface (for enhanced motivation).

2.1.3. BCI Approaches and Types

In 1967, Edmond Dewan (Dewan, 1967) described what seems to be one of the first accounts of a BCI communication. In his experiments, subjects controlled voluntarily the amplitude of their own alpha EEG waves which allowed a computer program to convert these changes and send corresponding Morse code messages. In 1973, Jacques Vidal, a computer science researcher at UCLA, described the working principles of a direct brain-computer interface (BCI) (Vidal, 1973) and four years later, he published the results of a successful online BCI implementation with 4 commands (Vidal, 1977). Vidal used visual evoked potentials (VEP) elicited by brief illumination of a checkerboard to estimate with over 90% success rate which one of the four preset gaze positions around the pattern was attended, in order to control a moving object in a maze. The data processing approach in his study was already built around the current online BCI architecture, including data acquisition, artifact rejection, preprocessing, feature selection, and classification modules.

The fundamental goal of BCI is to identify each user intention from its corresponding brain pattern in near-real-time. However, current recording techniques are unable to deliver unique patterns for each user intention for usage as unlimited commands. In practice, using a limited number of sensors results in overlapping of the measurable characteristics of the available brain patterns, which need to be controlled / separated using specific tasks for the user to perform during the BCI session.

The prevalent recording technique for BCI is electroencephalography (EEG). Current brain signal processing approaches distinguish between 'spontaneous' and 'evoked' EEG. Spontaneous EEG refers to the measurement of continuous brain waves, including the delta (up to 4Hz), theta (4-8Hz), alpha (8-12Hz), beta (12-30Hz), and gamma (30-100+Hz) waves, while evoked EEG represents brain potentials with limited duration which are recorded in response to specific stimuli, such as visual, auditory, somatosensory, or olfactory. BCI paradigms can be based on both spontaneous and evoked brain signals, for example, motor-imagery BCI using modulation of spontaneous 'mu' and 'beta' waves, or SSVEP-BCI (steady-state visual evoked potentials) using periodically evoked visual responses.

Currently, BCI tasks can be classified into two main categories:

1) Internally-supported – Voluntary generation of specific mental state patterns (usually based on modification of spontaneous brain activity)

The mental state BCI paradigms could be either cue-, or internally-paced, and are usually based on conscious control of naturally-occurring brain waves, such as mu-, beta- and alpha, slow potentials, or multi-unit neuronal activity.

There are two subtypes of mental load BCI tasks, both of which use response modification by feedback (Curran and Stokes, 2003):

- 1.1) Cognitive load (using specifically-defined imagination tasks like limb movement, grasping, mental arithmetic) (Pfurtscheller et al., 2006; Penny et al., 2000)
- 1.2) 'Operant conditioning' (no specific cognitive targets, "just do it" principle) (Wolpaw et al., 2000; Bensafi et al., 2003)

2) Externally-supported – Voluntary modification of the normal responses to external stimulation (usually based on modification of evoked brain activity)

2.1) Using selective attention to choose a target stimulus corresponding to a BCI command which evokes a specific recognizable brain response (Bakardjian et al., 2010; Gao et al., 2003; Farwell and Donchin, 1988). Examples for such attention-driven BCI tasks are:

- 2.1.1) Cognitive load (using specifically-defined imagination tasks like limb movement, grasping, mental arithmetic) (Pfurtscheller et al., 2006; Penny et al., 2000)
- 2.1.2) P300 oddball response (Farwell and Donchin, 1988)
- 2.1.3) SSVEP (steady-state visual evoked potentials) (Sutter, 1984; Gao et al., 2003; Müller-Putz et al., 2005)

2.1.4) SSSEP (steady-state somatosensory evoked potentials) (Müller-Putz et al., 2006)

2.2) Using voluntary modification to external stimulus responses in order to indicate a BCI command. An example is a 2-command BCI task based on self-controlled visual priming in which the subjects imagined (or not) observing smooth natural visual motion while actually viewing discrete apparent motion ('jumping') bar stimuli (Bakardjian, 2003).

Internally-supported mental-state tasks have the advantage that they do not usually require external stimulation equipment (except for the feedback of the results to the user). However, the complexity of the involved natural brain processes can be very high so that the reliability and number of commands is currently limited in mental-state paradigms. In order to create Brain-Computer Interfaces with enhanced information transfer rates for both the internally- and externally-supported BCI task paradigms, strict controls are imposed by using well-known cognitive imagery processes (such as motor imagery), and strong phase-locked sensory responses which are reliably detectable in single trials (such as SSVEP).

Table 2. **BCI experimental approaches** – Advantages and problems

Attribute	**Externally-Driven** (stimulated responses)	**Internally-Driven** (mental states)
Large Number of Commands	**YES**	**NO**
High Reliability of Commands	**YES**	**NO (in most cases)**
High Information Transfer Rates	**YES**	**NO**
Short User Tuning (before 1st usage)	**YES**	**NO**
Short Training	**YES**	**NO**
Self-Paced	**YES / NO**	**YES / NO**
Short Command Delays (±1sec)	**NO / YES**	**YES / NO**
ON/OFF Switch	**YES**	**YES (in most cases)**
No Stimulation Equipment Necessary	**NO**	**YES**
No Sensory Engagement Necessary	**NO**	**YES**
Resistant to High Subject Variability	**YES**	**NO**
Resistant to Mental Fatigue	**NO**	**NO**
Resistant to Passing Emotions	**YES (in most cases)**	**NO (in most cases)**
Resistant to Distraction	**NO (in most cases)**	**NO**
Resistant to Neurological Disorders	**YES (in most cases)**	**Unknown**
Attractive User/Neurofeedback Interface	**YES (possible)**	**YES (possible)**
Comfortable for User	**NO (in most cases)**	**YES**
EXAMPLES for BCI Approaches	*SSVEP (steady-state) (Sutter 1992; MacMillan 2000; Gao 2002)* *P300 oddball response (Donchin 2000)* *SCP (slow cortical potentials) (Kübler 2001)* *Visual motion response (Bakardjian 2003)*	*Motor imagery (Pfurtscheller 1994)* *Mental states (Millán 2003)* *Cognitive load (specific imagination tasks): (Pfurtscheller 2004; Penny 2000)* *Operant conditioning' ("just do it"): (Humphrey 1970;Birbaumer 1999; Wolpaw 2000; Nicolelis 2004)*

Apart from the BCI task dichotomy, another BCI classification is possible from the point of view of brain data acquisition, as there are two principal approaches (Vaughan et al., 2003):

1) invasive recording of individual or local neuronal activities (surgery necessary)

2) non-invasive measurement reflecting only large-scale neuronal activations (EEG, NIRS, time-resolved fMRI).

2.1.4. Invasive BCI

Neuronal spikes due to action potentials are measured using arrays of miniature electrodes implanted in the brain tissue. From 1996, Kennedy's group at Neural Signals Inc started implanting "locked-in" paralyzed human users with their special cone electrodes with hollow tips for growth of the neural tissue (Kennedy et al., 1998). One of their first subjects equipped with invasive BCI technology, was able to control a cursor on a computer screen and spell about three letters per minute (Kennedy et al., 2000).

Further invasive BCI studies have demonstrated increasingly complex usage of direct neuronal activity information, such as remote control of a TV set or a computer cursor by Donoghue's BrainGate device (Donoghue, 2002), or the operation of a robotic gripper arm controlled entirely by brain signals optimized by visual feedback (Taylor et al., 2002; Carmena et al., 2003; Chapin et al, 1999). In a less invasive procedure, local field potentials reflecting the activity of groups of neurons can be recorded from subdural or epidural locations under the scull to control, for example, a computer cursor (Schalk et al., 2008).

Table 3. Summary of **Invasive BCI** studies reviewed in this chapter

Invasive BCI Principle	**Studies**
Implanted Microelectrode Arrays (incl. the commercial BrainGate system)	*Donoghue, 2002; Carmena et al., 2003; Chapin et al., 1999; Taylor et al., 2002*
Implanted Neurotrophic Electrodes	*Kennedy et al., 1998-2004; Guenther et al., 2009*
Electrocorticographic (ECOG) Electrode Arrays	*Schalk et al., 2008*

2.1.5. Non-Invasive BCI

Success in non-invasive BCI has been also impressive in recent years, although arguably less spectacular due to the substantial challenges posed by the recording of large-scale synchronized activity often originating from multiple neuronal populations behind the layers of the cerebrospinal fluid, meninges, skull bone and scalp skin. The non-invasive approach offers promise for a wide range of immediate real-life applications, both for healthy and disabled users.

Table 4. Summary of **Non-Invasive BCI** studies reviewed in this chapter

(see Table 6 for further SSVEP-BCI examples)

Non-invasive BCI Principle (in alphabetical order)	**Studies**
Alpha-waves (1st BCI study)	*Dewan, 1967*
Hybrid SSVEP-SMR-BCI (feasibility)	*Pfurtscheller et al., 2010a,b*
Mental tasks	*Keirn and Aunon, 1990; Millan et al., 2004; Penny et al., 2000; Galan et al., 2008*
P300 (oddball paradigm)	*Farwell and Donchin, 1988; Donchin et al., 2000*
SCP (Slow Potentials)	*Birbaumer et al., 1993,2003*
SMR rhythms (motor imagery)	*Pfurtscheller et al., 1993-2010; Obermeier et al., 2001; Hashimoto et al., 2008*
SSSEP (Steady-State Somatosensory EP)	*Müller-Putz et al., 2006*
SSVEP (Steady-State Visual EP)	*Gao et al., 2003; Müller-Putz et al., 2005*
VEP	*Vidal, 1977*
Visual motion imagery	*Bakardjian et al., 2003*

2.1.5.1. Motor-imagery based BCI

Most of the BCI researchers to date use motor imagery tasks, which allow detection of changes in the brain's sensorimotor rhythm (SMR) in preparation for motor tasks (muscle movements). Motor-imagery BCIs use 'cognitive load' self-regulation type tasks (as described above), transmitting predictable commands due to the ease of detection and speed of the SNR changes, even though the number of commands and BCI reliability may be relatively limited. Pfurtscheller's group (Graz-BCI) was among the first research labs to actively develop and explore this BCI mode (Pfurtscheller et al., 1993). The introduction of the concepts of Event-related Desynchronization (ERD) and Event-related Synchronization (ERS) revealing non-phase-locked events in the frequency domain (Pfurtscheller et al., 2003) helped advance this paradigm to a point where a five-class BCI was reported (Obermeier et al., 2001).

Using this approach, Pfurtscheller's group was also able to demonstrate the successful artificial stimulation of the hand grasp function in a tetraplegic patient with direct brain control (Pfurtscheller et al., 2003). Beta- and mu-wave activity from surface EEG data was recorded and classified in real time while the tetraplegic subject imagined foot movement, after which the output signal directed a functional electrical stimulation (FES) device to help the paralyzed hand grasp a cylinder.

Recently, a team of researchers at Keio University demonstrated that within the 3-D virtual reality web environment Second Life a disabled person was able to communicate from his home with a student logged in 16 km away and to walk his avatar to him by using only his brain waves (Hashimoto et al., 2008). The system used 3 electrodes to identify hand and foot imagery and to show the feasibility of virtual contacts for disabled people.

2.1.5.2. Slow cortical potentials based BCI

Slow cortical potentials (SCP) for BCI control were pioneered by the Birbaumer group at Tübingen (Birbaumer et al., 1999; Birbaumer et al., 2003). They used SCP as an 'operant conditioning' type of BCI, and called it a Though-Translation Device (TTD). In their initial implementation, the users controlled a spelling device which two ALS patients learned to use at a rate of two characters per minute (after two months of training). In another setup, subjects tried to move a ball on the screen toward a target. Both healthy users and 'locked-in' patients were able to gain control of the system through their own strategies, including imagery.

2.1.5.3. P300 potentials based BCI

Donchin and Farwell were among the first researchers to design a BCI device based on the detection of the well-known P300 'target'/'surprise' brain wave (Farwell and Donchin, 1988; Donchin et al., 2000). In their design, a grid containing the letters of the alphabet and some other functions flashed randomly each character, while the user concentrated on the desired letter. When the target was flashed, a P300 wave indicated a selection. This principle allows high reliability, however, often it is necessary to use multiple trials to achieve selection, and the increased attention efforts may (arguably) cause fatigue faster than in some other BCI paradigms.

2.1.5.4. Non-motor cognitive tasks (mental tasks) based BCI

Keirn and Aunon (Keirn and Aunon, 1990) demonstrated that it is possible to distinguish between five specific mental tasks using the delta (0-3 Hz), theta (4-7 Hz), alpha (8-13 Hz), and beta (14-20 Hz) frequency bands, and a Bayes quadratic classifier.

Even though for this type of BCI a large number of commands is theoretically possible, it is still very challenging due to the high rate of command misclassifications. Recently, the most commonly used features are mental rotation or mental arithmetic. A study by Penny (Penny et al., 2000) utilized a pattern classifier with parameter uncertainty while the user's mental arithmetic task was to subtract sevens successively from a three digit number.

In recognition that a more flexible approach is necessary, later studies used a mixed paradigm in which both motor imagery and another mental task were involved. In one such study, subjects controlled the movement of a miniature robot in a small model house by first selecting and working with three of the following tasks: relaxation, left hand motor imagery, right hand motor imagery, visualizing a spinning cube, performing elementary subtractions by a fixed number (for example, 64–3=61, 61–3=58, an so on), and concatenating related words (Millan et al., 2004).

For wheelchair control, a recent BCI design used a combination of left-hand movement imagery, rest, and a word association task in which the subjects had to find mentally words starting with the same letter (Galan et al., 2008).

Since BCI is a single-trial approach, spatial-domain information can also be utilized in addition to the time- and frequency-domains to increase the efficiency of the brain pattern recognition. One such successful technique, which is increasingly popular in many recent studies, is the Common Spatial Patterns (CSP) algorithm (Ramoser et al., 2000). Another method to use multichannel data for pattern separation is Independent Component Analysis (ICA) / Blind Source Separation (BSS) (Cichocki and Amari, 2003). Yet, online implementation for ICA/BSS has been feasible so far only for some very fast BSS algorithms (Martinez et al., 2007). A general survey of the most common BCI classification approaches, as well as guidelines how to choose a classifier, can be found in (Lotte et al., 2007). (Bashashati et al., 2007) offer a complimentary overview of the algorithms used in the various signal processing stages of recent BCI systems.

The Brain-Computer Interfaces are a very rapidly developing and promising platform, which, depending on progress in contactless sensors, has the potential to become a gateway for brain technology to enter everyday life, and change society.

BCI approaches using Steady-State Visual Evoked Potentials (SSVEP) have the capability to satisfy many of the strict requirements of an optimal BCI. In this stimulus-driven type of BCI, each command is assigned to a separate visual stimulus, as multiple lights or patterns flicker or reverse at slightly different frequencies. The BCI system recognizes the synchronized brain responses to the specific SSVEP stimulus which the user is currently directing his/her attention to.

2.2. Steady-State Visual Potentials (SSVEP)

Steady-State Visual Evoked Potentials (SSVEP) are brain responses that are precisely synchronized with fast (e.g. more than 4Hz) repetitive external visual stimulation such as flashes, reversing patterns or luminance-modulated images. SSVEP responses can be measured within narrow frequency bands (such as ±0.1 Hz) around the visual stimulation frequency, or using other signal processing methods that exploit the specific characteristics of the SSVEP signal, such as rhythmicity and synchronization. The strongest responses occur in the primary visual (striate) cortex, although other brain areas are also activated in varying degrees.

2.2.1. Cortical Frequency Responses to SSVEP Stimulation

David Regan was one of the early researchers to study extensively the various properties of the steady-state evoked potentials in human adults. In a series of studies he found three distinct frequency response regions which he termed low-frequency (LF), medium-frequency (MF) and high-frequency (HF) region (Regan, 1977; Milner et al., 1972; Regan, 1989). For large unpatterned flicker (with very low spatial frequency), the maximal mean response was produced by ~10 Hz stimulation in the LF region, while the peak in the MF region (13-25 Hz) was found at a flicker rate of about 18 Hz, and the HF (40-60 Hz) local maximum was between 45 and 50 Hz (Regan, 1968). The three peak amplitudes in the LF, MF and HF regions were in an inverse relationship with frequency, as brain responses declined at faster flicker rates.

The results for small-check reversals with 0.2° arc check size (high spatial frequency) showed stronger preference for low-frequency stimulation, peaking at about 7 Hz, while SSVEP responses for larger checks with 0.7° arc size were more distributed and more similar to unpatterned flicker. Both for small and larger checks, SSVEP amplitudes were measured only up to 20 Hz and no conclusions were offered for higher frequencies. Regan hypothesized that responses to stimuli with very high spatial frequencies have low temporal frequency preference, while increasing the check size leads to a mixture of the (different) pattern-specific and flash-specific mechanisms (Regan and Richards, 1973).

Pastor (Pastor et al., 2003) studied the EEG responses to 50μs white strobe flashes using 14 frequencies ranging from 5 to 60 Hz. They found the amplitude of the maximal EEG response at 15 Hz for occipital areas and at 25 Hz for frontal areas. The study presented also measurements of the regional cerebral blood flow using positron emission tomography (PET) during visual stimulation at 5, 10, 15, 25, and 40 Hz. Their PET results showed activation of the primary visual cortex with the maximum at 5 Hz when comparing the five tested stimulation frequencies. Earlier PET research had found the strongest response peak in the occipital cortex in the LF region at 7-8 Hz using both goggles with a grid of embedded red lights (Mentis et al., 1997), as well as large black-red checkerboards (Fox and Raichle, 1985). Pastor et al explained the difference with the limited frequency sample of their scans.

NIRS measurements demonstrated results consistent with PET studies. Koch (Koch et al., 2006) reported that the NIRS vascular response to red LED light with 5 ms duration indicated a maximum at 7-8 Hz. They used the deoxy-hemoglobin changes as a measure, since they inversely correlate with BOLD contrast as assessed in fMRI. The same study by Koch (Koch et al., 2006) measured also the EEG responses to the flicker stimuli (1, 5-15 Hz). They found SSVEP peaks at 5 Hz and 11 Hz, with weaker maxima at 20-25 Hz.

Experiments comparing EEG and MEG responses to SSVEP demonstrated further disparities in measuring the frequency dependency of the brain as registered using different techniques. Thorpe (Thorpe et al., 2007) studied the frequency preferences to large black-white checkerboard reversals with driving frequencies between 2 and 20 Hz. Using EEG, they found peak SSVEP power in the 15-20 Hz range, which had no counterpart in the MEG data. In addition, both EEG and MEG recordings indicated also 4-8 Hz and 10-14 Hz maxima.

Some EEG studies have noted a lower frequency dominance of the brain's responses for some types of stimuli. Flickering green concentric rings evoked maximal SSVEP at 8 Hz (Ding et al., 2006) and for high-luminance LED flicker Krishnan (Krishnan et al., 2005) found a near-linear decline in the SSVEP response with frequency, peaking at 4 Hz. However, a recent EEG experiments by Srinivasan, Bibi and Nunez (Srinivasan et al., 2006) showed that dense random dot pattern stimuli flickering at 16 frequencies between 3 and 30 Hz elicited maximal occipital evoked responses at 8 and 12 Hz. Interestingly, when they used a Laplacian transformation to process the EEG data, separate peaks appeared at 7 Hz and 11 Hz for the left and right hemispheres.

In spite of the numerous attempts to reveal the frequency dependence of the brain to fast periodic visual stimuli, as described above, the results are rather diverse. Different measurement techniques may be also useful in establishing indisputable evidence about the optimal frequency of the SSVEP stimuli. In one such promising approach, transcranial magnetic stimulation (TMS) was used to suppress the normal response to briefly flashed letters, as the delay between the visual stimulus onset and the delivery of the magnetic pulse to the occipital cortex was varied between 0 and 200 ms in 20 ms steps (Amassian et al., 1989). The suppression of the flash response was maximal when the lag was 80 ms in two of the subjects and 100 ms in one subject. This important finding points to the significance of the processes occurring in the occipital cortex at SSVEP frequencies of 10-12 Hz.

Computer displays use commonly refresh rates of 60-75 Hz, which, in spite of the lack of conscious perception in direct gazing, can also evoke steady-state visual responses. Lyskov (Lyskov et al., 1998) specifically measured these brain responses and found significant differences for 60 Hz and 72 Hz screen refresh, and for luminances of 65 cd/m^2 and 6 cd/m^2. Bright white stimulation elicited twice stronger amplitudes for 60 Hz than for 72 Hz (0.51 vs 0.26 μV), while the amplitudes for dark-blue screens were substantially lower and closer in value (0.15 vs 0.11 μV). Herrmann (Herrmann et al., 1999) also found 75-80 Hz monitor-induced SSVEP transients in their data, even though they didn’t record control measurements as in (Lyskov et al., 1998) to determine the influence of residual electrical fields from their computer screen equipment.

2.2.2. Time Dynamics of the SSVEP Response

Recent EEG studies examine mostly relatively short-term SSVEP oscillations or otherwise ignore the oscillation envelope changes in time (Krishnan et al., 2005) which could be substantial especially at higher frequencies.

Even though researchers were using more limited equipment several decades ago, van der Tweel (van der Tweel, 1964) offered an SSVEP onset example in one subject in which the baseline levels were exceeded after about 300 ms of stimulation, while a subsequent study by Regan (Regan, 1966) showed the long-term SSVEP responses in an 'idealized' representation of 15.5 Hz SSVEP responses to large 14° arc stimuli. Following the initial onset transient rise and time course over the first 14 s of stimulation, he found a gradual increase, after which the synchronous activity dropped substantially. Regan postulated the existence of an adaptive neural mechanism which was suppressed after 12-20 sec of stimulation. No psychophysiological correlates (perception) of these response amplitude changes were observed by the experimental subjects.

These studies used hardware filters with long time constants and researchers assumed that the narrow-band SSVEPs exhibit very little variability in the running average. However, when Regan compared these results to data filtered by a digital computer, he found much larger variability in the SSVEP dynamics (6Hz) (Regan, 1977). Regrettably, he dismissed the possibility for a time-variable SSVEP response by suggesting that it was due to the wider pass-band of the computer filter as compared to the hardware Fourier analyzer (with 7 s filters), so that more 'noise' passed through from the adjacent EEG frequencies. Nevertheless, he pointed out that the SSVEP dynamics is also dependent on stimulus control (e.g. accommodation, fixation).

Interestingly, Watanabe (Watanabe et al., 2002) found fast activation of parieto-occipital areas at 100-400 ms which was followed by slower occipital responses which developed until up to 1000 ms after the 10 Hz stimulation onset. They suggested that the initial parieto-occipital response may be part of a defensive mechanism temporarily inhibiting the occipital response to prevent brain hyperactivity due to the flicker.

Attentional mechanisms have also been shown as a possible mediator responsible for time delays of 0.6-0.8 s between cue onset and SSVEP facilitation (Müller et al., 1998).

2.2.3. Additional Parameters of the SSVEP Response

While part of the differences in the reported frequency dominance may be due to the diversity of the captured brain processes and areas depending on the recording modality, SSVEP stimulus parameters such as spatial frequency, luminance, contrast and color also play a crucial role (Regan, 1989). Regan showed that patterned checkerboard stimuli with small checks (such as 0.2° arc side) exhibit low-frequency preferences with response peaks at ~7 Hz, while patterns with larger checks (such as 0.7° arc side) have a higher frequency preference, similarly to unpatterned flicker stimuli (Regan, 1977; Regan, 1989). It has been hypothesized that checks or gratings of less than 0.5° arc stimulate predominantly spatial frequency and contrast detectors, and those with size of more than 0.7° arc activate luminance detectors (Maffei, 1982). As demonstrated by Regan (1977) in measurements with varying check sizes (up to 1.3° arc in size) for the normal eye, the relatively small check sizes of 0.25°-0.5° arc elicited maximal evoked responses. This supported other evidence that patterns with a high spatial frequency (3-4 cpd) enable maximal contrast sensitivity (Kelly, 1976).

However, for subjects with pooh visual acuity (less than 20/20) patterns with very high spatial frequency may become blurred (Sokol and Moskowitz, 1981), thus weakening the brain activation. Age (Sokol et al., 1981; Birca et al., 2006) and gender (Emmerson-Hanover et al., 1994) may also alter the pattern evoked potentials, although some studies did not find a gender effect (Birca et al., 2006).

Cortical SSVEP oscillations have been shown to depend strongly also on the proximity of simultaneously displayed stimuli (Fuchs et al., 2008). In addition, selective spatial attention and covert attention facilitate strong modulations of the SSVEP responses (Müller et al., 1998; Müller and Hillyard, 2000; Fuchs et al., 2008) which may be dependent on frequency (Ding et al., 2006).

2.2.4. Activation of Brain Areas During the SSVEP Response

Simple one-dipole sensory models may be inadequate to explain the processes participating in the SSVEP dynamics. Mentis et al (1997) suggested that synchronized striate responses at all frequencies are due primarily to input from the subcortical lateral geniculate nucleus (LGN), while slower activation in the middle temporal (MT) gyrus reflects the perception of apparent motion. Indeed, in a direct measurement with implanted electrodes in nonphotosensitive epileptic patients, Krolak-Salmon (Krolak-Salmon et al., 2003) demonstrated clear responses to high-frequency 70 Hz screen refresh rate flicker in the LGN, the optic radiation and in V1/V2 cortex. They suggested that flicker responses were driven along the retinogeniculostriate pathway. One probable hypothesis is that, diverging from the M and P layers of the LGN, responses to stimuli with high temporal frequency are carried along the faster magnocellular (M) pathway, while the parvocellular pathway are responsible for responses to stimuli with high spatial frequency.

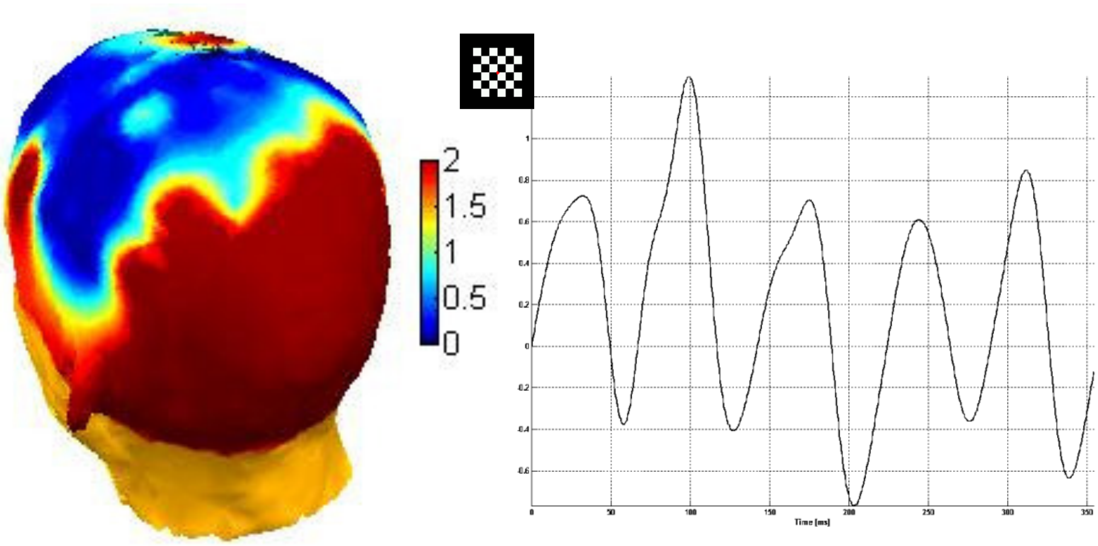


Fig. 3. SSVEP brain responses to fast repetitive 14Hz stimulation using a small checkerboard (Bakardjian et al., 2007a). SSVEP brain responses are most prominent in the visual (occipital) cortex and parieto-occipital areas, although fronto-lateral areas are also activated.

The main cortical SSVEP activation occurs in the primary visual cortex (V1), but there is also fMRI evidence of more lateral visual sources (MT/V5) in the motion-sensitive areas of cortex for 6 Hz circular grating stimuli (Di Russo et al., 2007). Using 10 Hz stimulation, Watanabe (Watanabe et al., 2002) found also activation of parieto-occipital areas followed by slower occipital responses.

Another study demonstrated, using fMRI for 3-14 Hz responses, that apart from the occipital cortex medial frontal cortex activity was also significantly increased (Srinivasan et al., 2007). However, the frontal cortex was substantially more frequency-dependent, with maximal peaks between 3 and 5 Hz, as well as further local maxima between 10 Hz and 14 Hz (strongly dependent on the individual subject). The same study also found that some occipital voxels were positively correlated to frontal voxels, and others were negatively correlated, thus forming functionally-synchronized and functionally-distinct large-scale networks.

2.2.5. Photosensitive Epilepsy and Its Prevention

Between 4 and 9% of the population carries the risk of sensitivity to visually-induced seizures (Erba, 2001), which are induced by the physical characteristics of a visual stimulus. Photosensitivity is greatest for flash frequencies between 9 and 18 Hz, although nearly 50% of sensitive patients respond to frequencies of up to 50 Hz, and the range of reactivity extends from 1 to >60 Hz (Jeavons and Harding, 1975). An epileptiform EEG response to visual stimulation is called a photoparoxysmal response (PPR).

The “pocket monster” (Pokemon) incident on December 16, 1997 received a world-wide attention, as almost 700 people (mostly children) in Japan were urgently treated for seizure symptoms after watching a television animated cartoon (Takahashi and Tsukahara, 1998). Large 12-Hz red frames alternated with blue frames lasting for 4 s in this cartoon induced seizures both in healthy people and people with latent photosensitivity but who had never had seizures.

Since then strict guidelines for television broadcasting have been successfully implemented to ensure appropriate visual content regarding flicker frequency and size, alternating patterns and color composition, especially regarding the red color (Takahashi and Fujiwara, 2004; Fisher et al., 2005). For pattern stimulation, these guidelines for prevention of photosensitive epilepsy set the following requirements (Harding et al., 2005; Wilkins et al., 2005): If the pattern occupies no more than 25% of the displayed screen area, and if the pattern luminance of the lightest stripe is >50 cd/m^2, and if the pattern is presented for ≥0.5 s, then the pattern must contain ≤5 light-dark pairs (if moving, oscillating, flashing or reversing in contrast), or $\leq$8 light-dark pairs (if stationary), or $\leq$12 light-dark pairs (if drifting smoothly). Red-cyan color combinations are most epileptogenic.

Other prevention measures include also individual filtering of the visual information, for example, using glasses that are blue and cross-polarized (Kepecs et al., 2004) or goggle-based compound optical filters to provide reliable PPR inhibition (Takahashi et al., 2001). Reducing the relative size of the stimulus according to guidelines above by moving further back from it (e.g. distance of >2.5 meters for a television set) may also serve as an immediately available and helpful measure.

Table 5. Summary of **Steady-State Visual Evoked Potentials (SSVEP)** studies reviewed in this chapter

SSVEP-Related Property	Studies
Frequency Response	*Regan, 1968-1989 (white squares); Watanabe et al., 2002; Milner et al., 1972; Fox and Raichle, 1985 (large black-red checkerboards); Mentis et al., 1997 (goggles with embedded red lights); Srinivasan et al., 2006 (random dots); Srinivasan et al., 2007; Krishnan et al., 2005 (LED flicker); Koch et al., 2006 (red LED flicker, using NIRS&EEG); Ding et al., 2006 (green concentric rings); Pastor et al., 2003 (white strobe flashes); Thorpe et al., 2007 (large black-white checkerboards); Amassian et al., 1989 (using TMS - transcranial magnetic stimulation)*
High-frequency response to computer screen flicker	*Lyskov et al., 1998; Herrmann et al., 1999; Krolak-Salmon et al., 2003*
Effect of Spatial Frequency	*Kelly, 1976; Sokol and Moskowitz, 1981*
Effect of Size	*Maffei, 1982*
Effect of Spatial Attention	*Ding et al., 2006 (green concentric rings); Fuchs et al., 2008; Müller et al., 1998; Müller and Hillyard, 2000*
Effect of Covert Attention	*Müller and Hillyard, 2000*
Effect of Proximity	*Fuchs et al., 2008*
Response Onset	*Müller et al., 1998; Van der Tweel, 1964*
Response Time Dynamics	*Watanabe et al., 2002; Krishnan et al., 2005 (LED flicker)*
Activated Brain Areas	*Di Russo et al., 2007; Srinivasan et al., 2007; Mentis et al., 1997 (goggles with embedded red lights); Watanabe et al., 2002; Krolak-Salmon et al., 2003*
Effect of Age	*Birca et al., 2006; Sokol et al., 1981*
Effect of Gender	*Emmerson-Hanover et al., 1994; Birca et al., 2006*
Photosensitive epilepsy and prevention	*Wilkins et al., 2005; Takahashi and Tsukahara, 1998; Takahashi et al., 2001; Takahashi and Fujiwara, 2004; Fisher et al., 2005; Harding et al., 2005; Jeavons and Harding, 1975; Kepecs et al., 2004*

2.3. SSVEP-Based BCI Approaches

Recently, SSVEP BCI systems have gained a special place in the BCI paradigms continuum due to the possibilities they offer. SSVEP-BCIs are useful in applications which present the following major requirements:

1) large number of BCI commands is necessary (in SSVEP BCI limitations are mostly defined only by the design)

2) high reliability of recognition is necessary (in SSVEP BCI patterns are clearly distinguishable by frequency)

3) no training (or just a few minutes of classifier training) is allowed

4) self-paced performance is required

as well as the following restrictions:

5) equipment for visual stimulation is permissible (e.g. computer display, LED panel)

6) command delays of 1-3 s are allowed

7) user is capable of small eye movements

8) user is capable of mild but sustained attention effort

9) user's visual system is not engaged in other activities

2.3.1. Designs of SSVEP-Based BCI Systems

Recognizing the promise of the SSVEP-based BCI approach, Sutter (Sutter, 1984) described one of the earliest successful online implementations of this paradigm. The BCI system suggested by him featured 64 targets, with best success rates of more than 90 %, as well as decision delays in the 1.5 s range. Since the system was designed to use a single flash frequency of 10 Hz, the selections were based on a technique called binary m-sequence, in order to avoid the unacceptably long lags in case of purely sequential testing of all targets.

Subsequently, two different approaches to SSVEP BCI were proposed by researchers at the US Air Force Research Laboratory. The first approach (McMillan and Calhoun, 1995; Middendorf et al., 2000) required the users to consciously modulate the relative amplitude and phase of their SSVEP responses to 13.25 Hz flicker as a result of neurofeedback training. This allowed them to roll a simple flight simulator in 0.5° increments, to the right if the SSVEP amplitude was increased, and to the left, if the amplitude was suppressed. Most operators achieved satisfactory control after 30-minutes of training, while trained users reached success rates of 80-95%. Two more applications were tested with the same amplitude/phase method – knee angle control with a functional electrical stimulator, and a switch selection design. In the second approach (Jones et al., 1998; Middendorf et al., 2000), two stimuli flickering at 17.56 and 23.42 Hz were shown, and the command selection was based on their relative spectral amplitudes. The task was to select one of two virtual buttons on a computer screen. The users achieved a 92% mean success rate, and command delays were in the 1.2-3 s range (mean 2.1 s). This more efficient approach applied the basic principles of most current SSVEP BCI systems which identify synchronized brain responses to flickering or reversing visual stimuli on the basis of their different frequencies.

The advantages of SSVEP-based BCI systems, regarding a relatively very high number of commands when compared to other BCI paradigms, were demonstrated at Tsinghua University. In a phone number selection design, they presented a 12-command BCI, using 6-14 Hz flicker and threshold command selection, even though the inter-subject variability was quite high (Cheng et al., 2002).

Later, another study from the same group demonstrated a 48-command BCI system, which was designed with light emitting diodes (LEDs) in blinking buttons (Gao et al., 2003).

They used flicker with frequencies in the 6-15 Hz range, detected with FFT, as well as specialized hardware, which removed the need for a computer. For the single subject in that study, they reported a mean success rate of 87.5% and an average delay of 3.8 s for command recognition (68 bits/min transfer rate).

Gaming could be a natural target application for the SSVEP BCI paradigm, as shown by Lalor (Lalor et al., 2004). In a 3D immersive game application called MindBalance, the player's goal is to balance an animated character on a tightrope by gazing at two reversing checkerboard patterns. In the preliminary phase, the individual EEG responses to reversal frequencies between 6 and 25 Hz were tested and two best frequencies were selected. Three feature extraction methods were applied offline – squared FFT (Welsch's power spectral density estimate), FFT of the autocorrelation function, and autoregressive model of order 5 which yielded best results across users. Methods 1 and 2 were evaluated online with the second harmonic of the reversal frequencies, and a linear-discriminant classifier showed success rates between 77 and 90 %.

Müller-Putz (Müller-Putz et al., 2005) studied the performance of their 4-class SSVEP BCI system when three harmonics of each target frequency were included in the classification. They used LED flicker of 6, 7, 8, 13 Hz frequency attached on top a computer screen with a cockpit design providing the feedback. The evaluation was performed in 5-second trials and repeated 4 times on different days, including a different classifier, and a simplified screen without the cockpit. The online success rate varied between the four conditions, ranging from 35.1 % to 95.8 %. A subsequent study sought to clarify the best measurement and classification parameters, which resulted in an improved mean performance of 74 % (Müller-Putz et al., 2008).

The NASA Ames Research Center also studied the possibilities of SSVEP-based BCI control in a 4-command design called Think Pointer BCI. The user attempted to follow a line drawn on a world map by attending to one of the four reversing checkerboards with fixed positions on the edges of the computer screen (Trejo et al., 2006). The temporal frequencies used were between 5 and 7 Hz, and the user intent was evaluated using a kernel partial least squares classifier (KPLS) which utilized the EEG responses at the second harmonic, as well as at the fundamental frequency of the SSVEP. They reported accuracy of 80-100 % across subjects and sessions, while the command lag was 1-5 s. An observation was noted that apparently auditory guidance resulted in longer delays than a visual guidance for the BCI commands.

In the past decade, an increasing number of SSVEP BCI systems have been presented to the signal processing and neuroscience research communities and each of these systems offer their own advantages. One such system is, for example, the 2-class Braunschweig SSVEP BCI which directs the movements of a remote-controlled truck using capacitive EEG sensors without direct contact with the scalp skin (Oehler et al., 2008). Further implementations include the Aalborg SSVEP BCI (Nielsen et al., 2006), the Geneva SSVEP BCI (Grave de Peralta et al., 2008), the Bremen SSVEP BCI (Friman et al., 2007; Allison et al., 2008), also with an application for wheelchair control (Teymourian et al., 2008), the Lodz SSVEP BCI (Materka and Byczuk, 2006), and the Keio SSVEP BCI (Ogawa et al., 2008).

2.3.2. Signal Processing Methods in SSVEP-Based BCI Systems

The most wide-spread signal processing technique to extract the SSVEP responses of the brain from the raw EEG data is based on power spectral density estimates using Fast Fourier Transform (FFT) of a sliding data window with a fixed length (usually more than 3 s). The main idea of this method is that the frequency component with the highest spectral power corresponding exactly to one of the SSVEP stimulation frequencies will be considered as a BCI command (Middendorf et al., 2000; Gao et al., 2003; Trejo et al., 2006; Lalor et al., 2004). Template matching (Sutter, 1984) and recursive outlier rejection (Vidal, 1977) have also been used to show the feasibility of SSVEP-BCI systems in spite of their disadvantages. Other methods which attempt to improve on robustness upon the FFT-based methods are autoregressive spectral analysis (Allison et al., 2008; Penny et al., 2000), and the frequency stability coefficient (SC) which has been shown to be better than power spectrum for short data windows; although training necessary for building the SC model (Wu et l., 2008). Furthermore, canonical correlation analysis (CCA) is also an efficient method for online SSVEP-BCI, as the required data window lengths are shorter than those necessary for power spectrum estimation (Bin et al., 2009).

2.3.3. Can effective SSVEP BCI control be achieved without dependence on eye movements?

SSVEP-based Brain-Computer Interfaces are considered 'dependent' on the user's ability to move the gaze (foveal vision) in order to attend the selected stimulus. However, following the lead of the SSVEP research community (Müller and Hillyard, 2000), several studies have undertaken to demonstrate that even disabled users with very limited eye movements may be able to use SSVEP BCIs. Kelly and coworkers found a 20% drop in the classification accuracy when nearby flicker stimuli were attended covertly as compared to overt attention (Kelly et al., 2004). In two more studies they attempted to quantify the effects of covert spatial attention as subjects were presented with two rectangular flicker stimuli flickering at different rates and were asked to attend to the letters (A to H) on the top of them. In the first study (Kelly et al., 2005a), a realistic BCI system was tested with a pilot version of the visual-spatial attention control (V-SAC) design. Only two electrodes and flicker of 10 and 12 Hz were used (these frequencies were found to be optimal). Six out of eleven subjects were able to produce the brain responses to achieve at least 72% in at least one out of five trials. The best subject achieved up to 93.3 % success in selecting a covertly attended flickering target. Their online SSVEP selection procedure employed weighted spectral ratios and thresholding. In another report (Kelly et al., 2005b), 64 channels of EEG were recorded during a similar (modified) task including two couples of frequencies, one in the alpha band range (9.45 and 10.63 Hz), while the other was higher (14.17 and 17.01 Hz). In this study, linear discriminant analysis (LDA) was employed and the direction of spatial attention was determined with a mean success rate of 70.3 % for the higher-frequency flicker (information transfer rate of 2.1 bits/min). A combination of SSVEP and the alpha band modulation yielded higher classification rates. The authors noted that the SSVEP topography across subjects was not consistent enough, so that the BCI channel selection should be performed individually for each subject, but concluded that using covert attention to visual flicker is indeed feasible for BCI.

In a recent development, Zhang and colleagues (Zhang et al., 2010) demonstrated an SSVEP-BCI system based on covert attention to two large sets of flickering and rotating color dots. The system achieved an average online classification accuracy of 72.6 % for two commands.

Allison (Allison et al., 2008) also showed that covert attention to checkerboard reversal and line stimuli without gaze shifts can enable sufficiently strong SSVEP responses for BCI control in about half of their subjects. Checkerboard patterns elicited much stronger responses than lineboxes. The checkerboard reversal rates were chosen at 6 and 15 Hz in test runs among 6 frequencies (6-30Hz). After showing the general feasibility of SSVEP BCI without gaze shifts, they suggested that “the labels ‘dependent’ and ‘independent’ BCI might be best regarded not as absolutes, but endpoints of a continuum.”

Table 6. Summary of **SSVEP-BCI** studies reviewed in this chapter

Number of Commands	**Type of Flicker**	**Design Specifics**	**Study**
2	Very large checkerboards	Video camera mounted on remote-controlled toy truck	*Oehler et al., 2008 (Braunschweig group)*
2	Checkerboards	MindBalance game	*Lalor et al., 2004*
2	White squares on computer screen	Covert attention	*Kelly et al., 2004, 2005a,b*
2	Luminance control on computer screen	One of the first feasibility studies	*Jones et al., 1998*
2	Large boxes on screen	User modulates SSVEP amplitude/phase	*McMillan and Calhoun, 1995*
2	White 'buttons' on computer screen	First comparison of amplitude- and frequency-controlled SSVEP-BCI	*Middendorf et al., 2000*
2	White fluorescent tubes	User modulates amplitude/phase of SSVEP	*Middendorf et al., 2000*
2	Large stripes, checkerboards	Covert attention	*Allison et al., 2008*
2	Rotating color dots	Covert attention	*Zhang et al., 2010*
2 - 3	Large color boxes	Virtual environment	*Grave de Peralta et al., 2008 (Geneva group)*
4 -	Checkerboards	Think Pointer BCI (NASA world map)	*Trejo et al., 2006 (NASA group)*
4	LEDs	Airplane cockpit design	*Müller-Putz et al., 2005*
4	LEDs	Grid of lights	*Müller-Putz et al., 2008*
2 - 4	LEDs	Simulated wheelchair	*Teymourian et al., 2008 (Bremen group)*
4	LEDs	Lights mounted under computer screen	*Ogawa et al., 2008 (Keio group)*
6 (sequential presentation)	LEDs	Study of methods: not actual BCI	*Friman et al., 2007 (Bremen group)*
2 - 8	LEDs	Anti-phase flicker of LED couples	*Materka and Byczuk, 2006 (Lodz group)*
10	LEDs	Phone number selection	*Cheng et al., 2002 (Tsingua group)*
48 (1 subject)	LEDs	Grid of lights	*Gao et al., 2003 (Tsinghua group)*

2.4. Affective Processes in the Brain (Emotions) and Connection to SSVEP Research

Emotional reactions in humans are the result of complex interactions between external sensory stimuli, brain circuitry, personal experiences and neurotransmitter systems. Emotions involve widespread affective activities in the nervous system, from the cerebral cortex to the autonomic nervous system. These processes aim to mobilize rapidly an individual's motor and cognitive reactions to situations appraised as threatening or beneficial.

2.4.1. Models of the Emotional Continuum and classification Schemes

Emotions involve different affective dimensions (Heilmore and Gilmore, 1998), such as emotional experiences (inner feelings), emotional expression (display of feelings), emotional memories (recall, encoding) (Banich et al., 2009), and emotional imagery (Holmes and Mathews, 2010), *Emotional experiences* are usually relatively short-term responses to environmental or cognitive stimuli. However, when the corresponding affective states are sustained over substantially longer time spans, this may lead to neuropsychological phenomena such as moods (e.g. depression, anxiety, and elation), plots (e.g. love, hate, grief, jealousy), or affective personality traits (e.g. hostility) (Ekman, 1999). *Emotional expression* involves subtle or more overt changes in physiological and communicative responses, such as facial expression and skin color, voice pitch, body posture and various aspects of behavior.

Emotions are measured using a variety of classification schemes, ranging from simple evaluation of emotional reactions to complex classes involving social communication (Adolphs, 2002; Mauss and Robinson, 2009). Emotional experiences are often studied in terms of valence (from positive to negative) (Rozenkrants et al., 2008), or arousal (from low to high intensity) (Bradley et al., 2007). Russell's two-dimensional model of affect (Russell, 1980) uses valence (positive-negative axis) and arousal (low-high intensity) to map the emotion experience continuum (Posner al., 2009). Plutchik's three-dimensional circumplex cone model adds two more dimensions – similarity (from same to polar opposites) and orthogonality (from primary emotions to mixed ones) (Plutchik, 2001). This model, however, is based on eight discrete primary emotions which are arranged as four pairs of opposites (joy versus sadness, trust versus disgust, fear versus anger, and surprise versus anticipation). Secondary emotions with varying similarity can be produced by mixing the primary ones, in the same way as the colors of the spectrum. For example, according to this model love is a combination of joy and trust, while disapproval is a combination of sadness and surprise, or submission – between trust and fear. Other researchers have also proposed models assuming a small number of fundamental emotions, such as emotion hierarchy trees (Fischer et al., 1990) featuring emotion clustering with a top-down organization – positive emotions: love (fondness, infatuation) and joy (bliss, contentment, pride); negative emotions: anger (hostility, annoyance, jealousy, contempt), sadness (grief, agony, loneliness, guilt), fear (horror, worry). Using facial muscle responses, Izard has identified another set of ten basic emotions: interest, enjoyment, surprise, distress, anger, disgust, contempt, fear, shame/shyness, and guilt (Izard, 1977). However, in a critical view of the concept of 'basic' emotions, Ortony and Turner argued that even though their origins may be traced to biologically 'hardwired' affective systems, these emotions cannot be singled out as special, the criteria for their selection are controversial and different in each approach, and it is not clear how basic emotions can be actually combined (Ortony and Turner, 1990). They proposed that actually emotions may consist of *emotional components* (some of them basic) instead of other emotions. In spite of the ensuing scientific controversy (Ekman, 1992;

Panksepp, 1992; Izard, 1992) which was not fully resolved (Ortony and Turner, 1992), these differing points of view have raised interesting questions about how emotions are shaped, controlled and quantified.

2.4.2. Emotion-Cognition Interactions

Emotions (affective processing) and thinking (cognitive processing) are two important tools for the brain to evaluate and influence the environment in a most efficient way. It is often difficult to separate clearly emotion and cognition, because they may have common components (Gray et al., 2002; Simpson et al., 2000). Recent studies have begun to improve the understanding of the complex and mutually beneficial relationship between emotion and cognition. Extending previous theories of universal emotion building blocks, Izard has drawn a sharp distinction between two types of emotions – brief *basic emotions* (such as infant's joy for seeing her mother's face) and complex *emotion-cognition interactions (emotion schemas)* (Izard, 2009). Although affective-cognitive interactions are often elicited by conscious *appraisal* processes, they can also be influenced by memories, imagination, thoughts, or changes in hormonal levels and neurotransmitters. Furthermore, according to this view of affect, frequently recurring emotions schemas could stabilize as emotion traits (temperament or personality traits). Nevertheless, the processes involved in the cognitive mapping of the emotional value of stimuli are not fully understood yet. Cognitive reappraisal may depend on factors such as regulatory goals and deployed strategy. For example, conscious self-reappraisal of negative emotions in a positive or detached way (down-regulation) can aid successful coping with anxiety or depression, while excessive worry (up-regulation) can enhance them (Ochsner et al., 2004). Furthermore, emotion-cognition interactions facilitate emotion regulation depending on how we appraise the self-involvement in a situation.

Interestingly, there is some evidence that different appraisal patterns of the same situation are sufficient to cause different emotions (Siemer and Mauss, 2007).

2.4.3. Emotions – Cultural Influences and Gender

Some aspects of emotion can be strongly influenced by additional factors such as cultural / social differences (Russell, 1991; Soto and Levenson, 2009), gender (Sabatinelli et al., 2004), neurotransmitter levels (Kemp et al., 2004b), sleep (Walker and van der Helm, 2009) and even emotion stimulus position in the visual field (Liu and Ioannides, 2010).

In spite of many similarities, ***cross-cultural*** differences in emotion-cognition interactions could be significant, especially regarding emotion appraisal, expression and regulation (Mesquita and Frijda, 1992; Jack et al., 2009). When Japanese subjects viewed facial expressions at low affective intensities, they tended to think that the poser was experiencing a more intense feeling of the emotion than was actually portrayed. On the other hand, when Americans viewed high-intensity expressions, they perceived emotions as being portrayed in an exaggerated way and therefore were inclined to assume that the poser did not feel the emotion as intensely as the facial expressions suggested (Matsumoto et al., 2002). Wide-ranging cultural differences in emotion regulation (reappraisal and suppression) were further demonstrated in a study across subjects from 23 countries (Matsumoto et al., 2008). Higher scores on emotion suppression, as well as positive correlation between reappraisal and suppression, were measured in participants from cultures which valued highly social order and hierarchy, while subjects from cultures that valued individual affective autonomy tended to elicit lower scores on suppression, with negative correlation between cognitive reappraisal and emotion suppression. In line with the observation that Japanese subjects typically exhibit lower levels of emotional expression, a study with 15 French and 15 Japanese volunteers viewing neutral and affective pictures in their respective countries showed significant differences in their late evoked brain responses. Cultural modulations between the two groups were found in the parieto-occipital brain areas starting from 170ms after an affective picture was shown, and especially in the 250-450ms range, with decreased emotional component amplitudes in the Japanese population (Hot et al., 2006). Nevertheless, in this study similarities were found the early brain responses (105-140ms) showing no cross-cultural differences in this early time range, although emotion-related effects were detected in both groups.

Russell et al. (1989) also found some common points in the emotion experience between cultures as participants from several countries judged emotional words and facial expressions in a way that supported a similar circular representation of a set of feelings in their two-dimensional circumplex model. Nevertheless, later he initiated another scientific controversy and a round of useful discussions by questioning the universality of emotions recognition from facial expressions across cultures. Specifically, he concluded that the association between facial expressions and emotion labels may vary with culture while the forced-choice format of experiments to gather data inhibits this diversity (Russell, 1994, 1995). Opponents of this critical review reiterated intensely the universality of emotion and emotional expressions (Ekman, 1994; Izard, 1994). As always, the most plausible explanation may be found between the extremes, in the view that emotions contain both culture-specific and pan-cultural components (Russell, 1991).

Gender influences in emotion processing have been demonstrated in a number of studies (Codispoti et al., 2008; Sabatinelli et al., 2004; Kemp et al., 2004a). Gender may shape emotional experience and expression due to genetic or hormonal balance differences, as well as developmental factors such as traditional educational constraints during upbringing of the young. Women may be more accurate than men in judgments of emotional expressions

(Hall and Matsumoto, 2004). Female subjects also responded stronger to stressful emotional stimuli (Yang et al., 2007), and exhibited enhanced early negative ERP components (N100 and N200) to emotional pictures, when compared to men, especially for unpleasant stimuli (Lithari et al., 2010). Men, on the other hand, responded to positive visual stimuli with a stronger brain activity in the frontal lobe (inferior and medial frontal gyrus), as well as with a stronger activation of the amygdala for pleasant stimuli, while in women stronger brain activations in the anterior and medial cingulate gyrus were observed for pictures evoking negative emotions (Wrase et al., 2003).

2.4.4. Empathy

The recent discovery of the mirror neuron system (Gallese et al., 1996), which was shown to activate both when a monkey observed and performed a goal-directed action (see (Keysers and Fadiga, 2008) for a review), provided a neural substrate and boosted substantially the understanding of another neuropsychological phenomenon – empathy. The ability to empathize, or share another individual's emotions, may well be considered one of the building blocks of civilized society (Adolphs, 2009). Mirroring the mental states and emotions of others is an efficient way to simulate and understand them better, and to respond to critical situations in a more flexible way. Impairment of this essential social communication mechanism may be related to neurological disorders such as autism (Dapretto et al., 2006). Empathy can be not only emotional but also cognitive, involving inferential processes. There is some evidence that both types of mental simulation activate separate anatomical brain substrates (areas). Broadmann area 44 was found to be critical for ***emotional empathy***, while areas 10 and 11 were important for the proper functioning of ***cognitive empathy*** (Shamay-Tsoory et al., 2009). Another study demonstrated that emotional empathy is special, as it allowed stronger mirroring of the observed mental states than the cognitive empathy. Differences in neural processing involved both limbic areas (the thalamus), and cortical areas (fusiform gyrus and the inferior parietal lobule) (Nummenmaa et al., 2008). Furthermore, in contrast to emotional empathy, ***sympathy*** (empathic concern) (Decety and Chaminade, 2003) may involve higher cognitive processes such as the projected costs and benefits of helping, as well as other mental manipulations (Izard, 2009). Empathic accuracy may also depend on cultural differences (Soto and Levenson, 2009).

Brain activity during observation or imitation of emotional facial expressions has been a principal tool for studying empathy in many studies. Both observation and imitation activated a similar network of emotion-related brain areas, although imitation evoked stronger responses in the inferior frontal cortex, the superior temporal cortex, the insula, and the amygdala (Carr et al., 2003; van der Gaag et al., 2007). Another interesting difference between these 'passive' and 'active' types of empathy was that during observation of affective faces only the right ventral premotor area was activated, while imitation resulted in a bilateral activation (Leslie et al., 2004).

2.4.5. Neuroanatomical Correlates of Emotion

Historically, emotional processing has been attributed to the limbic system of the brain (Papez, 1937). Extensive recent studies have extended this knowledge and have identified a complex emotion-related network between cortical, limbic and paralimbic brain areas. Even though no single region of the brain has been found to activate in relation to all emotions, the medial prefrontal cortex (MPFC) was shown to be active across multiple emotions, especially during emotional awareness, which points to the possibility that MPFC may be involved in the cognitive aspects of emotion (Phan et al., 2002).

A critical involvement of the amygdala has been implicated in the generation and maintenance of fear-related processing (Phelps and LeDoux, 2005), extending to visual (face) and linguistic (Isenberg et al., 1999) stimuli. The amygdaloid complex itself is not a homogeneous structure but it consists of subnuclei each with a specific function. Inputs to the amygdala may involve two separate routes. A fast thalamic pathway provides simple low-level sensory information which may also play a role in amygdala priming in expectation of further more detailed information about the stimulus (danger verification). The other route, a thalamo-cortical-amygdala pathway, involves inputs from multimodal areas and carries more complex/processed information (Fellous et al., 2003). For example, such amygdala connections with areas of the frontal cortex are able to regulate negative affect following cognitive reappraisal (Banks et al., 2007). Furthermore, it has been also shown that **the amygdala is able to provide direct neural feedback to neurons in ventral visual cortical areas** V1, V2, V4, TEO and TE (Amaral et al., 2003; Freese and Amaral, 2006), thus modulating substantially visual sensory responses and perception.

The anterior cingulated cortex (ACC) is another essential part of the limbic system involved in emotion and cognitive processing. Some evidence points to the hypothesis that the ACC may serve as an attentional gateway that regulates competing emotional and cognitive processes by correspondingly activating and inhibiting its emotional and cognitive subdivisions. For example, during a cognitively demanding and emotionally neutral task, important parts of the limbic system (the ACC affective subdivision, amygdala, insula and the orbitofrontal cortex) were found to be suppressed (Bush et al., 2000).

Investigating the neuroanatomical correlates of basic emotions, sadness activated the subcallosal cingulated cortex (SCC), while happiness (including happy faces) and positive arousal activated the basal ganglia. However, the basal ganglia area also activated for disgust which may point to a role invoking a state of motor preparedness triggered by an emotional stimulus towards a desired goal (Bush et al., 2000). Emotional valence (the positive-negative dimension of emotion) may be related to brain processing in cortical midline areas – the orbitomedial prefrontal cortex (OMPFC), the dorsomedial prefrontal cortex (DMPFC), the medial parietal cortex (MPC), and the insular cortex, as concluded by a recent fMRI study (Heinzel et al., 2005). Some of the neighboring frontal brain regions, the orbitofrontal and the ventromedial prefrontal cortices, could be responsible for regulating emotions. Damage to the orbitofrontal cortex is associated with disinhibited behavior and other social emotional deficits, while the ventromedial prefrontal cortex has been associated with storing memories of particular experiences, and may be an important element of a brain network related to empathy (Decety and Jackson, 2004).

Table 7. Summary of **emotion** studies reviewed in this chapter

Emotion - Related Aspect	**Studies**
Taxonomy of emotions	*Plutchik, 2001 (circumplex cone model); Adolphs, 2002; Mauss and Robinson, 2009; Fischer et al., 1990 (emotion clusters,hierarchy); Izard, 1977 (10 basic emotions based on faces); Papez, 1937 (limbic model)*
Dimensions for emotion measurement	*Posner al., 2009 (valence-arousal); Bradley et al., 2007; Heilmore and Gilmore, 1998; Rozenkrants et al., 2008; Russell, 1980*
Brain areas	*Bush et al., 2000; Heinzel et al., 2005; Decety and Jackson, 2004; Isenberg et al., 1999 (faces and linguistic stimuli); Phan et al., 2002 (MPFC); Banks et al., 2007 (amygdala); Fellous et al., 2003 (amygdala); Phelps and LeDoux, 2005 (amygdala)*
Emotion-cognition interactions	*Izard, 2009; Siemer and Mauss, 2007; Simpson et al., 2000; Gray et al., 2002; Ochsner et al., 2004 (self-appraisal); Phan et al., 2002*
'Are there basic emotions?' controversy	*Ortony and Turner, 1990; Ekman, 1992; Izard, 1992; Ortony and Turner, 1992; Panksepp, 1992*
Gender differences	*Hall and Matsumoto, 2004; Wrase et al., 2003; Yang et al., 2007; Kemp et al., 2004a; Sabatinelli et al., 2004; Lithari et al., 2010; Codispoti et al., 2008*
Cross-cultural differences	*Matsumoto et al., 2002, 2008; Jack et al., 2009; Hot et al., 2006; Mesquita and Frijda, 1992; Russell et al., 1989-1995; Ekman, 1994 (universality across cultures); Izard, 1994 (universality)*
Social differences	*Russell et al., 1989-1995*
Emotional memories	*Banich et al., 2009*
Emotional imagery	*Holmes and Mathews, 2010*
Long-term changes	*Ekman, 1999*
Effect of neurotransmitters	*Kemp et al., 2004b*
Effects of sleep	*Walker and van der Helm, 2009*
Stimuli: Position in visual field	*Liu and Ioannides, 2010*
Empathy	*Adolphs, 2009; Carr et al., 2003; Izard, 2009; Van der Gaag et al., 2007; Dapretto et al., 2006 (impairments)*
Empathy: Brain areas	*Leslie et al., 2004; Nummenmaa et al., 2008; Shamay-Tsoory et al., 2009*
Empathy: Mirror Neuron System (MNS)	*Keysers and Fadiga, 2008; Gallese et al., 1996*
Empathy: Cross-cultural differences	*Soto and Levenson, 2009*
Sympathy (empathic concern)	*Decety and Chaminade, 2003*

2.4.6. Affective Picture Processing

Electroencephalography (EEG) studies on the affective processing in the brain have been successful in distinguishing of high-arousal emotions from a neutral state observing augmented evoked responses to affective pictures (Lang et al., 1993; Fusar-Poli et al., 2009; Lang et al., 1998; Keil et al., 2002). Some studies aiming to classify positive and negative emotions in general have indicated valence-dependent hemispheric dominance during emotional activation (Rusalova and Kostyunina, 1998). Other researchers have investigated emotion differences based on cortical oscillations, such as gamma waves (Keil et al., 2001) and theta waves (Aftanas et al., 2001). A classification of eight emotions in response to emotional pictures (neutral, anger, hate, grief, platonic love, romantic love, joy, reverence) with an accuracy of 81% was reported by the MIT Media Laboratory's Affective Computing Group (Picard et al., 2001) based however on non-cortical measures.

Numerous studies have reported event-related potential (ERP) modulations due to affective picture processing by the brain (see (Olofsson et al., 2008) for an extensive review). The presented emotional picture stimuli in such studies have been varied in estimated valence (positive-negative) and arousal levels, typically using the International affective picture system (IAPS) database (Lang et al., 2005), which offers standard valence and arousal ratings for each stimulus.

The earliest emotion-mediated modulations in the visual cortex, reported using EEG, measurements, appear in the short latency range (P1: 100-200ms) after the onset of observation of static affective pictures at occipito-temporal and centro-medial cortical sites (Schupp et al., 2003a). Enhanced early visual processing (120-170ms) in the occipito-temporal region was confirmed also using magnetoencephalography (MEG) and minimumnorm estimates (MNE) source analysis (Peyk et al., 2008). Middle-latency affective visual responses (N2: 200-300ms) reflect further perceptual qualities of the stimuli, and are influenced by both the valence and arousal levels of the emotional content, even it is presented rapidly (Peyk et al., 2008; Olofsson et al., 2008). The P300 component (300-400ms) reflects the brain responses in oddball-type experimental paradigms, in which the task relevance, motivation, arousal and attention are major determinants, while even slower evoked responses (400-600ms) to affective pictures may be involved in top-down cognitive processes and memory formation (Olofsson et al., 2008). Measurements using near-infrared spectroscopy (NIRS) have also confirmed the effects of emotion, with significant decreases in deoxygenated haemoglobin levels at occipital locations after affective picture viewing as compared to neutral pictures (Herrmann et al., 2007).

2.4.7. Emergence of Affective SSVEP

Adding emotional content to rapid SSVEP stimulus sequences may provide valuable insights about affective and visual processes in the brain. Several studies have provided strong evidence for regulatory feedback projections from emotion-processing areas to the visual sensory cortex, including the amygdaloid complex (Amaral et al., 2003; Baizer et al., 1993) and the posterior orbitofrontal cortex (Barbas, 2007). However, the effects of affective modulation of cortical activity are not limited only to picture stimuli but have also been shown to evoke rapid brain response amplitude enhancements after presentation of emotional words (Keil et al., 2006).

Two basic approaches have emerged recently for combining visually-evoked emotions and SSVEP. One approach involves superimposing flickering visual components over affective pictures to measure brain response interactions, while the other method requires the direct presentation of flickering emotional pictures.

The first approach to affective SSVEP was pioneered by Kemp and colleagues (Kemp et al., 2002) who used the subtractive steady-state probe topography (SSPT) method, previously developed by a team including one of the authors (Silberstein et al., 1990). 13 Hz white SSVEP flicker was presented using half-mirrored goggles, as the subjects directed their attention to affective pictures from the IAPS database on a computer monitor in the background. The responses were statistically compared to those from neutral images. This method employed SSPT-defined SSVEP 'latency' (phase-related) and SSVEP 'amplitude' measures which were modulated by cognitive and emotional brain activity changes during the task. Viewing of both pleasant and unpleasant pictures was associated with frontal SSVEP 'latency' reductions, while the frontal SSVEP amplitude decreased for unpleasant images. Interestingly, a subsequent study showed that the frontal 'latency' reductions measured for unpleasant images were predominantly observed for female subjects and not for male ones (Kemp et al., 2004a). Since for the SSPT approach the SSVEP stimulation represents a concurrent, competing activity which is processed in parallel with the main task, SSVEP amplitude reductions using this method may indicate attentional resource sharing and increase in visual vigilance (Silberstein et al., 1990), while 'latency' reductions can be interpreted as enhanced excitatory processes during emotional and cognitive tasks. Müller and colleagues (Müller et al., 2008) also investigated this visual-affective resource competition approach by superimposing small white squares flickering at 7.5 Hz on static emotional images. In line with previous research, the occipital SSVEP amplitude decreased for competing emotional content, especially for aversive images.

Another method to evoke affective SSVEP is to present directly affective images flickering rapidly at rates higher than ~6Hz (e.g. at 10Hz). Similarly to basic SSVEP, an oscillatory brain response would be observed in the visual cortex which is synchronized with the fundamental stimulation frequency. Keil and colleagues (Keil et al., 2003; Keil et al., 2008) applied this method using static pictures from the IAPS database, and found emotion-related SSVEP amplitude enhancements at parieto-occipital sites (maximum response at electrode Pz). The phase delay of the SSVEP response was also sensitive to the affective content of the visual stimuli. The delay decreased at posterior brain areas associated with visual processing, and increased at fronto-temporal electrodes, possibly reflecting affective reentrant modulation of the task-related brain activity. In addition to emotional content, spatial attention also increased the SSVEP response amplitude (Keil et al., 2005), especially in the right hemisphere. The same study also found enhanced phase changes associated with negative emotions. In a further investigation of the properties of affective SSVEP, varying the image presentation rates between 1 and 16 Hz showed that SSVEP amplitude enhancement due to passive emotion experience was maintained for flicker frequencies up to 12Hz (Peyk et al., 2009). Results were inconclusive for presentation rates higher than 12Hz, using the experimental procedures employed in that study.

The second method of direct presentation of flickering emotional images is able to enhance the visual SSVEP responses of the brain (Keil et al., 2005), possibly by engaging re-entrant pathways from emotion-regulating structures including the amygdaloid complex and the orbitofrontal cortex (Amaral and Price, 1984; Amaral et al., 2003; Freese and Amaral, 2005; Freese and Amaral, 2006). Self-regulated affective functional enhancements of the sensory brain responses could be investigated further for practical applications such as BCI by using new types of engaging affective stimuli and sensitive signal processing techniques for SSVEP estimations, as described in Chapter 6.

Table 8. Summary of affective vision studies reviewed in this chapter

Emotion-Vision – Related Aspect	**Studies**
Brain responses to affective pictures **The International affective picture system (IAPS) database**	*Lang et al., 1993, 1998, 2005; Olofsson et al., 2008 (review); Keil et al., 2002, 2003, 2005, 2008; Fusar-Poli et al., 2009; Keil et al., 2001 (gamma waves); Aftanas et al., 2001 (theta waves)*
Brain responses to Steady-State Probe Topography (SSPT) using half-mirrored goggles (superimposed flicker)	*Silberstein et al., 1990; Kemp et al., 2002, 2004a*
Brain responses to static affective pictures with superimposed flickering white squares	*Müller et al., 2008*
Brain responses to flickering affective pictures	*Peyk, Schupp, Keil et al., 2009*
Left-right hemispheric differences	*Rusalova and Kostyunina, 1998*
Affective pictures based classification of 8 emotion (non-cortical measures)	*Picard et al., 2001*
Emotion-mediated modulations in the visual cortex (VEP)	*Schupp et al., 2003a; Peyk et al., 2008; Herrmann et al., 2007 (NIRS)*
Amygdala – Visual cortex connections	*Amaral et al., 2003; Baizer et al., 1993; Freese and Amaral, 2005, 2006*
Amygdala – orbitofrontal cortex connections	*Barbas, 2007*
Amygdala feedback connections	*Amaral and Price, 1984*
Brain responses to emotional words	*Keil et al., 2006*

Chapter 3:

Optimization of SSVEP Brain Responses Using Small Checkerboard Stimuli

This chapter describes the experimental design and results from a series of experiments with the main goal to investigate objectively the properties of the brain response to steady-state visual stimulation with very small neutral stimuli (Bakardjian et al., 2010). The term 'neutral' is used here in the sense that the presented stimuli did not have an emotional or cognitive content, but aimed instead to reveal the characteristics of the visual sensory processing when a rapidly reversing/flickering pattern was observed by a human subject.

3.1. Objectives – SSVEP Using Small Stimuli

One of the main objectives (1) of the first study in this chapter was to evaluate the possibility of extracting reliably the brain responses to very small visual patterns in view of subsequent application for BCI. Although using small patterns may result in weaker visual responses (due to lower signal-to-noise ratios), a substantial advantage is that visual occlusion is minimized and screen estate can be made available for other purposes in practical applications.

It is known that SSVEP stimuli with different shapes and sizes result in varying brain responses (Regan, 1966). Constructing a basic frequency response curve for very small checkerboard SSVEP stimuli is another important objective (2) addressed in this chapter. The optimal selection of SSVEP stimulation frequencies based on objectively measured EEG data is essential for reaching maximal information transfer rates in a BCI design.

A further goal (3) is to understand the time dynamics of the SSVEP response to small stimuli as used for BCI. As SSVEP-BCI commands require a few seconds to be recognized, it is important to understand to what extent these time delays are due to inherent SSVEP signal-to-noise limitations (baseline brain activity versus post-onset SSVEP activity), even if the online signal processing algorithms are relatively fast.

And finally (4) , it is essential to address the question if it is feasible to record SSVEP from brain areas other than the visual occipital cortex. In practical BCI applications it would be highly advantageous to avoid application of wet electro-gel between the EEG electrodes and the skin of the head. Dry electrodes could be easily applied on the forehead, or behind the ears using correspondingly head caps / headbands or glass frames. This possibility requires the investigation of the differences between SSVEP responses in pre-frontal and temporal, as compared to occipital locations on the head.

3.2. Methods

3.2.1. Experimental Subjects

Four healthy subjects participated in both studies. The average age of the group was 38.2 ± 2.4 years. All subjects had normal or corrected-to-normal vision. The participants were fully informed of the procedures in advance. In preparation for the experiments, each subject was screened for history of epilepsy and photosensitivity, and signed an informed consent form including a statement that she/he had no known neurological disorders. In addition, before each experiment the subjects were shown a brief stimulus sequence with increasing frequency in order to test for photosensitive epilepsy and to further decrease the probability of seizure.

3.2.2. EEG Data Acquisition – EEG system

Brain signal acquisition was performed using a BIOSEMI EEG system with sintered Ag/AgCl active electrodes. Active electrodes contain miniature electronics to allow substantially higher EEG signal-to-noise ratio and better sensitivity to weak brain signals. Two additional electrodes, the passive Driven Right Leg (DRL) electrode, and the active Common Mode Sense (CMS) electrode (Metting van Rijn et al., 1994), both located just posterior to the vertex, were used to determine the common mode voltage of the Biosemi EEG system against which all other electrode measurements were recorded. This active-electrode arrangement replaced the traditional reference electrode(s) used by previous passive EEG systems.

In this study investigating SSVEP characteristics and optimization, the experiments were performed with a 128-channel whole-head configuration, using the highest available sampling rate of 2048 Hz. A chin rest was used by all subjects to prevent excessive contamination of the EEG data with EMG artifacts due to upper body muscle movements.

3.2.3. SSVEP Stimuli and Display

Subjects were seated 0.9m from a 21” CRT computer display operated at a high vertical refresh rate (setting 170 Hz, measured – 168 ± 0.4 Hz Hz).

SSVEP stimulation was achieved using small reversing black and white checkerboards with 6 x 6 checks. Each check was 0.3° arc in size so that the diameter of the pattern was 2.5° arc which is slightly larger than the approximate size of the fovea. The stimulus luminance was 12.5 cd/m^2 for the white checks, and 0.05 cd/m^2 for the black ones (Michelson contrast of 99.2 %). Each pattern included a small red fixation point in its center and subjects were instructed to position their gaze on that point.

The actual light stimulation which was emitted by the display and reached the eyes was verified using a small photosensitive semiconductor sensor. Fig. 4 shows the time course of the light emitted by the CRT display during a single pattern reversal cycle (8.4 Hz). The peaks mark the time points when the image under the sensor was refreshed by the display to show a white check.

Since the visual stimuli reversed on screen with a relatively high frequency, the stimulus control module needed to ensure that they were shown properly (completely) on any programmable visual display which was using discrete refresh rates (CRT, LED, LCD or any other display based on refresh cycles). That is why it was essential that the oscillations of the stimuli were precisely synchronized with the start of each display refresh cycle. This requirement imposed some limitations on the possible SSVEP frequencies, because each stimulus state was calculated to be shown for an integer number of display cycles, to avoid improper partial display. A higher display refresh rate of the display allowed a larger number of frequencies/commands.

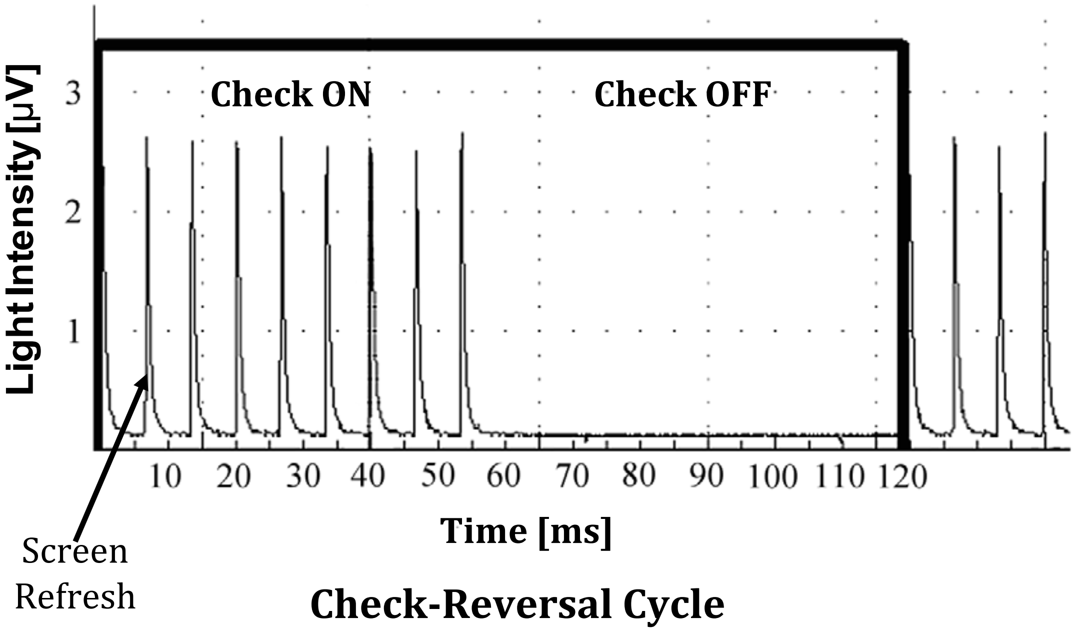
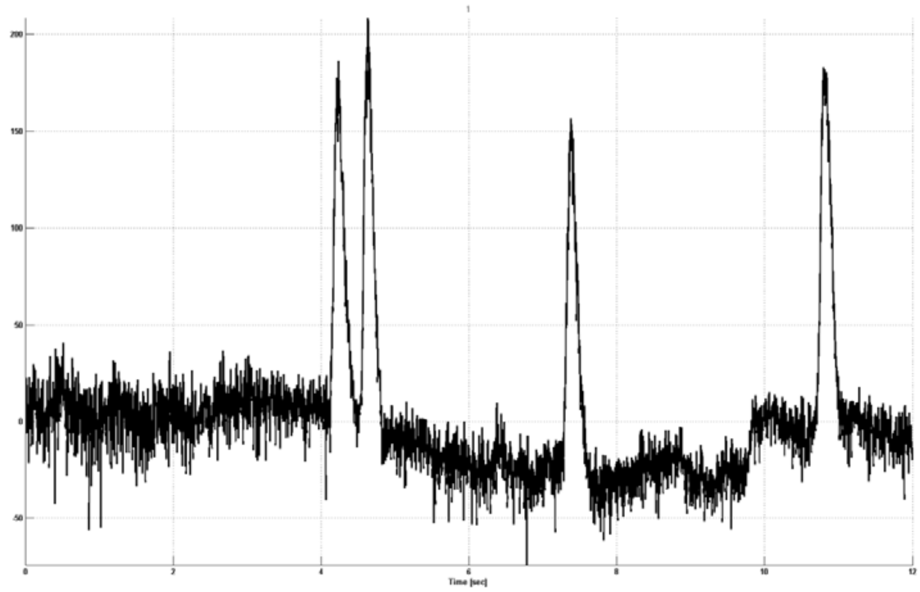


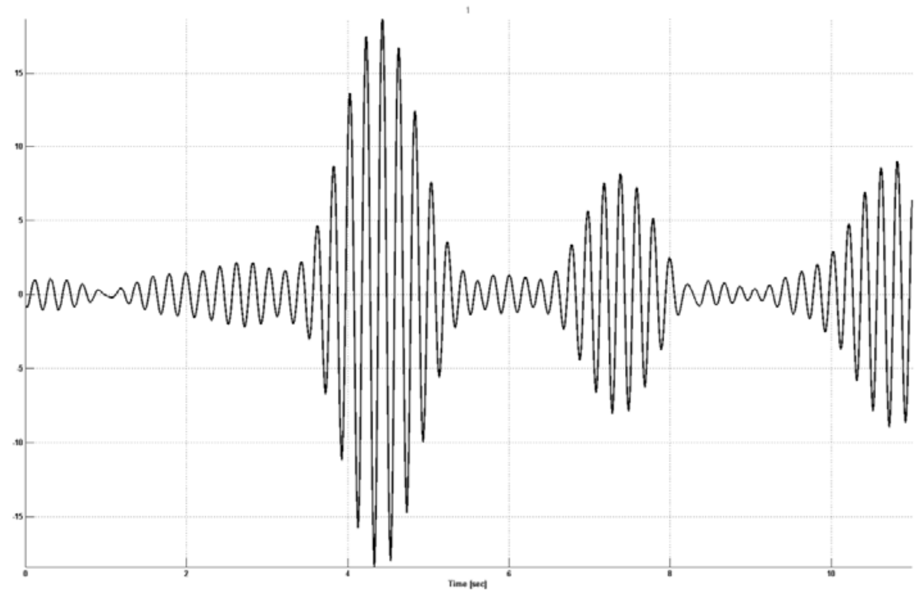
Fig. 4. Time course of the actual light emitted by a CRT display during checkerboard reversal (8.4 Hz). The peaks mark the time points when the image under the photosensor was refreshed by the display every 5.8 ms to show a white check. Note: compare to LCD display stimulation in Fig. 24.

3.2.4. Data Pre-processing - Artifact Rejection Using ICA/BSS

After re-referencing the original EEG data to the central CZ electrode, independent component analysis (ICA) / blind source separation (BSS) was used to remove eye blink and other artifacts (see Appendix A for more details). In general, ICA/BSS represents the input array X as a linear superposition of the component vectors S, assuming the following model:



(a)



(b)

Fig. 5. Negative impact of ocular artifacts on the SSVEP signal. If left unhandled, artifacts can have a distinct negative impact on the SSVEP in spite of its narrow-band nature. Eye blinks can cause false positive identification of commands in SSVEP-based BCI due to signal transients of non-cortical origin. After proper application of ICA/BSS such disruptive artifacts are removed almost entirely. (a) raw EEG response with multiple eye blink artifacts; (b) The SSVEP narrow-band response masked substantially by the much stronger overlapping ocular artifacts. A two-second resting baseline is included in this figure before the stimulus onset.

$$x(k) = A \cdot s(k) \tag{1}$$

where $x(k) = [x_1(k), \ldots x_Q(k)]^T$ are the Q observed sensor signals at each time point k, $s(k) = [s_1(k), \ldots s_N(k)]^T$ is a vector of N unknown sources (components) within the sensor space, and A is a non-singular unknown mixing matrix with size $Q \times N$.

Here, a modified Robust Second Order Blind Identification with Joint Approximate Diagonalization (SOBI) procedure followed by automatic Hoyer sparsity ranking of the components were applied in order to extract and remove eye blink and muscle artifacts (Cichocki and Amari, 2003). Top-ranking sources with the highest sparsity and low-frequency dominance were identified as eye-blink or eye-movement artifacts. These components were removed automatically and the remaining data was reconstructed back to EEG space. Even though this method achieved good results, the reconstructed data was verified further by EEG mapping to ensure that there are no remaining identifiable artifacts.

3.2.5. Methods - The SSVEP Frequency Response of the Brain

The visual cortex, although highly robust, does not need to respond in the same way to all stimulation frequencies. In order to uncover the specific frequency relationships for the small patterned stimuli, a single reversing 1.8°x 1.8° checkerboard was presented on a black background in the middle of the screen, in an arrangement designed to minimize competing stimuli, and to enhance attention.

The rate of reversal of the pattern was changed every 6 s and increased stepwise, with larger steps at higher stimulation frequencies due to the limitations imposed by the discrete refresh cycle of the computer display (Bakardjian et al., 2007a; Bakardjian et al., 2010). Overall, 32 reversal frequencies were shown: 5.1, 5.25, 5.4, 5.6, 5.8, 6.0, 6.2, 6.5, 6.7, 7.0, 7.3, 7.6, 8.0, 8.4, 8.85, 9.3, 9.9, 10.5, 11.2, 12.0, 12.9, 14.0, 15.3, 16.8, 18.7, 21.0, 24.0, 28.0, 33.6, 42.0, 56.0, 84.0 Hz. Due to the discrete vertical refresh rate of the computer monitor and to avoid improper partial display, these frequencies were obtained by dividing the measured refresh rate of 168 Hz by integer values (33, 32, …, 2). In that way, the maximal stimulation frequency was at the limit of half the display refresh rate (using one refresh frame for the white check and one frame for the black one).

Each frequency response was recorded for 6 seconds before switching to the next higher frequency without a pause, which emulated conditions during user command changes in a BCI system.

After ICA/BSS pre-processing (see Appendix A), the artifact-free responses from the 6-second windows for each stimulation frequency were separated and band-passed using a zero-phase finite impulse response (FIR) filter configured for a 0-dB magnitude response at the center frequency of the passband.. Each of the 32 frequency bands was centered at its corresponding pattern reversal rate and its width was set to ±0.1 Hz.

The response strengths for each band and subject were estimated as the mean z-score of the band power throughout the stimulation interval. The average z-score across all subjects was calculated for each pattern reversal rate as a measure of the frequency response of the brain.

3.2.6. Methods - The Time Dynamics of the SSVEP Response

In this experimental setup, a single small reversing checkerboard was displayed in the middle of a black screen, similarly to the previous experiment. Three separate reversal frequencies were used sequentially (8 Hz, 14 Hz and 28 Hz) in order to cover different components in the brain frequency response (Regan, 1977). Six trial repetitions were used for each frequency. Each trial consisted of 5 s baseline rest (black screen) and 15 s stimulation (Bakardjian et al., 2007a; Bakardjian et al., 2010).

Processing of the EEG data involved steps similar to those described for the previous experiment, including artifact removal by ICA/BSS and band-pass filtering of the single-trial responses. However, for this experiment, the detailed dynamics of the single-trial SSVEP onset responses was of interest, instead of measuring the SSVEP strength. To remove the interference caused by the synchronous SSVEP response oscillations, and to observe their envelope, a demodulation procedure was applied (Müller and Hillyard, 2000). Demodulation has been used successfully in the past for envelope analysis of oscillating EEG waves (Walter, 1968). Here, a modified quadrature amplitude demodulation (QAD) method was used to recover the amplitudes of phase-shifted messages Y_1 and Y_2 in a modulated carrier input signal X (SSVEP)

$$Y_1 = X\cos(2\pi ft), \quad Y_2 = X\sin(2\pi ft) \tag{2}$$

and reconstructed the original modulating signal using the following equation:

$$Z = \left|H^f(Y_1)\right| + \left|H^f(Y_2)\right|, \tag{3}$$

where f is the counterphase modulation frequency, and H^f is a low-pass Butterworth filter at cutoff frequency f applied to filter out the carrier signal. The QAD model output Z represented the recovered single-trial SSVEP response envelope, which could be used further to measure the characteristics of the signal dynamics (Fig. 6).

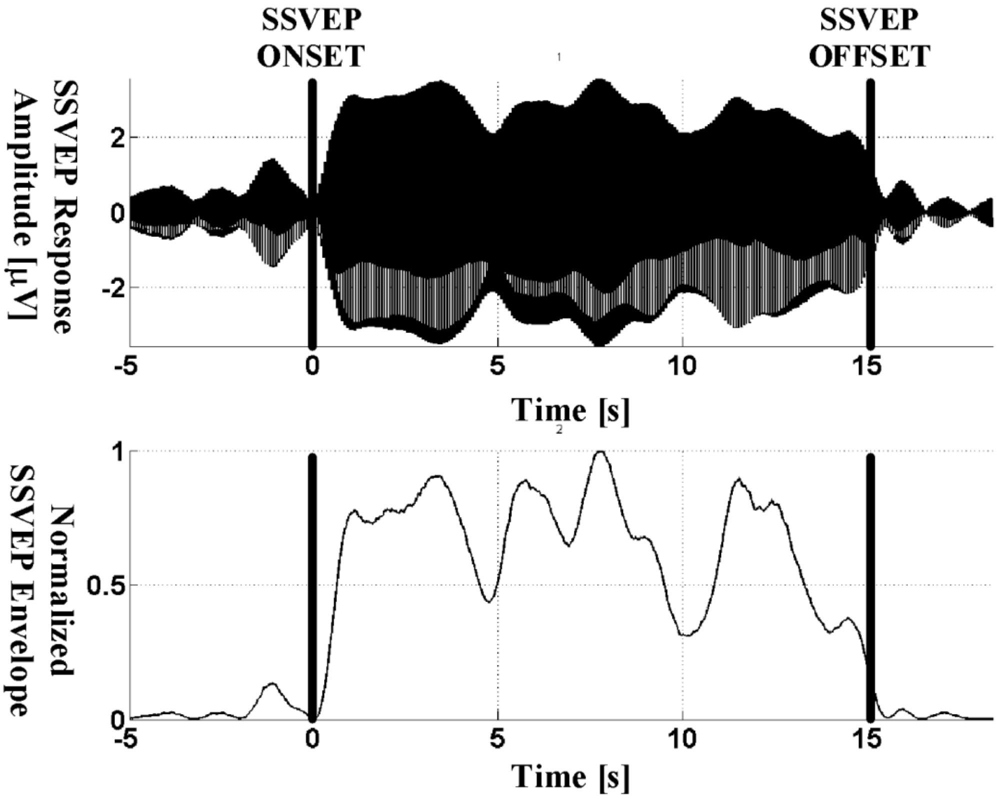


Fig. 6. Single-trial SSVEP response to 14-Hz pattern stimulation.

(top) narrow band-passed SSVEP response, where the lines show the onset and offset of the stimulation; (bottom) normalized quadrature amplitude demodulation (QAD) envelope of the signal showing the dynamics of the response for this frequency.

3.2.7. Statistical Evaluations

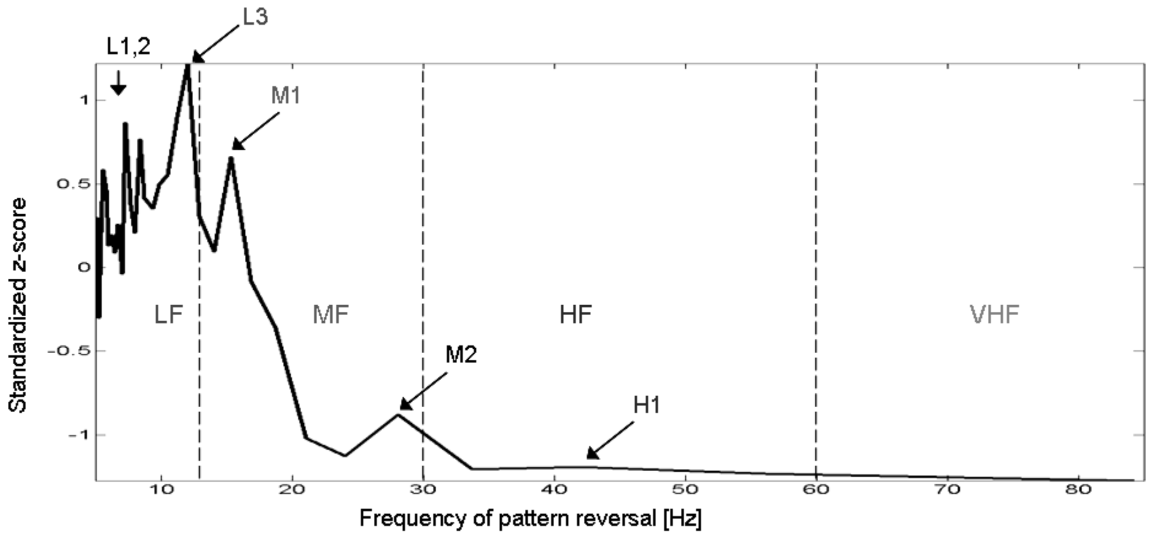
The demodulated, squared and normalized SSVEP brain responses in the time dynamics study were used to calculate peak analysis measures for SSVEP onsets and first peaks. The SSVEP measures were evaluated for statistical significance for each frequency, trial and subject. The SSVEP onset was defined as the envelope value on a rising slope for which the baseline oscillation maximum was exceeded by 10%. The first peak was defined as the first extremum of the signal following the onset point. All single-trial latencies for the SSVEP onset and first-peak delays were measured and evaluated through two-factor statistical analysis of variance (ANOVA). Data series were considered significantly different if the probability that they do not belong to the same sample populations was above the 95% threshold ($p < 0.05$).

3.3. Results

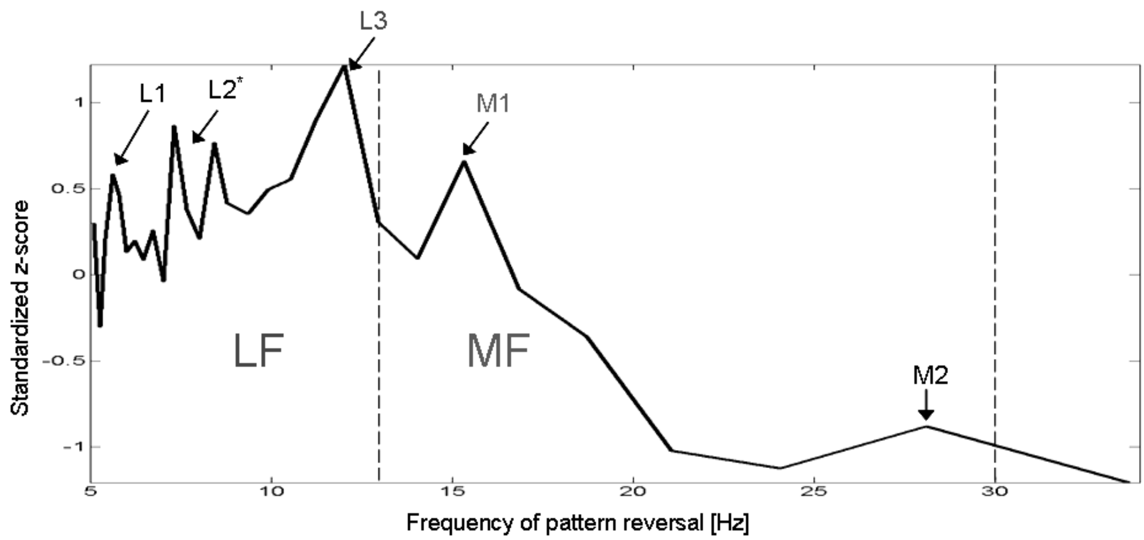
3.3.1. SSVEP Frequency Response of the Brain

In spite of using the adaptive modeling method and spectrum normalization, it is important for the BCI system accuracy to ensure sufficiently high signal-to-noise ratios (SNR). For an SSVEP-based BCI this means that the frequency bands for all commands need to be preselected within a spectral range featuring optimal brain sensitivity.

Fig. 7 a shows the occipital SSVEP frequency dependency results for all subjects in the entire stimulation frequency range 5.1 – 84 Hz, while Fig. 7 b presents in more detail the lower half of the SSVEP frequency response range 5.1 – 33.6 Hz. SSVEP frequency region definitions were adopted and extended from Regan (Regan, 1977) as follows: Low-Frequency (LF: 5-13 Hz), Medium-Frequency (MF: 13-30 Hz), High-Frequency (HF: 30-60 Hz), and Very-High-Frequency (VHF: >60 Hz).



(a)



(b)

Fig. 7. Frequency response curve of the occipital brain for small-checkerboard SSVEP stimuli. Stimulation for each of the 32 frequencies was maintained for 6 seconds, and the z-score of mean power throughout the stimulation interval was used for this representation. (a) entire measured stimulation frequency range 5.1 – 84 Hz; (b) zoom of the low- and medium-frequency responses for 5.1 – 33.6 Hz. The mean z-scores exceeded 0.5 in the 5.6 – 15.3 Hz frequency range, and the strongest response was observed at 12 Hz. Here, the SSVEP frequency region definitions by Regan (Regan, 1977) were partially adopted and extended: Low-Frequency (LF: 5-13 Hz), Medium-Frequency (MF: 13-30 Hz), High-Frequency (HF: 30-60 Hz), Very-High-Frequency (VHF: >60 Hz)

Table 9 lists the frequencies and strengths of the main identified peak responses in the occipital area of the brain. The obtained frequency characteristics indicated that during SSVEP stimulation with small neutral checkerboards the strongest response peaked around 12Hz. In addition, LF response peaks at 5.6 Hz and around 8 Hz (7.6-8.8 Hz) were also observed. In the MF range, the strongest response was detected at 15.3 Hz, while a much weaker peak was observed for 28 Hz stimulation. The HF region presented a small local enhancement at 42 Hz, while the VHF was characterized by a linear inverse relationship between frequency and brain responses up to the highest tested frequency of 84 Hz. Also, the highest inter-subject variability was observed at 5.6 Hz and 9.9 Hz (which overlaps with the occipital alpha band).

According to these results, and assuming a z-score threshold value of 0.5, it is proposed that the peak responses to SSVEP stimulation in the range 5.6 – 15.3 Hz are optimal for use in applications such as multi-command SSVEP-based BCI systems.

Table 9. Main peak-response **frequencies and z-scores** to SSVEP stimulation. The strongest responses were observed for 12Hz. The mean z-scores of all subjects in the range 5.6 – 15.3 Hz exceeded 0.5.

	L1 (LF)	**L2 (LF)**	**L3 (LF)**	**M1 (MF)**	**M2 (MF)**	**H1 (HF)**
Peak Freq.	5.6 Hz	8.0 Hz*	**12.0 Hz**	15.3 Hz	28.0 Hz	42.0 Hz
Z-Score	0.58	0.82*	**1.22**	0.66	-0.88	-1.19

3.3. 2. Time Dynamics of the SSVEP Response - SSVEP Onset- and 1st Peak Delays

In addition to obtaining the most efficient stimulation frequencies, it is also essential to look at the detailed time dynamics of the SSVEP responses to small checkerboards. Obtaining data on the response onset and stability is especially relevant in the context of BCI, as it would allow a general estimation of the inherent limits in the speed of information transfer using this technology.

The mean SSVEP responses for the three selected frequencies in this experiment (Fig. 8) indicated that in spite of their common periodic characteristics there may be differences in the underlying processes. The lowest frequency exhibited additional visual response waves overlaid on the main oscillation of 8 Hz (125 ms), while the waveform of the highest reversal rate demonstrated intermittent resetting of the main 28 Hz (~36 ms) response by the next stimulus.

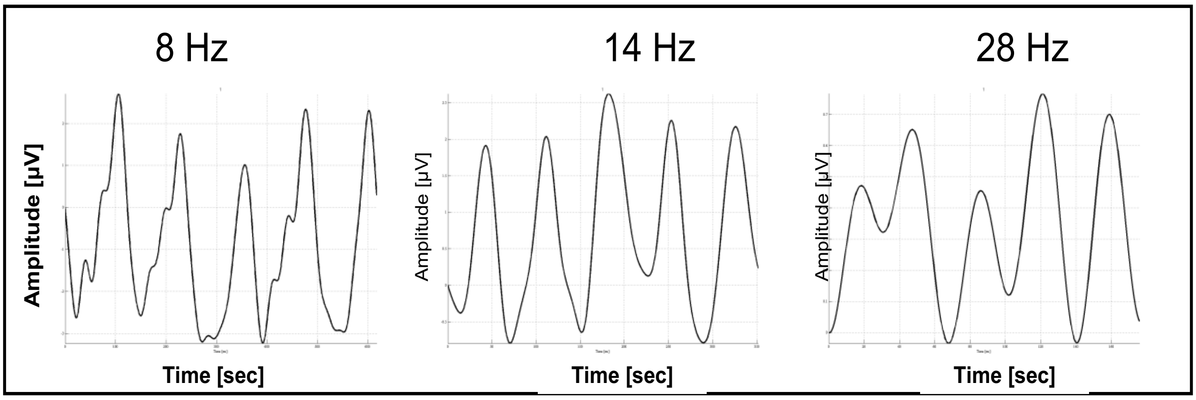


Fig. 8. Averaged 5-cycle waveforms for the 8 Hz, 14 Hz and 28 Hz SSVEP brain responses (small checkerboards). The 8 Hz oscillations exhibited additional waves overlaid on the main frequency response. With their shortest durations (~36 ms), the 28 Hz response cycles showed increased signs of possible intermittent resetting by the next stimulus.

However, the main goal of this experiment was the single-trial analysis of the SSVEP dynamics (see Fig. 6 for an example). For all subjects, highly non-stationary single-trial SSVEP responses were observed, which featured distinct peaks and valleys during the 15 s stimulation depending on frequency. For the purpose of this study, mainly the oscillation onset and the 1st peak were investigated, although in most cases the maxima of the observed responses followed later, delayed by several seconds. Among the 8Hz, 14Hz and 28 Hz responses studied in detail, the14Hz activity evoked the strongest and most global brain response.

Investigating the 8 Hz, 14 Hz and 28 Hz SSVEP dynamics, both the occipital SSVEP onset- and 1st-peak delays both showed statistically significant dependency on the stimulation frequency (Fig. 9), p=0.00001 for onsets, and p=0.002 for first peaks). Depending on frequency, the SSVEP responses were highly non-stationary in all 15-s trials. In most trials, the 14 Hz onset and 1st-peak were the fastest among the three measured frequencies, with the strongest, most stationary, and most global brain response. The 28 Hz activity onset and 1st – peak were the slowest and the oscillations most non-stationary. Statistical testing did not show significant inter-trial differences among all available trials (p=0.85 for onsets, and p=0.94 for first peaks). There was, however, frequency-dependent variability between individual subject responses, as also pointed out in other studies (Joost and Bach, 1990). The inter-subject variability almost reached significance (p=0.07) for the onset delay measurements, but was not significant for the first peaks (p=0.29).

Table 10. SSVEP **onset- and first-peak delays** of the brain response for three frequencies in the low-, medium- and high-frequency range.

	8 Hz	**14 Hz**	**28 Hz**
ONSETS	0.79 s	0.71 s	1.74 s
1.PEAKS	2.04 s	1.52 s	2.46 s

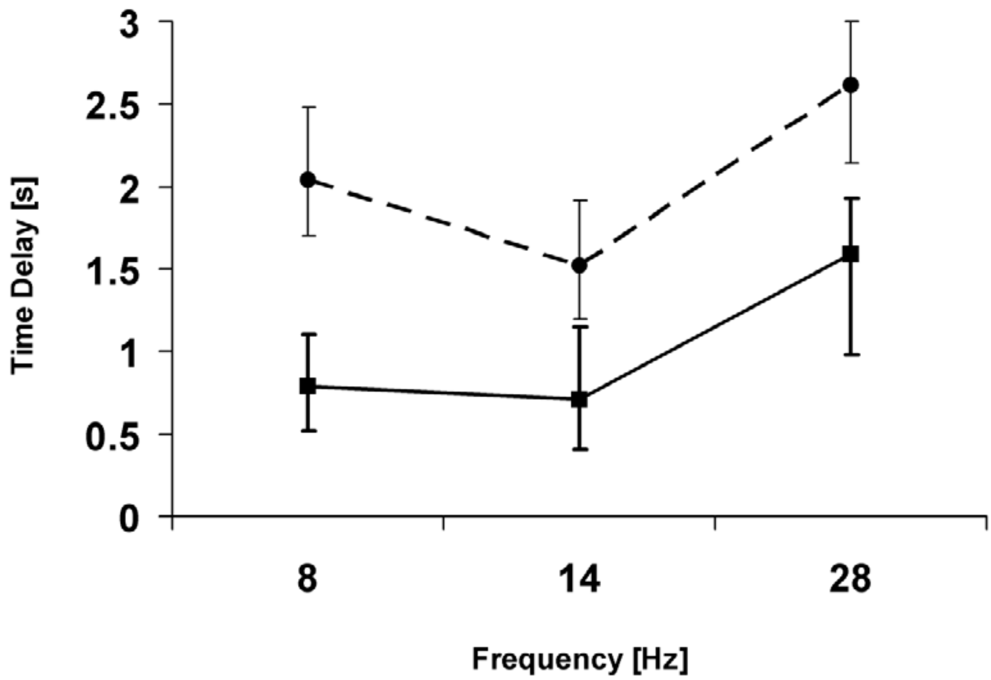


Fig. 9. SSVEP response delays for 8 Hz, 14 Hz, and 28 Hz stimulation with small patterns for SSVEP onsets (solid line) and SSVEP 1st peaks. The SSVEP onset is defined as exceeding the baseline by 10% and the 1st peak is the local maximum following the onset. The 14 Hz responses were fastest for both the onset- and the 1st peak delays, while the high-frequency 28 Hz activity was the slowest to elicit a measurable SSVEP response when using band estimate measures.

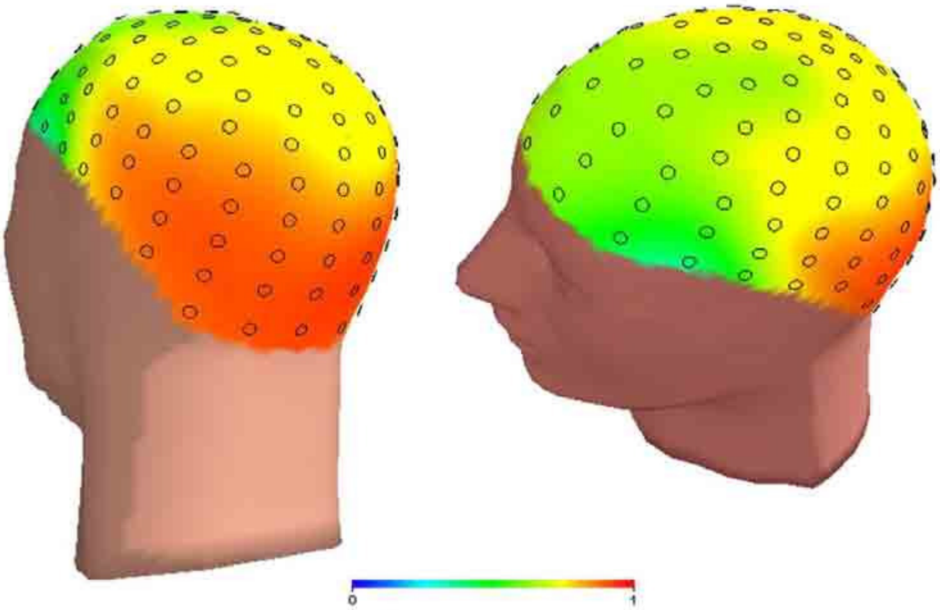


Fig. 10. Topographic patterns of activation at the first peak of the 14Hz SSVEP envelope (a single-trial example).

3.3. 3. Effects of Sensor Locations on SSVEP Properties

Although the main cortical SSVEP activation occurs in the occipital visual cortex, there is evidence of more lateral sources in the extrastriate visual cortex (Di Russo et al., 2007; Watanabe et al., 2002), as well as of sources in the frontal cortex (Srinivasan et al., 2007). The SSVEP responses in this study exhibited a clear dependency on the stimulation frequency and measurement location. Fig. 11 - Fig. 13 below show the SSVEP response-envelopes recovered using QAD, and demonstrate that the SSVEP responses (14 Hz here) decline in quality with increasing distance from the occipital cortex. Left parieto-temporal *(middle)* and frontal *(bottom)* responses are more inconsistent than occipital SSVEP *(top)*. This explains also why the BCI performance reported in the next Chapter 4 declined over the left parieto-temporal cortex (LPTC) and the frontal cortex (FC), and substantiates the need for fast adaptive SSVEP extraction algorithms.

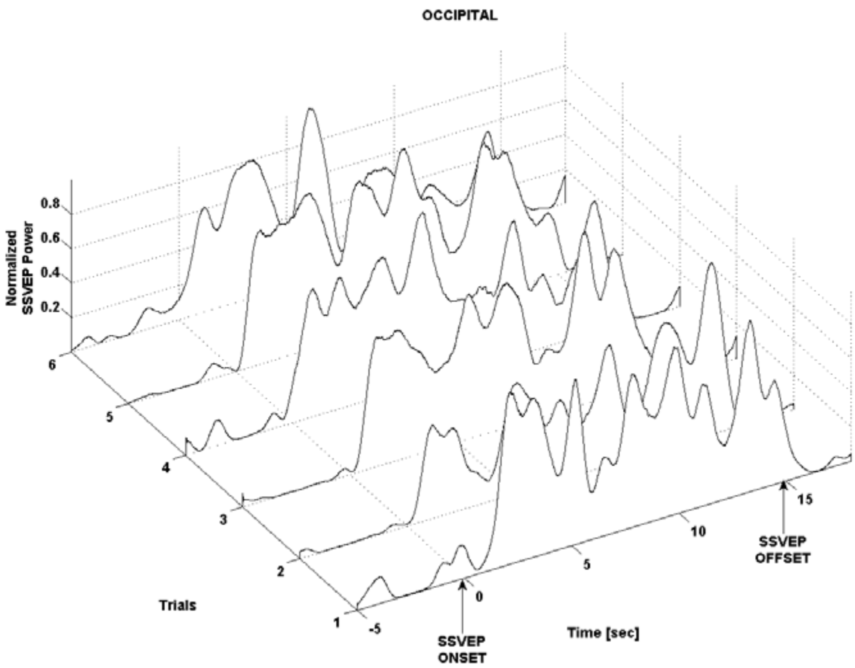


Fig. 11. Dynamics of single-trial responses at an optimal occipital location for 14 Hz stimulation and all 6 trials (single subject). Although SSVEP responses are also measurable at parieto-temporal (see Fig. 12) and frontal (see Fig. 13) locations, they become more transient with increasing distance from the occipital cortex.

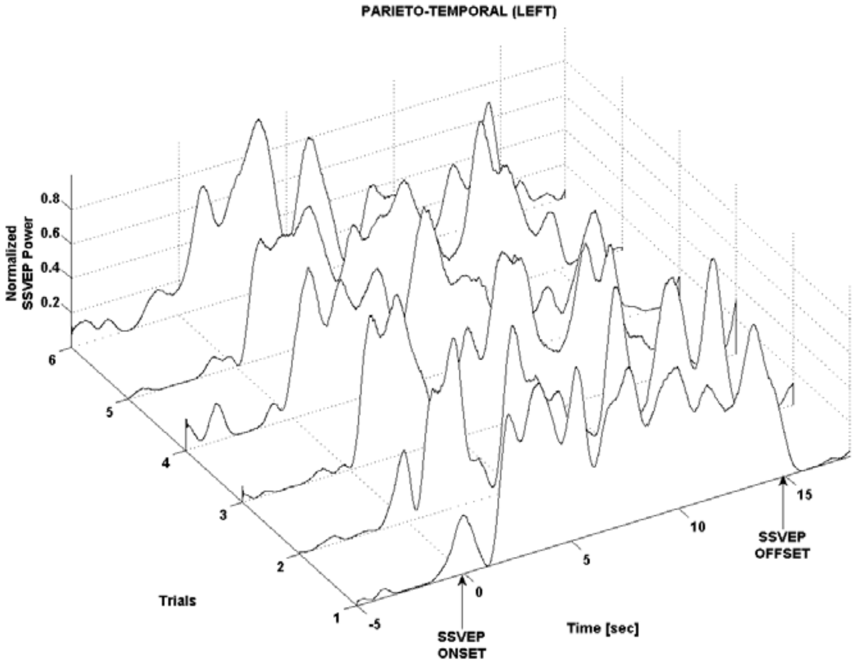


Fig. 12. Dynamics of single-trial responses at a left parieto-temporal location for 14 Hz stimulation and all 6 trials (single subject).

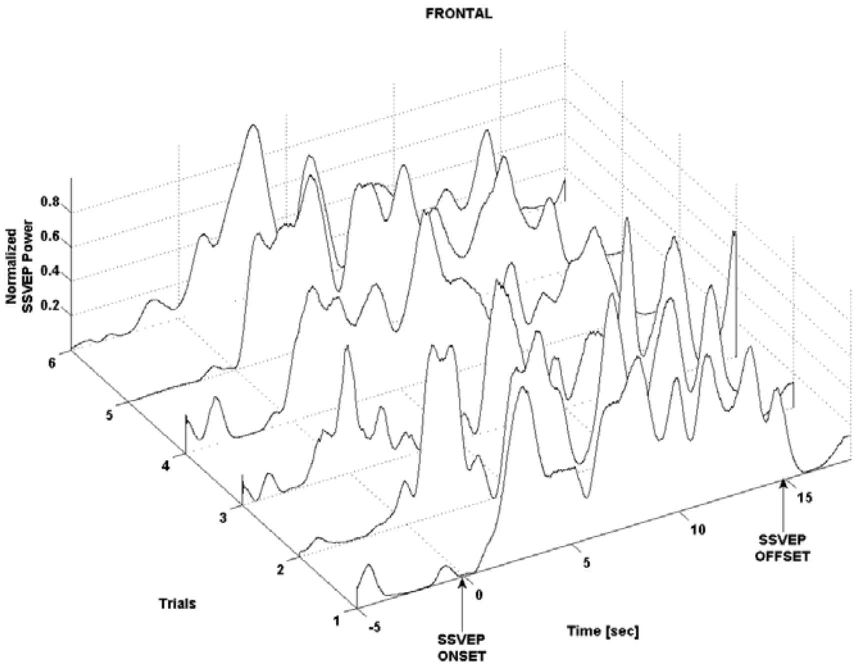


Fig. 13. Dynamics of single-trial responses at a frontal location for 14 Hz stimulation and all 6 trials (single subject). The responses were most transient among all 3 tested electrode locations.

3.3.4. Time-Frequency, Area, and Cross-Cumulant Measures for SSVEP Evaluation

Further, the SSVEP response-envelopes were subjected to three types of processing:

a) Time-frequency decomposition (using a Morlet wavelet basis)

b) Area analysis of the single-trial responses

c) Cross-cumulant measures for inter-trial reproducibility analysis.

Wavelet-based time-frequency decomposition of single-trial SSVEP was able to expose the relatively consistent brain oscillations corresponding to the external visual stimuli (Fig. 14). However, this technique also confirmed the hypothesis that the nature of the SSVEP brain response, as represented by the oscillation envelope, is highly non-stationary over time. This may call for an update of the original SSVEP definition by Regan stating that the steady-state evoked potentials are "a repetitive response whose constituent discrete frequency components remain constant in amplitude and phase over an infinitely long time period" (Regan, 2008).

Response area analysis (Fig. 15 a), in which the area under the brain response envelope was measured and compared between experimental conditions, confirmed that the occipital sensor location was optimal, and that a stimulation of 14 Hz evoked stronger responses than 8 Hz and 28 Hz. Notably, frontal responses were most sensitive to high-frequency stimulation (28 Hz), in agreement with reports from other studies showing that the frontal cortex SSVEP activation is more frequency-dependent (Srinivasan et al., 2007).

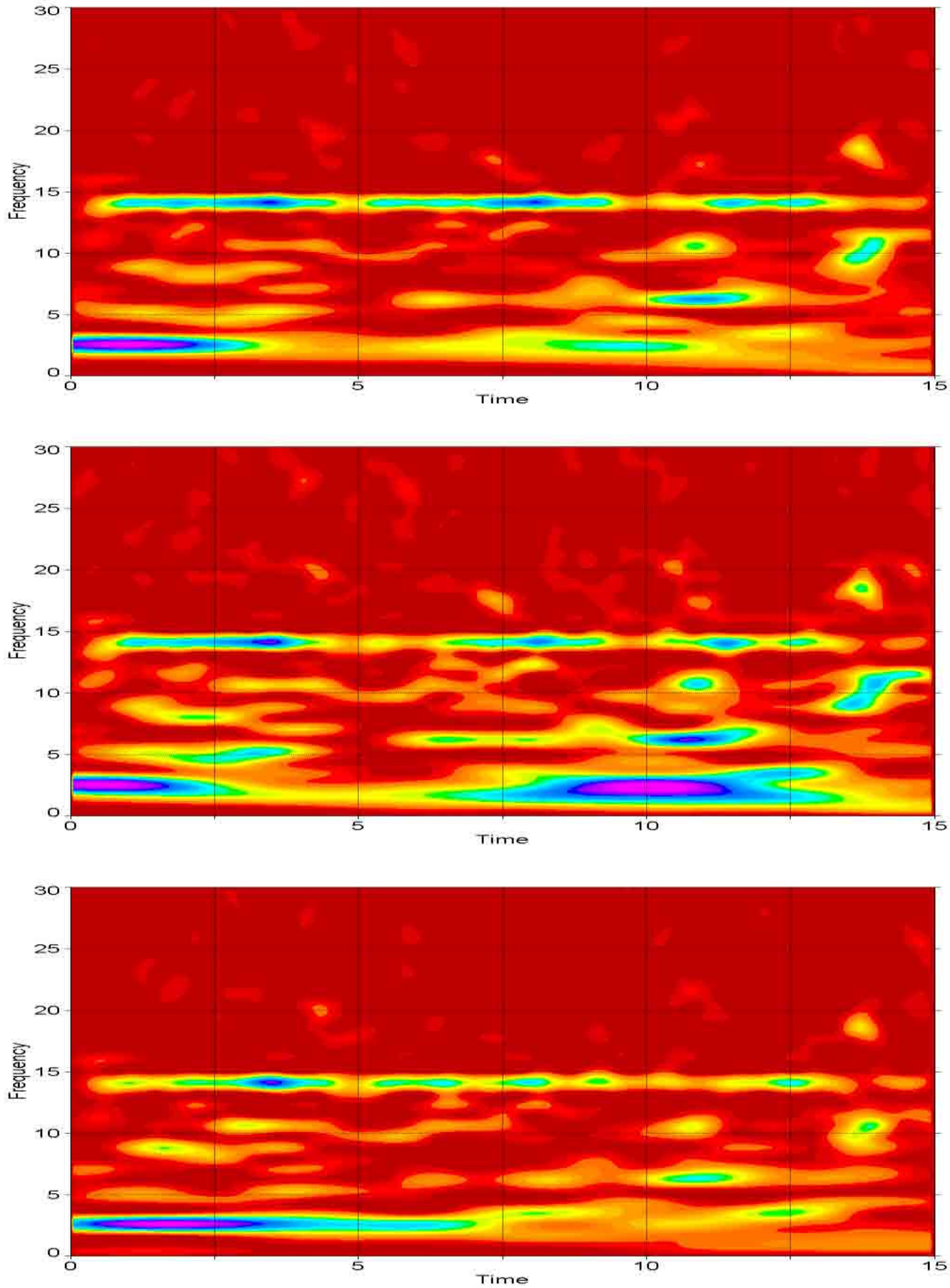


Fig. 14. Wavelet-based time-frequency decomposition of non-stationary single-trial SSVEP (15-sec duration) for 14 Hz stimulation. *(top)* occipital cortex location; *(middle)* left parieto-temporal location; *(bottom)* frontal location. SSVEP responses decline in strength and consistency at parieto-temporal and frontal locations with increasing distance from the occipital cortex.

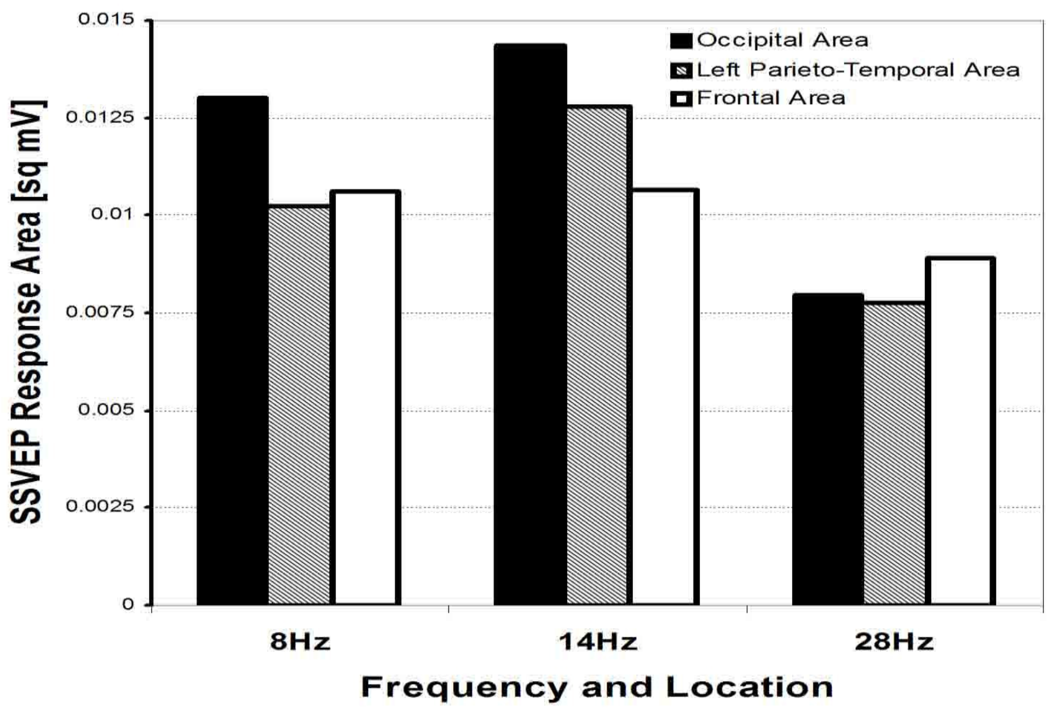
To reveal the level of consistency of the non-stationary SSVEP responses over several repetitions, using varying frequencies and locations, inter-trial reproducibility analysis based on cross-cumulant measures (Georgiev et al., 2006) was also applied. Cross-cumulants are useful for evaluating nongaussian signals corrupted by additive Gaussian noise, although higher order cumulants require longer data samples for proper estimation. Here, fourth-order cross-cumulants were used, corresponding to the normalized version of the crosscorrelation of energy, to compare signals from selected locations (channels) and frequencies for each unique trial pair.

For two zero-mean signals $x(t)$ and $y(t), t = 1,...,T$, the cross-cumulant is defined as:

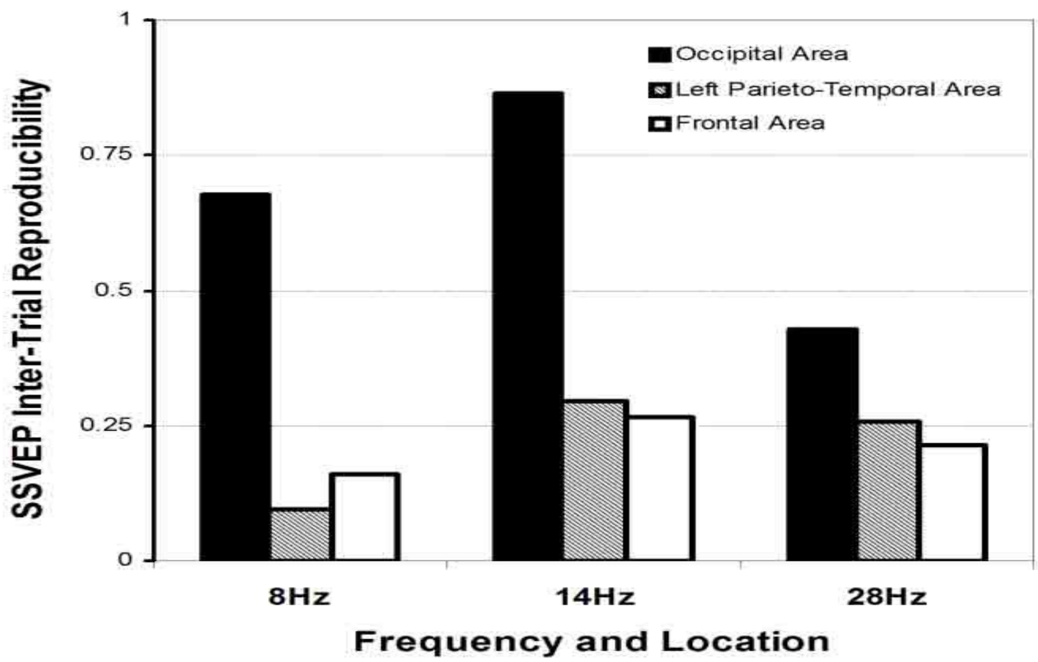
$$\begin{aligned} &Cum(x(t), y(t), x(t-\tau), y(t-\tau)) = \\ &E\{x(t)y(t)x(t-\tau)y(t-\tau)\} - E\{x(t)y(t)\}E\{x(t-\tau)y(t-\tau)\} \\ &-E\{x(t)x(t-\tau)\}E\{y(t)y(t-\tau)\} - E\{x(t)y(t-\tau)\}E\{y(t)x(t-\tau)\}, \end{aligned} \tag{4}$$

where τ is a lag constant, and E is the mathematical expectation of the signal.

The mean cross-cumulant values between trial pairs in each location and for each frequency showed (Fig. 15 b) that occipital sensor locations ensured the highest inter-trial reproducibility, as well as that repeated 14 Hz responses were most reproducible. The non-stationary SSVEP activity envelope was more transient and the shape of the responses was less predictable with repetition at the suboptimal parieto-temporal and frontal sensor locations for all studied stimulation frequencies.



(a)



(b)

Fig. 15. Properties of SSVEP responses at occipital (black), left parieto-temporal (gray) and frontal (white) sensor locations measured for 8 Hz, 14 Hz, and 28 Hz stimulation with small reversing checkerboards on a black background. *(a)* Response-area analysis; *(b)* Inter-trial reproducibility analysis using cross-cumulant measures.

Chapter 4:

ONLINE MULTI-COMMAND SSVEP-BASED BCI USING SMALL CHECKERBOARD STIMULI

Following the investigation of the basic properties of the SSVEP brain response in the previous chapter, the research described here aimed to optimize the paradigm and to evaluate objectively a novel online SSVEP-BCI system with eight independent commands using rapidly moving and reversing/very small checkerboards (Bakardjian et al., 2010).

4.1. Objectives - SSVEP-Based BCI

The main research objective in this chapter was to develop a robust online BCI system with very high information transfer rates, and novel design features. This included the following goals:

1) Reliable extraction of multiple (eight) independent BCI commands using the small SSVEP patterns which were investigated in detail in the first study
2) Using all SSVEP patterns in close proximity to each other to reduce visual occlusion without brain response degradation
3) Using successfully dynamically-moving SSVEP stimuli for the first time in an online BCI system in order to enable near-real-time control of a screen object

4) Achieving the highest possible BCI success rates and the lowest possible delay times for most SSVEP frequencies and users.

4.2. Methods

4.2.1. Experimental Subjects

The same four healthy subjects participated in these online BCI experiments as in the previous chapter. Again, all participants were fully informed of the procedures in advance and written consent was obtained. Each subject performed a short test run (~30 s) to practice rapid switching between the SSVEP command patterns on the computer screen.

4.2.2. Basic Structure of the Multi-command SSVEP-Based BCI

The multi-command online SSVEP-based BCI system consisted of the following modules:

1) ***EEG data acquisition module***

    1.1) EEG system

    1.2) Data transfer over network

    1.3) Online data reception and configuration unit

2) ***User interface module***

    2.1) Multi-pattern SSVEP stimulation unit

    (frame-by-frame flicker control)

2.2) Neurofeedback unit (control of executive device)

3) ***Analysis module***

3.1) EEG pre-processing unit

3.2) Feature extraction unit

3.3) Command recognition/classification unit

3.4) Command output unit

4.2.3. EEG Data Collection – SSVEP-BCI

In the SSVEP-BCI experiments, the BIOSEMI EEG system with sintered Ag/AgCl active electrodes was used again, as described already in the previous chapter.

For the online BCI study, brain signal acquisition was performed with the BIOSEMI EEG system using 6 active electrodes. The main electrode configuration was occipital, however, two other configurations were also tested, parieto-temporal and frontal, as shown in Fig. 16. In the occipital configuration, one of the electrodes was placed in an anterior location (FZ) to aid the automatic detection and removal of eye-related artifacts. The data was acquired at a sampling rate of 256 Hz. Two additional electrodes, the passive driven right leg (DRL) electrode, and the active common mode sense (CMS) electrode, were fixed in a standard position just posterior to the vertex, and determined the common mode voltage of the Biosemi EEG system against which all other electrode measurements were recorded.

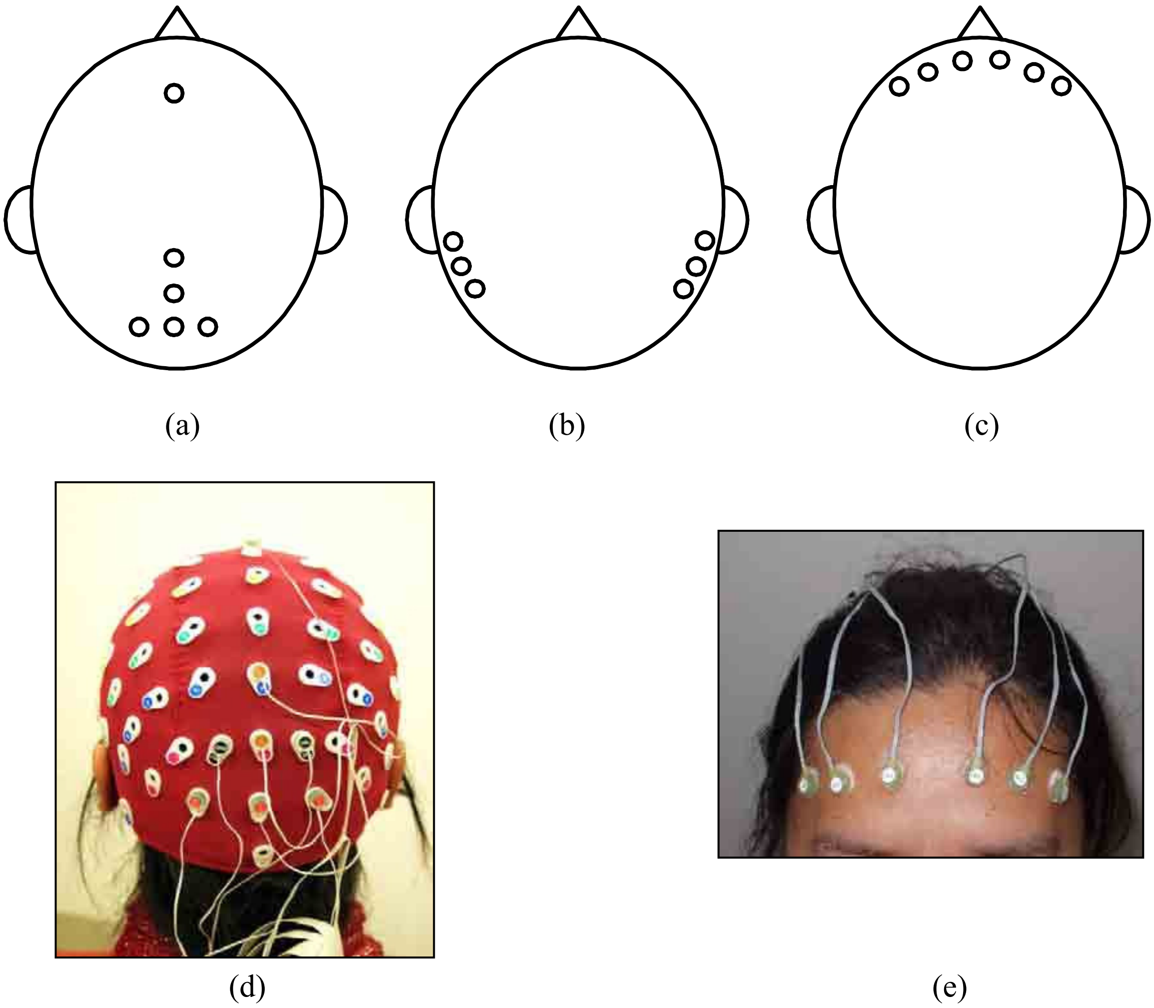


Fig. 16. Active electrode locations used in the SSVEP-based BCI design. (a) and (d) optimal occipital layout with 6 sensors (5 occipital and 1 prefrontal); (b) bilateral parieto-temporal electrode setup with 6 sensors; (c) and (e) frontal (forehead) electrode setup with 6 sensors

The online BCI analysis module was designed to utilize EEG data both from the BIOSEMI and the NEUROSCAN EEG systems as their corresponding EEG acquisition modules sent their real-time data over a TCP/IP network to the BCI system.

BCI experiments were performed in an unshielded environment, corresponding to a most realistic scenario for using a BCI system. The subjects were free to move (while maintaining attention to the task), and no chin rest was used.

4.2.4. BCI-SSVEP Stimulation and Real-Time Neurofeedback Module

The SSVEP stimulus characteristics for the multi-command online BCI system were either the same or derived from the SSVEP optimization study.

Figs. 17 and 18 show the user neurofeedback and stimulation designs as displayed to the user. The purpose of the stimulation and neurofeedback module was to enhance BCI control and to evoke optimal brain responses depending on user's intent and selective attention. To make the design most useful, non-intrusive, and to minimize fatigue, the following requirements were imposed:

1) The SSVEP stimulus size should be minimized

2) The stimuli should be grouped tightly together in order to reduce the covered areas of the visual field as much as possible (enabling a wider range of BCI applications), and to minimize user fatigue

3) The stimulation frequencies should be restricted to the optimal-response range of the brain (ensuring higher performance across subjects)

4) The SSVEP stimuli should evoke strong brain responses even during stimulus movement (used for neurofeedback)

5) The overall design should be easily extendable to more commands.

Eight small checkerboard patterns were displayed simultaneously, each allowing control of an independent BCI command. The patterns were fixed very close to a moving controllable object, and allowed its spatial translation in 8 directions with 45° resolution in 2-

D space (Fig. 17 a). The pattern reversal frequencies were 6.0, 7.3, 8.4, 11.2, 12.9, 14, 15.3, 16.8 Hz. This frequency range was found to be optimal for these stimuli in the experiments described in Chapter 3. As the subject directed the attention to a particular pattern, the synchronized brain responses were identified by the BCI system and online visual neurofeedback allowed the movement of the controlled object in the desired direction (UP, RIGHT, DOWN, LEFT, UPPER-LEFT, UPPER-RIGHT, LOWER-RIGHT, LOWER-LEFT).

Information about the currently recognized neural command was continuously transferred back to the user interface station and, corresponding to each command, the visual neurofeedback system indicated online the results of the automatic interpretation of the user intent. Spatial position changes in two-dimensional space were calculated by the neurofeedback module for every screen refresh cycle, and the controlled object (a small car in this case) moved in the desired direction (limited by the number of directions/ commands). The stimulus control subsystem of the user interface accepted commands every 120ms, and tested all incoming commands for proper syntax before each position update. In case of any mismatch, an idle state would be imposed (no command), otherwise the command was carried on. A separate byte in the incoming command data indicated the strength of the command probability. This allowed the stimulus control algorithm to change the power of the executed command (e.g. change the speed of the car object moving on screen). In that way, stronger SSVEP brain responses evoked more powerful command neurofeedback.

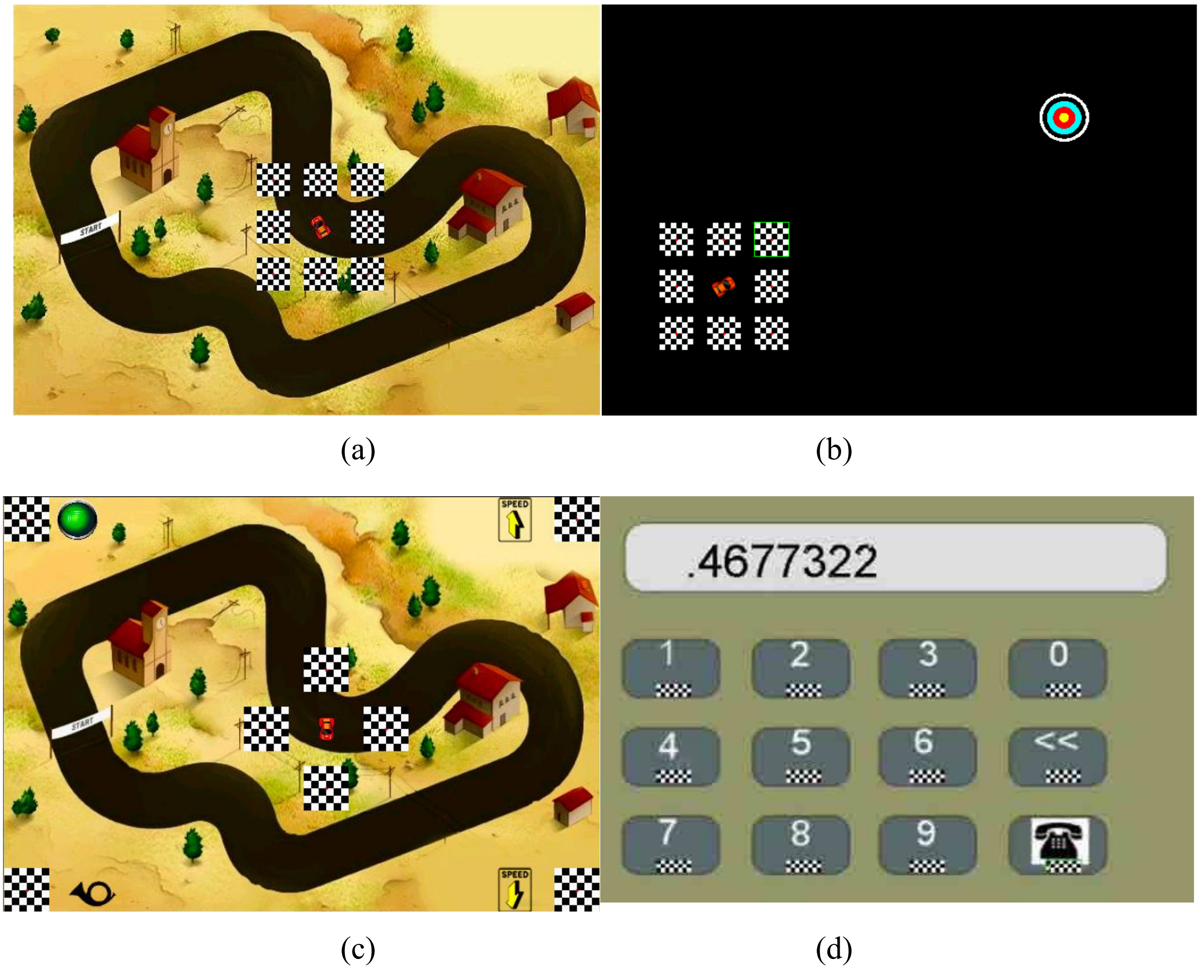


Fig. 17. SSVEP-based BCI designs with multiple independent commands. The stimulation patterns are fixed closely to a moving controllable object, so that directing the user's attention to a selected pattern enables 2D navigation in that direction. (a) a racing car design with 8 directions of movement; (b) bouncing ball design with a less distracting neutral black background and 8 directions of movement; (c) a racing car design with 4 directions of movement and 4 additional commands (speed up, speed down, stop, and horn); (d) a static phone design with 12 commands and very small stimulation patterns, for which a command is accepted after a short fixed period of consistent command recognition (e.g. the number 4).

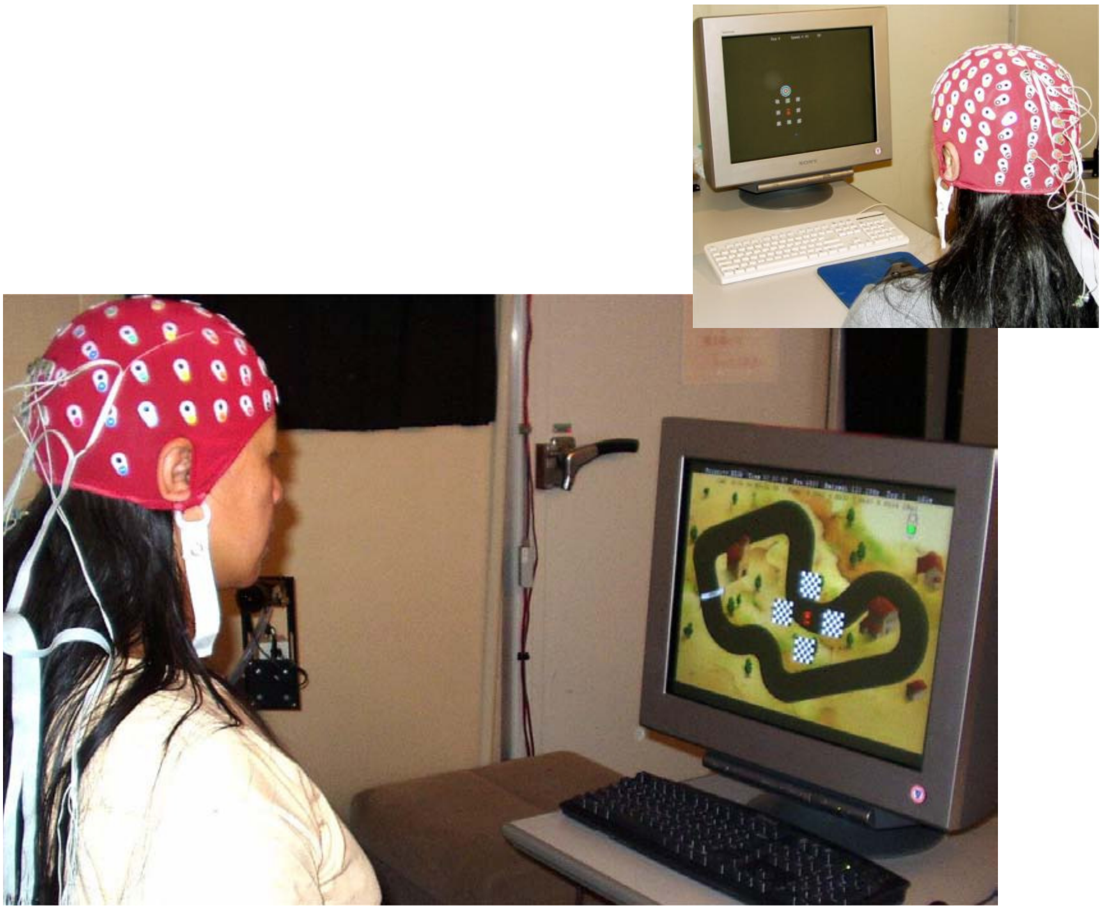


Fig. 18. An experimental subject during evaluation of the multi-command SSVEP-based BCI system with moving stimulation design (Bakardjian et al., 2010; Bakardjian et al., 2007a; Martinez et al., 2007)

4.2.5. Online BCI Data Analysis Module (Workflow)

The online data analysis module of the system was based on a multi-stage frequency band classification approach (Bakardjian et al., 2010; Martinez et al., 2007) with the following workflow (Fig. 19):

1) Automatic artifact rejection based on ICA/BSS for removal of eye- and muscle movement artifacts (EEG pre-processing unit)

2) Bank of narrow band-pass filters (Feature extraction unit)

3) Variance analyzer (Feature extraction unit)

4) Smoothing filter (Feature extraction unit)

5) Channel Integrator (Feature extraction unit)

6) Individual band normalization (Feature extraction unit)

7) Command classification (Command recognition unit)

8) Command output (Command output unit) .

Before the data was supplied to the analysis module, and as the multichannel biosignals were initially received from the EEG device via a TCP/IP connection, the online data reception and configuration unit continuously applied a fast high-pass infinite impulse response (IIR) filter with a cutoff frequency of 2 Hz. This measure was necessary in order to remove the substantial baseline shifts due to the DC coupling features and the wide dynamic range (24-bit) of the Biosemi EEG amplifiers.

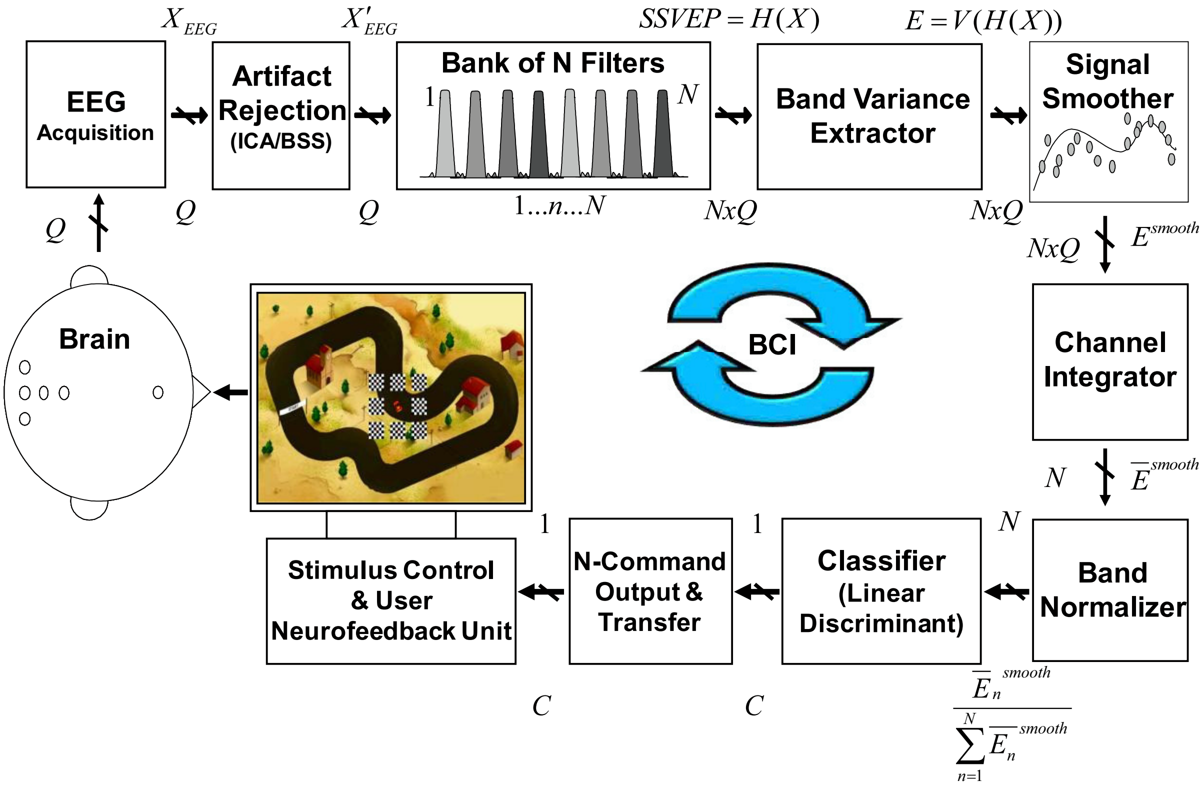
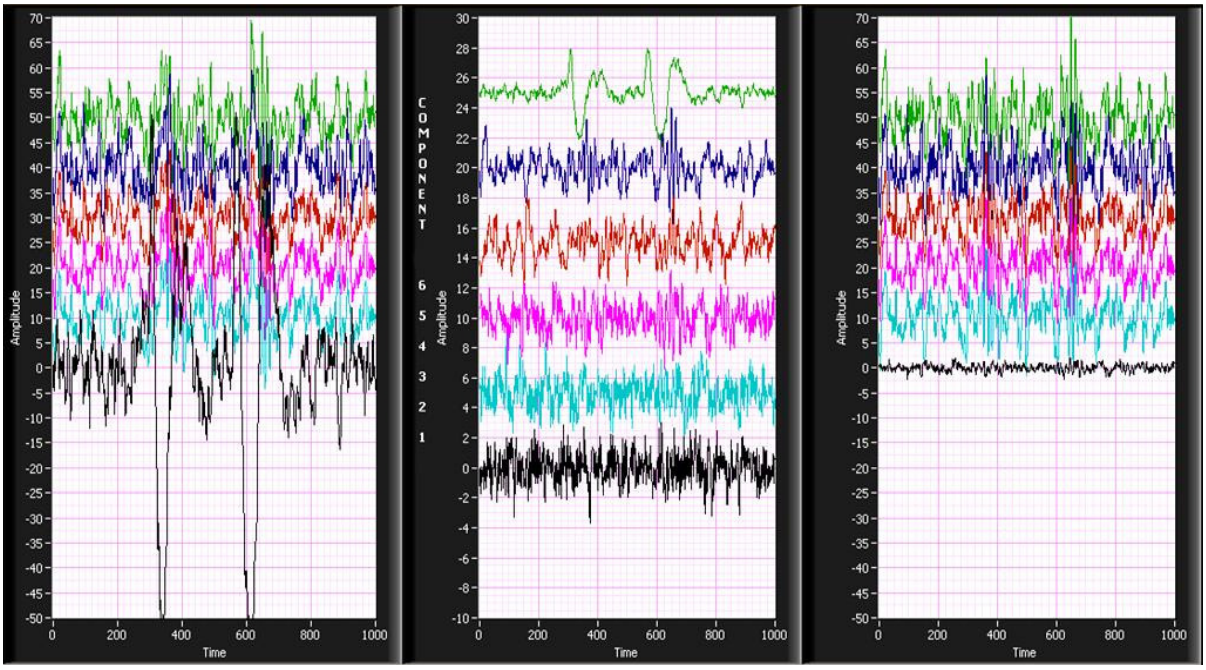


Fig. 19. Block diagram of all modules of the online 8-command BCI system.



(a) (b) (c)

Fig. 20. Online ICA/BSS-based artifact removal. The automatic rejection of eye blink and muscle artifacts was performed by using independent component analysis (ICA) / blind source separation (BSS). The second-order AMUSE algorithm was used to extract and rank the EEG components continuously within a 3-sec sliding window. The first and last components were removed and data was reconstructed for further processing. (a) EEG input data; (b) ranked ICA/BSS components; (c) artifact-free EEG output data.

1) In the first stage of the online analysis module, a fast second-order ICA/BSS algorithm, a modified fast AMUSE procedure (Cichocki and Amari, 2003) was applied for online artifact removal. An ICA/BSS pre-processing procedure serves to increase the success rate of the system by reducing the probability for false positive recognition of BCI commands. A practical real-time BCI system needs to remove properly user eye blinks and

other contaminating artifacts, while ensuring an uninterrupted data flow for continuous classification. That is why simple threshold rejection is not an appropriate approach. The online ICA/BSS procedure used in the SSVEP-BCI design was able to identify and remove the eye blink artifacts adaptively and efficiently (Fig. 20, see Appendix A for more details on ICA/BSS and the AMUSE algorithm).

The AMUSE algorithm ranked the EEG components automatically, so that the undesired first and last components corresponding to artifacts were canceled, and the remaining components were projected back to EEG space. The first components extracted the slowest brain activity, which in the case of fast SSVEP stimulation was due only to eye blinks, eye movements, or other slow artifacts. The last component contained the fastest activity, which had either muscle artifact origin, or was due to other high-frequency noise. In that way, the ICA/BSS pre-processing procedure removed any possibility that the BCI control was contaminated or due to eye / muscle activity instead of SSVEP responses.

2) The artifact-free EEG data was routed to a bank of elliptic narrow-band IIR filters $H(X'_{EEG})$ of 3rd order with center frequencies corresponding to the reversal rates of the command patterns and a bandwidth of 0.2 Hz (Fig. 21). An essential property of this filter bank was to ensure a minimal power overlap between adjacent frequency bands.

3) A variance analyzer calculated the variance of the band-power signals $E = V(H(X'_{EEG}))$ for all pattern reversal frequencies and all EEG channels.

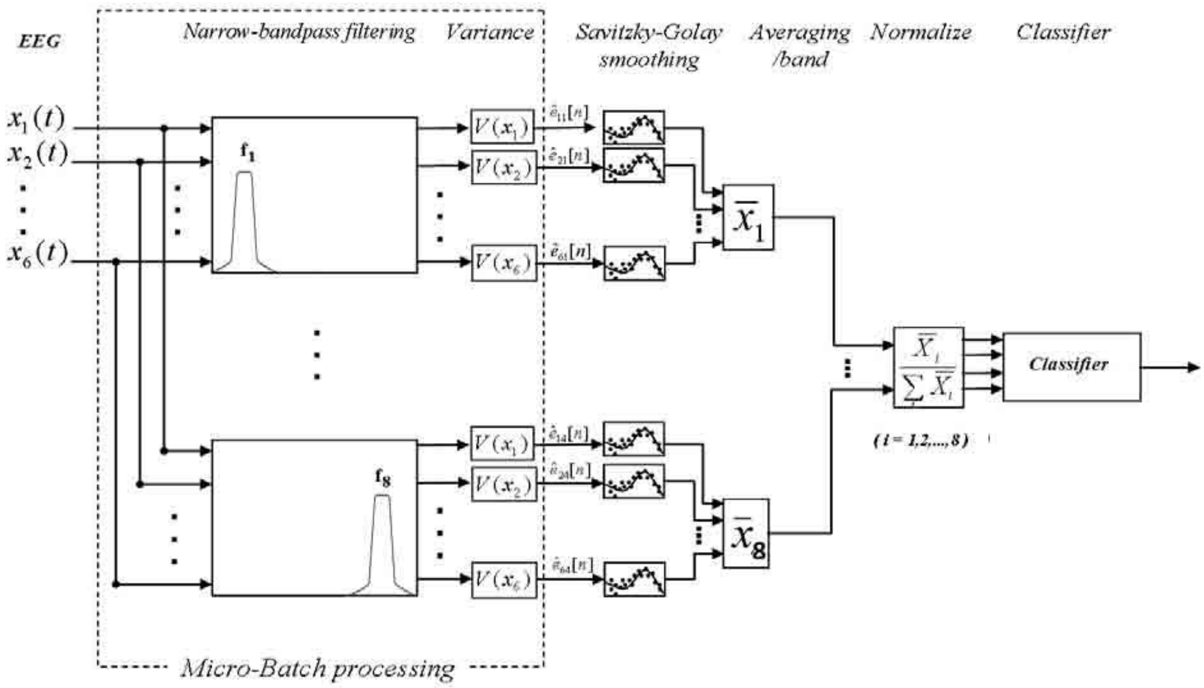


Fig. 21. Block diagram of the SSVEP-BCI online analysis module. A BCI command estimation is performed every 120ms.

4) The variance served as input for the next feature extraction step, a smoothing Savitzky-Golay (SG) filter using 2nd-order polynomial smoothing (Savitzky and Golay, 1964). The SG filter preserves important time-domain features, such as the signal extrema and high-frequency content. It approximates the signal with less distortion than other smoothing methods such as a moving average. The SG method uses a minimization of the least-square error by fitting a polynomial of order L to the noisy data X, instead of fitting a constant value as in the moving average. For each time point n, let's consider nL points before and nR points after n:

$$y[n] = \sum_{k=-nL}^{nR} c_n x[n+k] \tag{5}$$

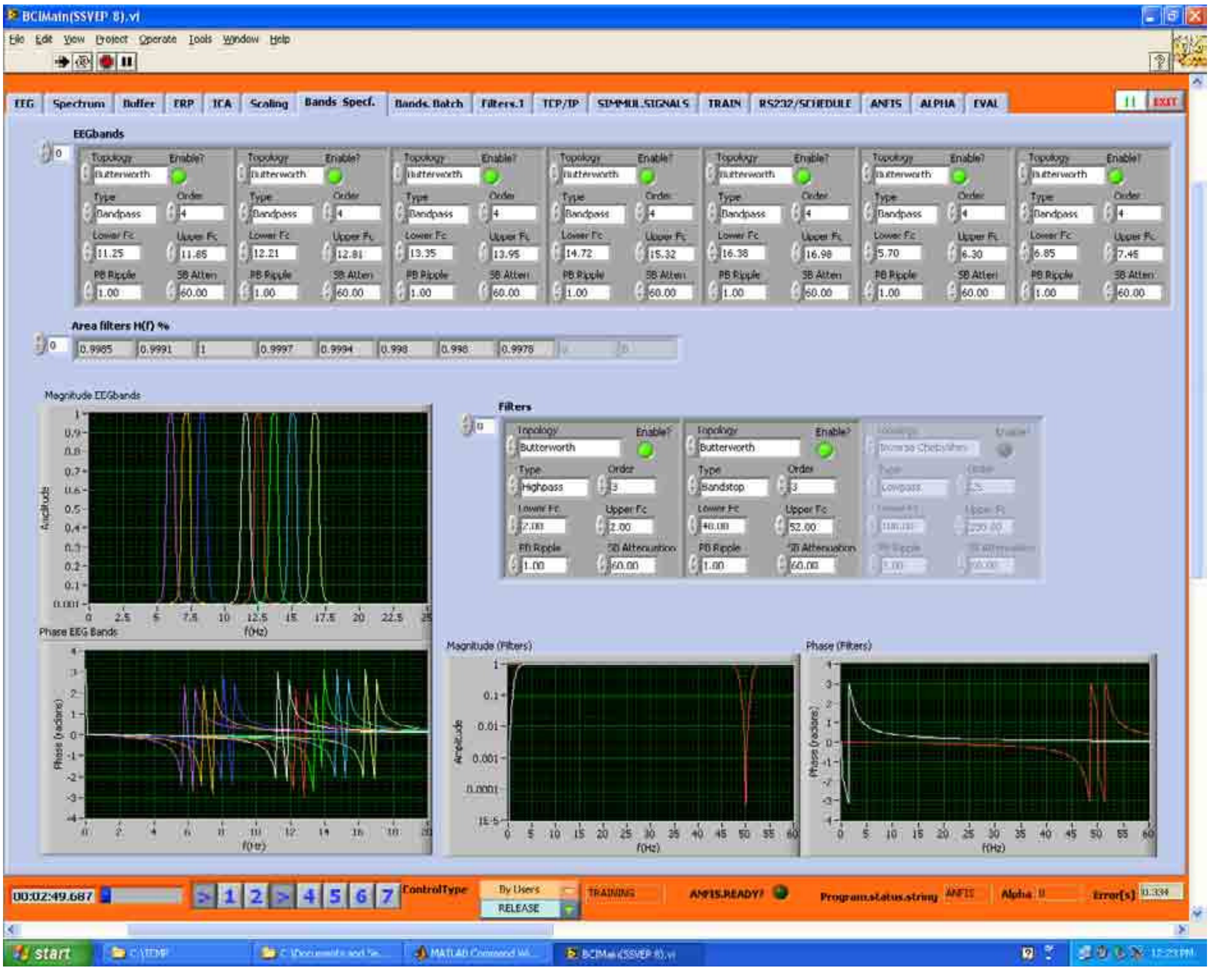


Fig. 22. An online bank of Butterworth filters to extract SSVEP power for all 8 stimulation frequency bands and 6 EEG channels

where the weighting coefficients c_n for the polynomial A are:

$$c_n = \sum_{l=0}^{L} \left[(A^T A)^{-1} \right]_{0,l} n^l \tag{6}$$

$$A_{ij} = i^j \qquad i = -nL, \ldots, nR \quad j = 0, \ldots, L. \tag{7}$$

Since the future data values are unknown, an online filter has $nR = 0$ to preserve causality. However, if $0 < nR << nL$, then the smoothness would be improved in spite of the introduction of a small time delay.

5) Following the smoothing procedure, a channel integrator is used to obtain the estimated energy per band, as the variance values are averaged between all Q channels

6) An individual inter-band normalization for each of the P bands serves to improve the performance by reducing variability

These procedures generate 8 time series describing the percentage of estimated normalized energy per band for each user:

$$E_j = \frac{\sum_{i=1}^{Q} e_{ij}}{\sum_{j=1}^{P}\sum_{i=1}^{Q} e_{ij}} \qquad \mathrm{i} = 1,\ldots,\mathrm{Q} \quad j = 1,\ldots,P \tag{8}$$

$$\sum_{j=1}^{Q} E_j = 1 \tag{9}$$

where e_{ij} is the energy of channel i and band j.

7) In the final analysis stages for online BCI, a linear discriminant analysis (LDA) classifier (Huberty, 1994) used the relative band energies E_j as input parameters to identify the user's target of attention every 120 ms (about eight times per second) , although the calculations were performed for each data sample. The classifier assigned each BCI state to one of the P commands by maximizing the inter-class scatter while minimizing the intra-class scatter.

8) The commands from the classification output were sent to the User interface module for immediate neurofeedback to the user (e.g. for fast movement of the controlled screen object and its surrounding SSVEP patterns).

4.2.6. Three Modes of Operation of the SSVEP-Based BCI System

In the online BCI Experiments (design as shown in Fig. 17 a), three different modes of operation were enabled. For all modes of operation the user's neural commands were detected and sent for visual feedback every 120 ms.

1) Classifier training mode

During the short classifier training mode (~2 min duration), each of the eight BCI commands was requested three times in random order, in addition to a no-stimulation command. After hearing a command request, the subject switched attention as soon as possible to the corresponding reversing pattern, or, in case of a no-stimulation request, to the controlled object between them. The voice requests were short pre-recorded messages asking the user to attend a specific pattern. Each command request was also accompanied by a thin red frame appearing around the requested pattern to minimize the searching delay. Neurofeedback was disabled during the training mode, and all user interface objects remained stationary.

2) Performance evaluation with random command requests

The second, evaluation mode served the purpose of measuring objectively the mean success rate and time delay of the BCI system. Six repetitions for each of the 8 commands were presented to the user in random order, after which the success rate was measured, as well as the recognition time delay. The dynamic neurofeedback was fully enabled in evaluation mode. A thin red frame aided the user to find the requested command pattern quickly, while a green frame showed which command was recognized. The time delay was measured as the difference in time between the end of a voice request for a specific command and its successful recognition by the analysis module.

3) Self-paced free roaming

The free roaming mode was necessary in order to estimate the overall BCI speed and robustness during fast self-paced command switching under natural usage conditions. One useful measure for free-roaming BCI performance evaluation was found to be the time it takes for each user to complete a fixed number of laps, as the time was compared against the best achievement among all tested users. These time measures could be compared only if the parametric settings for the object's (car's) 2-D movement speed were fixed at an optimal value for all users.

4.2.7. Computation of Information transfer rates (ITR) for Evaluation of the BCI Performance

To evaluate and compare the presented BCI design to other systems, a bit transfer rate measure (Pierce, 1980) was used which was based on a modified definition by Wolpaw and colleagues (Wolpaw et al., 1998), called here the Wolpaw method (WM). The information transfer rate (ITR) conveyed how much information can be transferred between the human brain and the brain-computer interface per minute. The WM method takes into account the number of commands *N*, the success accuracy *P* (probability between 0 and 1), and the command delay *T* in seconds:

$$B = \frac{\log_2 N + P\log_2 P + (1-P)\log_2\left[\frac{1-P}{N-1}\right]}{\frac{T}{60}} \qquad (10)$$

where *B* is the bit rate in bits/min.

Although to this date the Wolpaw method (WM) has been used in most BCI/BCI studies to present the BCI results in a standard form, recently it has been questioned and different bit-rate measures have been proposed (Kronegg et al., 2005; Furdea et al., 2009; Townsend et al., 2010). Nevertheless, the BCI performance in this study was presented using the WM (Eq. 10) due to following two reasons: (a) a different definitions may interfere with the basis for comparison with previous studies; (b) the proposal for new measures was based on the rejection (Kronegg et al., 2005) of the 4 assumptions in the Wolpaw method, which may be appropriate in general, or in some special cases, but not necessarily so for some BCI paradigms, such as the SSVEP-based system presented here.

1) The argument against the first WM assumption that it doesn't account for unrecognized commands can be answered by creating a separate 'idle' command, as was the case in the presented BCI system. Due to specific classification approach in the presented BCI system, no other outcome could occur apart from the N commands and the idle state (no command).

2) The criticism of the second assumption that all commands have the same probability of occurrence was also invalid for the presented design, as in a general setting any of the N directions of the controlled object were equally probable in 2-D space.

3) The third WM assumption that the classification accuracy *P* was the same for all commands held approximately true within the peak frequency range, as uncovered in the results, and was also ensured by the individual spectrum normalization procedure. Further outside the optimal range of brain response frequencies, however, the probabilities may begin to differ in spite of the normalization.

4) As for the fourth implicit assumption of the Wolpaw bit-rate formula that the error of classification 1-*P* is equally distributed among all commands, again the individual normalization strove to equalize the differences within the optimal frequency range, although additional compensatory measures may become necessary for higher frequencies.

5) The specifics of some BCI paradigms such as a P300-based speller may require special modifications of the information transfer rate (Furdea et al., 2009; Townsend et al., 2010) due to the necessity to erase first a wrong letter/syllable before replacing it with the proper command. Such corrections are not necessary in the presented BCI paradigm and as a result it would be wrong to bias the ITR estimate by using them.

4.3. Results

The online performance of the 8-command BCI system was measured in evaluation mode (request-response, see Methods) using patterns reversing in the optimal 6.0-16.8 Hz range as described above.

In order to estimate the feasibility of using this type of BCI with more practical sensor sets, performance was evaluated separately with electrodes in three different locations (occipital, parieto-temporal and frontal) for each subject. The BCI performance results are shown in Table 11. As expected for visual responses, occipital brain locations were optimal, featuring the highest mean success rate (98 %) and the shortest mean time delay (3.4 s) necessary for the online analysis algorithm in this experiment to capture reliably the user's intent. The more convenient parieto-temporal and frontal recordings were also found feasible for BCI control, however at the cost of substantially reduced performance.

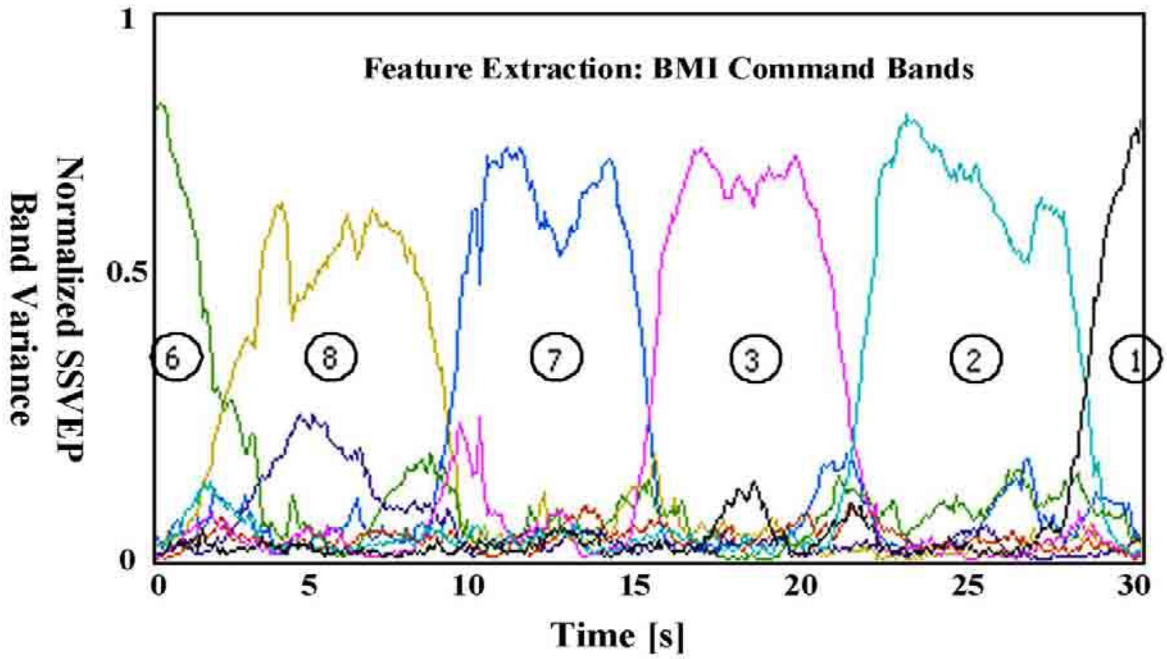
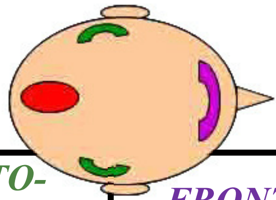


Fig. 23. Running comparison of the extracted SSVEP band features for all 8 BCI commands in steps of 1/8 s. In this 30 s segment, the user responded to preprogrammed voice requests (performance evaluation mode) by attending consecutively the reversing pattern sequence 6-8-7-3-2-1 ([upper-right] → [lower-left] → [lower-right] → [down] → [right] → [up]). The frequency bands corresponding to these sequential commands were 14, 16.8, 15.3, 8.4, 7.3, 6.0 Hz. In spite of differences in the frequency response curve of the brain, as demonstrated earlier, the individual normalization approach allowed direct comparison of all running BCI command features.

Table 11. **Performance summary for SSVEP-based BCI with 8 commands**, and comparison of the effects of electrode placement over three different brain locations – occipital, left-parieto-temporal, and frontal (forehead).



Electrode Location	***OCCIPITAL***	***PARIETO-TEMPORAL***	***FRONTAL***
Success Rate	**98 %**	81 %	74 %
Time Delay	**3.4 ± 0.7 sec**	4.0 ± 1.2 sec	4.3 ± 1.5 sec
Bit Rate Measure	**50 bits/min**	26.5 bits/min	20.1 bits/min

Table 12. **Individual performance of the SSVEP-based BCI system for each subject**, including the effects of electrode placement over 3 different brain locations.

	OCCIPITAL		
	SUCCESS RATES	**MEAN DELAYS**	**STD OF DELAYS**
Subject 1	100 %	3.63 sec	0.75 sec
Subject 2	98 %	3.27 sec	0.72 sec
Subject 3	95.5 %	3.35 sec	0.82 sec
Subject 4	100 %	3.92 sec	0.69 sec
Mean	98.38 %	3.54 sec	0.74 sec

	PARIETO-TEMPORAL		
	SUCCESS RATES	**MEAN DELAYS**	**STD OF DELAYS**
Subject 1	82.75 %	3.98 sec	1.21 sec
Subject 2	83.25 %	4.02 sec	1.26 sec
Subject 3	76.75 %	3.92 sec	1.31 sec
Subject 4	80.75 %	3.96 sec	1.18 sec
Mean	80.88 %	3.97 sec	1.24 sec

	FRONTAL		
	SUCCESS RATES	**MEAN DELAYS**	**STD OF DELAYS**
Subject 1	73.35 %	4.55 sec	1.56 sec
Subject 2	72 %	4.16 sec	1.35 sec
Subject 3	76.25 %	4.36 sec	1.52 sec
Subject 4	74.25 %	4.23 sec	1.46 sec
Mean	73.96 %	4.32 sec	1.47 sec

Chapter 5:

BRAIN RESPONSES TO FLICKERING EMOTIONAL FACE VIDEO SSVEP STIMULI

This chapter describes the design and practical results from a series of experiments with the main goal to investigate the properties of the brain response to affective face video SSVEP stimuli, and to evaluate the hypothesis that such more complex stimuli could enhance the SSVEP response as compared to neutral patterns (Bakardjian et al., 2011). If the mutual modulation of sensory- and affective-face – related brain activations can be objectively measured and controlled, this phenomenon could increase substantially the scope of possible robust and practical BCI applications for healthy and disabled users.

5.1. Objectives

It is known that emotional arousal exerts a modulatory effect on sensory input, including vision through feedback mechanisms (Amaral et al., 2003), and that face stimuli enhance visual attention. Even though basic brain responses to visual flicker have been studied in the past, designing increasingly successful real-time BCI systems which offer multiple commands and high reliability presents a crucial challenge for researchers. The main goal in such a task would be to achieve a breakthrough in the reliable, rapid estimation of the typically weak single-trial SSVEP oscillations buried in strong brain 'noise' (ongoing activities of the brain) by using better stimuli and better analysis techniques.

The new approach and experimental results presented here aim to achieve that goal and to demonstrate that using emotional faces in short flickering affective videos as visual stimuli instead of the standard neutral checkerboards can enhance the basic cortical SVEP responses over a range of flicker frequencies as compared to neutral stimuli.

5.2. Methods

5.2.1. Experimental Subjects

Eight healthy subjects (four male and four female), with an average age of 26 ± 9 years and normal or corrected-to-normal vision, participated in these experiments. The subjects were fully informed of all procedures and signed an informed consent agreement, in accordance with the Declaration of Helsinki, and including a statement that they have no known neurological disorders. Before each experiment they were briefly tested for photosensitive epilepsy, and during the experimental sessions their EEG patterns were continuously monitored for epileptic spikes.

5.2.2. EEG Data Acquisition and Collection

The brain signal acquisition in these experiments was performed using a BIOSEMI EEG system (Biosemi Inc, Amsterdam, The Netherlands) with sintered Ag/AgCl active electrodes, as described in the previous chapter. EEG data was collected simultaneously from 128 active electrodes in a whole-head layout, using a sampling rate of 512Hz for all experiments.

5.2.3. Stimuli and Display - SSVEP Using Emotional-Face Video Stimuli

The subjects were seated 1m from a 40” LCD display with a vertical refresh rate of 60Hz (measured 59.7 ± 0.35Hz). Five different stimuli (Fig. 25) were shown to each subject: two short video clips (duration ~4s, dimensions 7°x 7°arc, frame rate 25 fps, no audio) with faces of actors depicting dynamically emotions of joy and anger on a white background (Baron-Cohen et al., 2004), as well as their block-blurred versions, and a reversing 6x6 checkerboard. The subjects were asked to empathize with the observed emotional states as much as possible.

Each video stimulus was shown at five flickering frequencies (5, 6.6, 8.5, 10, and 12 Hz (see Fig. 24)), which are not discussed in detail in this work. The blank periods in the video SSVEP stimuli were replaced with 50% gray squares of the same size. Each video clip stimulus was replayed continuously until the end of the trial. Each trial was 10s long and was preceded by a 2s blank-screen baseline.

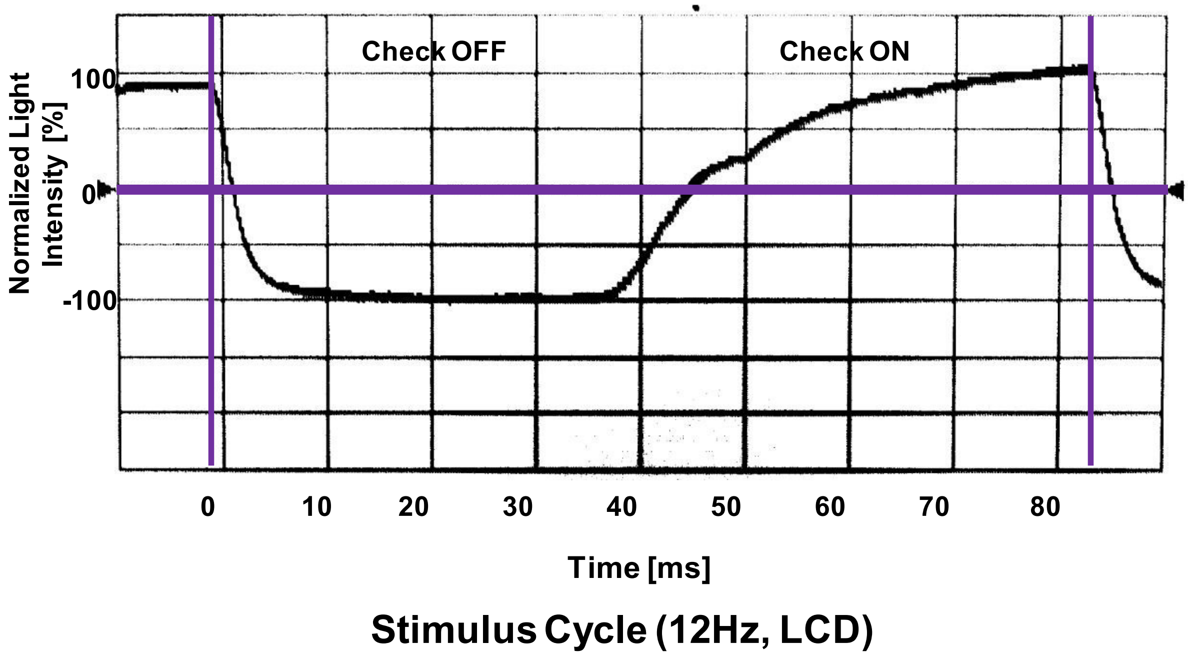
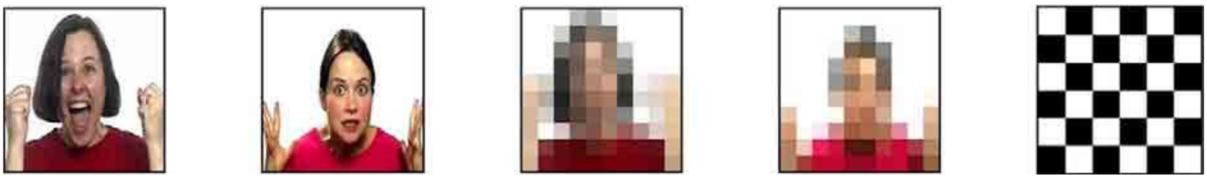
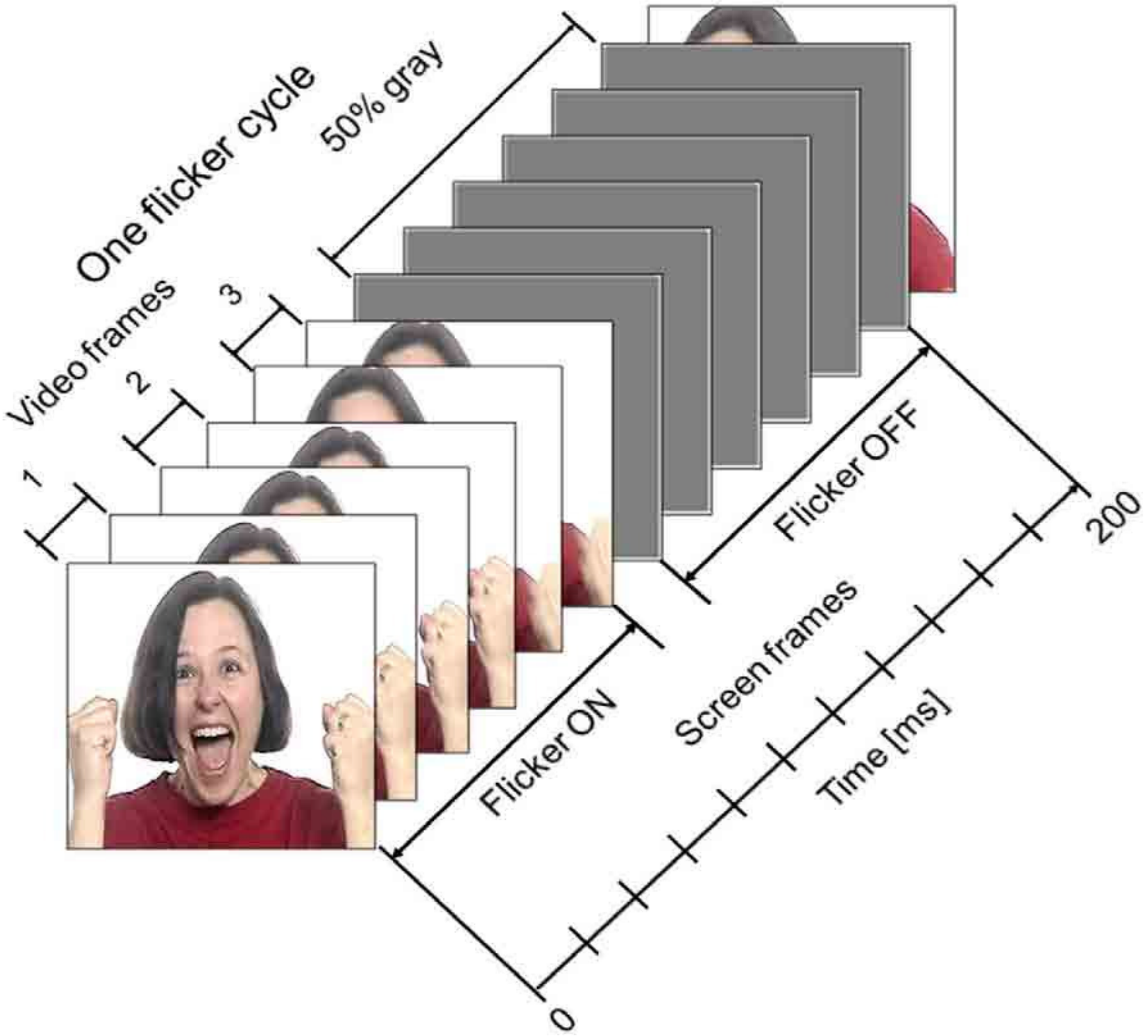


Fig. 24. Time course of the actual light emitted by a LCD display (60Hz vertical refresh rate) during checkerboard reversal of 12Hz. Measurement was performed using a photo-sensor and an oscilloscope. Unlike CRT displays (Fig. 4), the display vertical refresh does not result in separate illumination peaks, but the stimulation picks up gradually when the stimulus is on (right side). This illustrates also why LCD displays cannot be used properly for high-frequency SSVEP stimulation (above ~25Hz) or for precise onset time delay measurements.



(a)



(b)

Fig. 25. Affective-face video SSVEP stimuli. (a) From left to right: two short video clips interrupted with gray flicker with faces of actors depicting emotions of joy/happiness and anger, the same videos blurred to preserve the general image properties but to conceal the emotions and facial features, and a neutral reversing checkerboard for control. (b) A block diagram illustrating the design of a 5 Hz video flicker stimulus, assuming 60 Hz screen refresh rate and 25 frames per second video frame rate. Each flicker cycle should span over an integer number of screen refresh frames in order to display the stimulus properly. For the flicker frequency in this example, 12 screen refresh frames / cycle were required, where the stimulus was displayed during half of the cycle (ON), and a blank 50% gray square image of the same size was shown during the other half (OFF). During each ON-period, a video frame was displayed for 2 screen refresh frames, which is the integer ratio of the screen refresh rate and the video frame rate. Individual video clips were replayed continuously.

5.2.4. Data Pre-processing and ICA/BSS-based Artifact Removal

The original EEG data was subjected to average-referencing, followed by SSVEP trial segmentation and baseline correction, in order to remove any large baseline shifts from the DC-coupled 24-bit Biosemi EEG system. All ocular artifacts were removed using Independent Component Analysis (ICA) employing the Unbiased Quasi-Newton Algorithm for ICA (UNICA) (Cruces et al., 2000). The ICA/BSS approach and UNICA are described in more detail in the Appendix A. The UNICA algorithm was selected for this analysis after testing the performance of more than 20 ICA methods (Cichocki et al., ICALAB Toolboxes).

5.2.5. SSVEP Onset Detection Using Phase-Locking Value Reset and Wavelet Energy Variability Measures

In Chapter 3, a procedure was described allowing the estimation of the single-trial SSVEP responses in the brain using modified quadrature amplitude demodulation (QAD) (Bakardjian et al., 2010). In this analysis, the SSVEP estimations were performed by calculating and comparing the performance of two other measures – a single-trial phase-locking value variability $PLVV^f$ and a single-trial wavelet energy variability WTV^f. Both measures were designed to quantify individual rapid changes in brain activity immediately after SSVEP onset.

Single-trial phase-locking values used here were computed for each fixed SSVEP frequency *f* over time *t* as follows:

$$SPLV^f(t) = \frac{1}{N}\left|\sum_{i=1}^{N} exp(j\{\Phi_{EEG}^i(f,t) - \Phi_{ref}^i(f,t)\})\right| , \qquad (11)$$

where N=12 was the number of EEG channels (over the occipital cortex, in this case), j^2 = -1, and $\Phi^i_{EEG}(f)$ and $\Phi^i_{ref}(f)$ were the phases of the normalized EEG signal $\mathrm{s}^{\mathrm{i}}_{\mathrm{EEG}}$ (i=1,...,N) and the flicker reference signal s^i_{ref}, respectively. The reference s^i_{ref} (Pockett et al., 2009) was an artificial sine wave corresponding exactly to the flicker frequency f of the visual stimulus. The phase Φ for SSVEP frequency f was calculated using the imaginary and real components of the convolution of an input signal s^i with a complex Gabor wavelet $W(f)$:

$$\Phi^i(f,t) = arctan\frac{imag[W(f) * s^i]}{real[W(f) * s^i]} . \qquad (12)$$

Using these definitions, the normalized single-trial phase-locking value variability measure $PLVV^f$ was defined as the ratio:

$$PLVV^f(t) = \frac{\Delta SPLV^f(t)}{SPLV^f(t_0)} , \qquad (13)$$

And the phase-reset change $\Delta SPLV^f(t)$ as calculated for each SSVEP frequency f was:

$$\Delta SPLV^f(t) = SPLV^f(t^{1s}_{max}) - SPLV^f(t_0) , \qquad (14)$$

where $SPLV^f(t^{1s}_{max})$ was the maximum phase-locking value reached within one second after the onset of the SSVEP stimulation, while $SPLV^f(t_0)$ was the baseline phase-locking value at SSVEP onset t_0, driven by the flicker phase reset of the occipital brain activity.

The phase-locking value PLV^f (Lachaux et al., 1999), ranging from 0 to 1, is a measure used to represent the degree of phase stability for a signal frequency f. While often in multi-trial studies the PLV measure is computed over several trials, here only single trials were evaluated due to real-time applications such as BCI. Measuring a smoothed single-trial PLV between channel pairs and over multiple time windows (Brunner et al., 2004) is also inappropriate in this case since it was essential to associate the PLV changes with the exact time of the SSVEP onset. That is why the single-trial phase-locking changes at the onset of SSVEP in this investigation were computed for each sample by measuring the degree of wavelet phase stability over a block of *N* occipital channels, in reference to the phase of a sine wave corresponding to the frequency of the SSVEP flicker stimulus.

The second measure, that was applied to estimate SSVEP, was the single-trial Gabor wavelet energy variability which was used to quantify the normalized energy increase of the brain response at the flicker frequency during the first second following the SSVEP onset:

$$WTV^f(t) = \frac{\Delta SWT^f(t)}{SWT^f(t_0)} \ , \tag{15}$$

where:

$$\Delta SWT^f(t) = SWT^f(t_{max}^{1s}) - SWT^f(t_0) \ , \tag{16}$$

$SWT^f(t_{max}^{1s})$ was the maximum wavelet band energy value reached within one second after the onset of the SSVEP stimulation, and $SWT^f(t_0)$ was the baseline energy value at SSVEP onset t_0.

5.2.6. Statistical Evaluations

The PLVV and WTV measures for all subjects and experimental conditions were evaluated for statistical significance through a two-factor analysis of variance. Compared SSVEP measure types were considered significantly different if the probability that they do not belong to the same sample populations was above the 95% threshold ($p < 0.05$).

5.3. Results

The analysis of the occipital brain response changes after the emotional-face SSVEP onset (averaged over all five flicker frequencies) showed that both for the phase-locking measure $PLVV^f$ (Fig. 26, upper panel), and for the wavelet energy measure WTV^f (Fig. 26, lower panel), the happy or angry face video flicker stimuli provided significantly stronger SSVEP activity than their blurred versions or neutral checkerboards. The optimal (strongest) mean responses were observed at 10Hz flicker (Fig. 27) for both SSVEP measures.

Statistical analysis using two-way analysis of variance tests revealed that the SSVEP activity was significantly dependent on the flicker stimulus type (p=0.0007 for the phase-locking measure $PLVV^f$ and p=0.002 for the wavelet energy measure WTV^f) (Fig. 28, green bars). Testing specifically for the effect of emotion, the affective faces provided significantly stronger SSVEP responses than their blurred versions (p=0.0005 for $PLVV^f$ and p=0.0004 for WTV^f) (Fig. 28, red bars). The mean of the normalized PLV increase after SSVEP onset was stronger for emotional stimuli by a factor of 2.2, while the normalized wavelet energy variability measures showed a similar but slightly lower amplification factor of ~2.

However, there were no significant differences in the occipital SSVEP responses due only to emotional valence differences (joy vs. anger, p=0.61 for $PLVV^f$ and p=0.82 for WTV^f) (Fig. 29, dark blue bars), even though the video stimuli with a positive valence (joy/happiness) tended to elicit slightly higher measures than negative ones (anger/irritation). Furthermore, there were also no statistically significant differences between the brain responses of individual subjects (p=0.85 for $PLVV^f$ and p=0.78 for WTV^f) (Fig. 29, purple bars).

When comparing both measures, the normalized single-trial phase-locking value variability measure $PLVV^f$ exhibited lower variability and better sensitivity and reliability than the wavelet energy measure WTV^f. Nevertheless, repeated signal analysis indicated that both measures could serve as complementary and valuable tools for the optimal estimation of SSVEP.

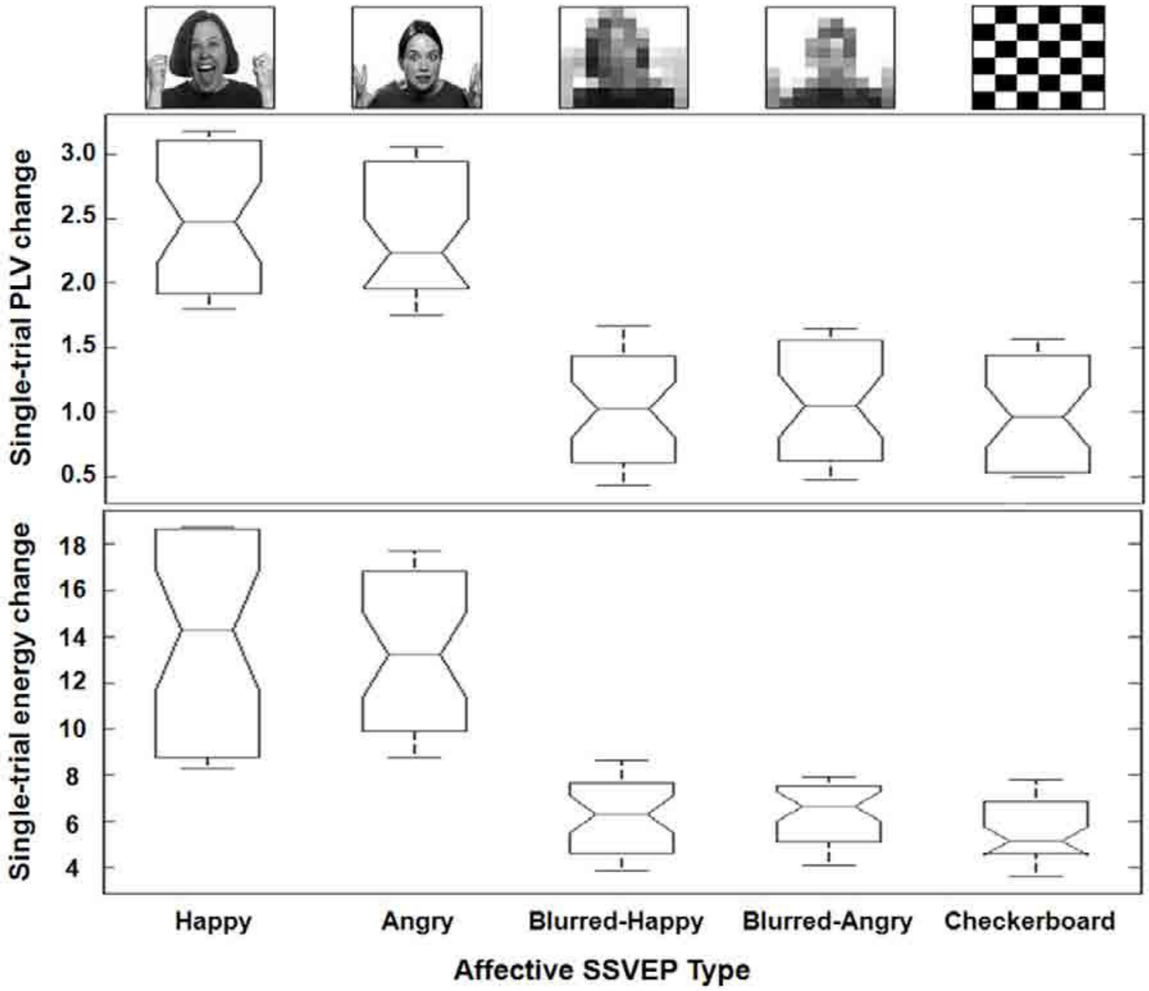


Fig. 26. Cortical changes at the onset of affective-face SSVEP and neutral SSVEP (mean values for all 5 measured frequencies). Affective SSVEP video stimuli evoked significantly stronger responses than their blurred versions or the neutral checkerboard. (upper panel) Strength of the response using a normalized single-trial phase-locking variability measure; (lower panel) Strength of the response using a normalized single-trial wavelet energy variability measure. The phase synchrony measure was more stable and sensitive to weak SSVEP oscillations than the wavelet energy.

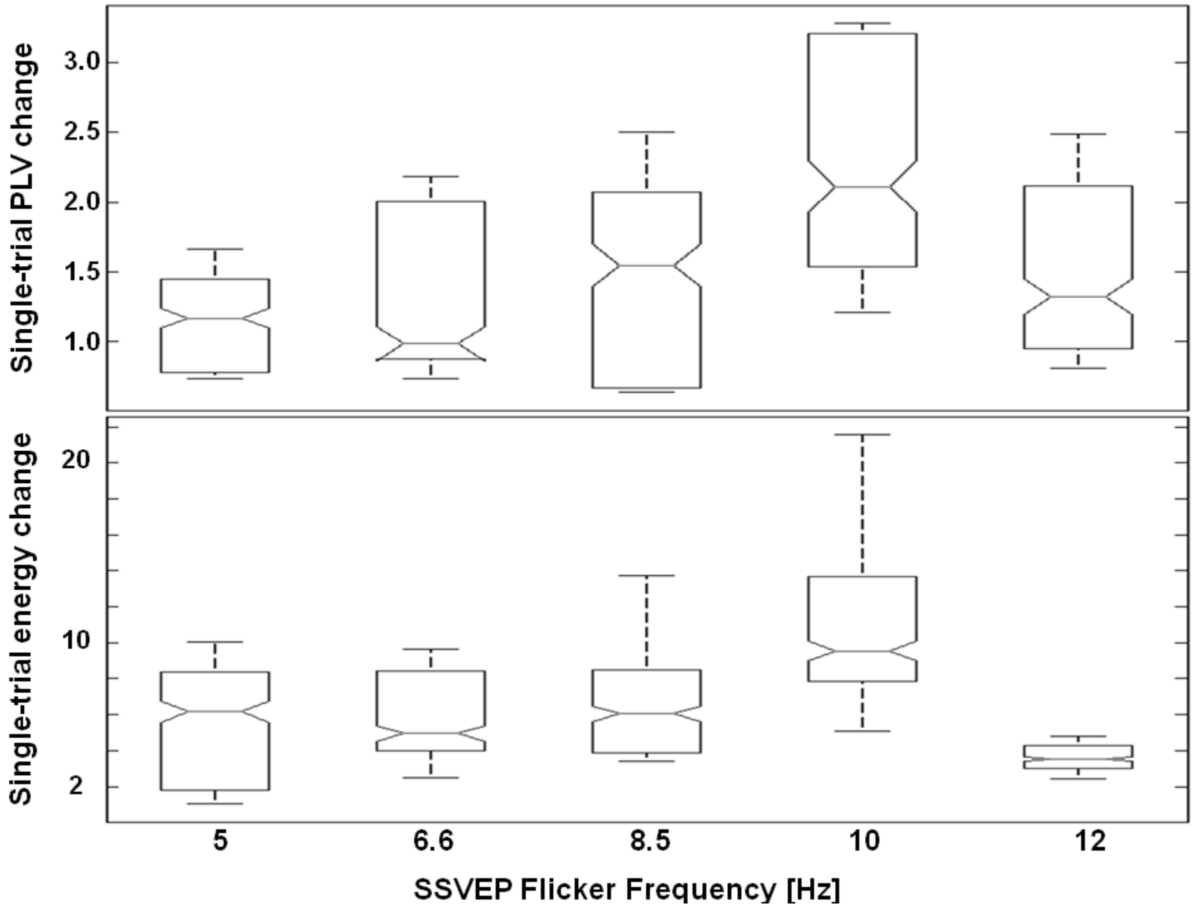


Fig. 27. Frequency response curve of the occipital brain for affective-face SSVEP and neutral SSVEP (mean values for all 5 types of stimuli). Stimulation frequency of 10 Hz evoked the strongest average changes, although the effect of flicker frequency did not reach statistical significance (p=0.26 for the phase measure and p=0.47 for the energy measure). (upper panel) Frequency response using a normalized single-trial phase-locking variability measure; (lower panel) Frequency response using a normalized single-trial wavelet energy variability measure. The phase synchrony measure shows slightly higher frequency dependence but lower variability than the wavelet energy measure.

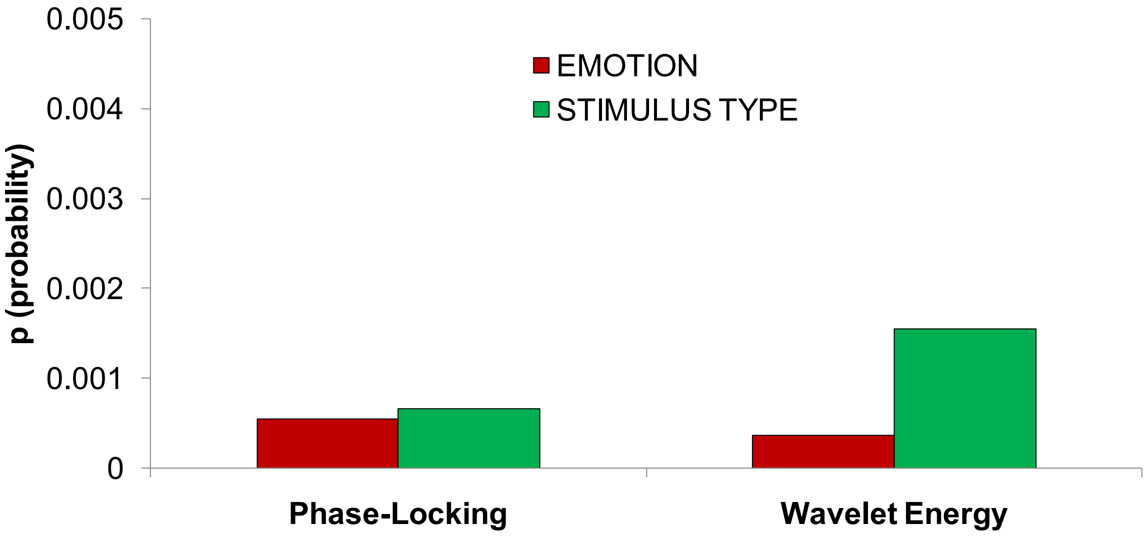


Fig. 28. Statistically significant SSVEP onset changes due to emotional-face contents of the flicker stimuli ($p < 0.05$). The probability bar marked 'Emotion' (red color) represents the statistical comparison between emotional-face SSVEP measures and their blurred versions. The bar marked 'Stimulus Type' (green color) represents the statistical comparison between SSVEP measures for all 5 available stimuli.

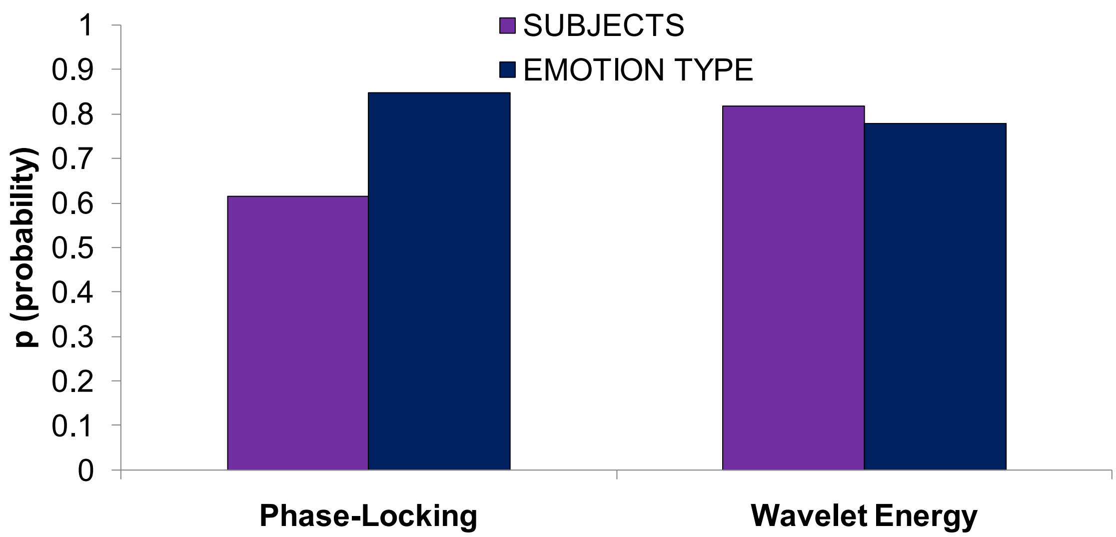


Fig. 29. No significant SSVEP differences due to inter-subject variability (purple color) and emotion type/valence (positive-negative emotions, dark-blue color) ($p > 0.05$)

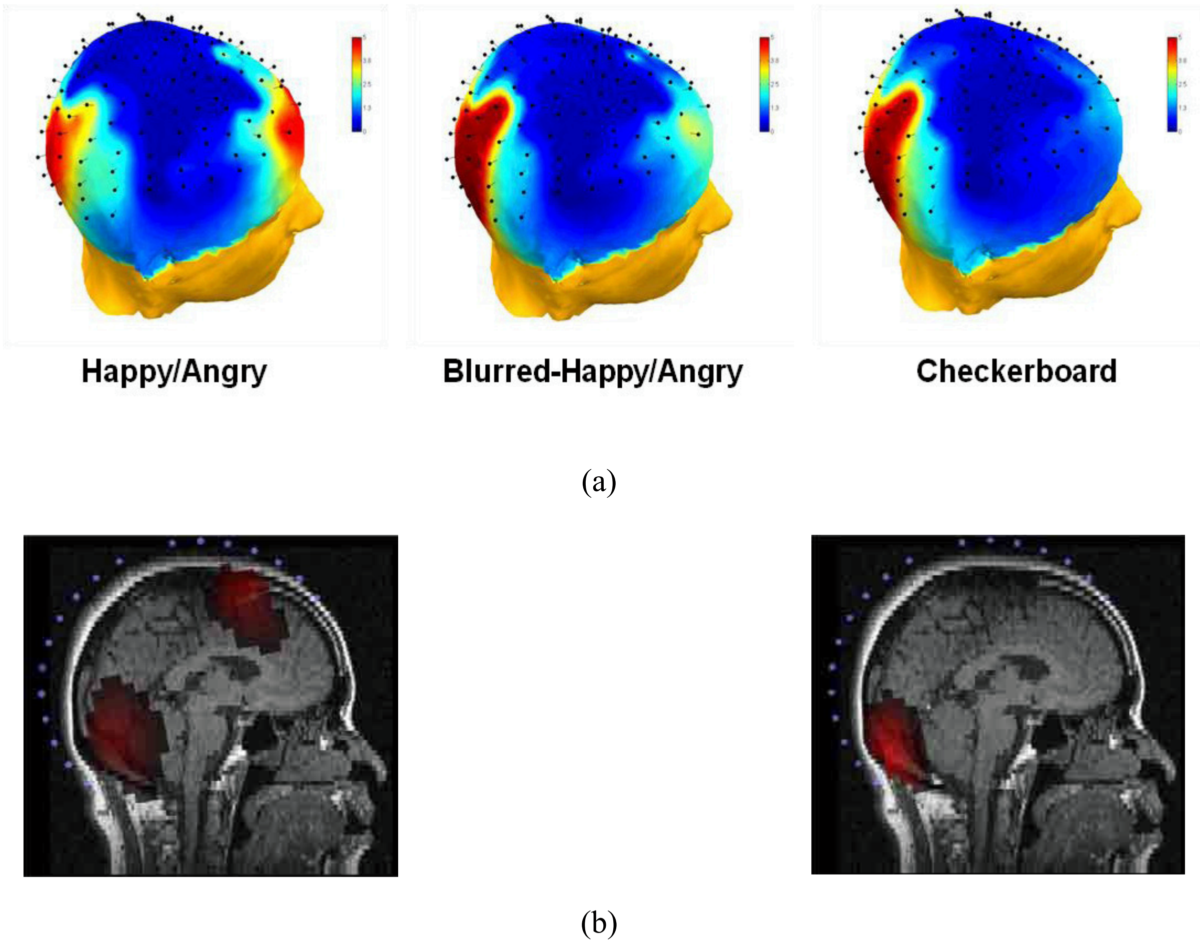


Fig. 30. Brain activation during affective-face and neutral SSVEP stimulation at 8.5Hz. (a) 128-channel whole-head topographic maps of the SSVEP power calculated using Slepian multitaper spectrum estimation of the power spectral density (PSD) (Thomson, 1982) for each channel. This method has low time resolution but it can detect rhythmic activity robustly even if the signal-to-noise ratio is low. Frontal activity was observed in the affective conditions (happy and angry) for the narrow-band (±0.5Hz) SSVEP signal, while such activity was substantially reduced for neutral and blurred stimuli; (b) Source analysis of the brain activation in the SSVEP frequency band for affective (left) and neutral (right) stimuli.

Chapter 6:

ENHANCED MULTI-COMMAND SSVEP-BCI USING FLICKERING EMOTIONAL FACE VIDEOS

This chapter gives details on the design and evaluation of a new type of an online SSVEP-BCI system using affective face video stimuli (Bakardjian et al., 2011) in order to improve upon the results described in Chapter 4.

6.1. Objectives

Based on result from the previous Chapter 5, this chapter investigates the hypothesis that the visual flicker of images of human faces expressing strong emotion could optimize the the performance of a multi-command SSVEP-based Brain-Computer Interface (BCI) application by increasing the signal-to-noise ratio of the measured brain activity. In Chapter 3 of this thesis it was shown that optimizing the stimulus features was essential for achieving stronger SSVEP and high performance of the SSVEP-BCI system.

The objective of the new approach and experimental results presented in this chapter was to show that using short flickering affective-face videos as visual stimuli instead of the standard neutral checkerboards can lead to an essential advantage in creating faster, more reliable and easier to use Brain-Computer Interface systems for disabled and healthy users. If achieved, an increased SSVEP-BCI efficiency of the combined emotional-visual BCI paradigm should translate into an improvement of the information transfer rates.

6.2. Methods

6.2.1. Experimental Subjects

The same eight healthy subjects (see Chapter 5) participated in the BCI experiments. All subjects were fully informed of all procedures and signed an informed consent agreement.

6.2.2. EEG Data Acquisition and Collection

The brain signal acquisition in these experiments was performed using a BIOSEMI EEG system (Biosemi Inc, Amsterdam, The Netherlands) with sintered Ag/AgCl active electrodes, using a sampling rate of 512Hz. To enable a proper comparison, the 6-electrode layout was similar to the occipital configuration described previously in Chapter 4.

6.2.3. SSVEP-BCI Stimulation - SSVEP Using Emotional-Face Video Stimuli

Although the general experimental setup was similar to that in the previous experiment, there were several notable exceptions. Eight different emotion-loaded video clips (Fig. 31) flickered simultaneously at different frequencies (5, 5.4, 6, 6.7, 7.5, 8.5, 10, 12 Hz). Each affective video was assigned as an independent command.

Fig. 31. Affective-face BCI interface with 8 commands. (a) The BCI stimulus control and neurofeedback user interface, featuring 8 short flickering affective videos with various emotions within the joy, anger and surprise categories

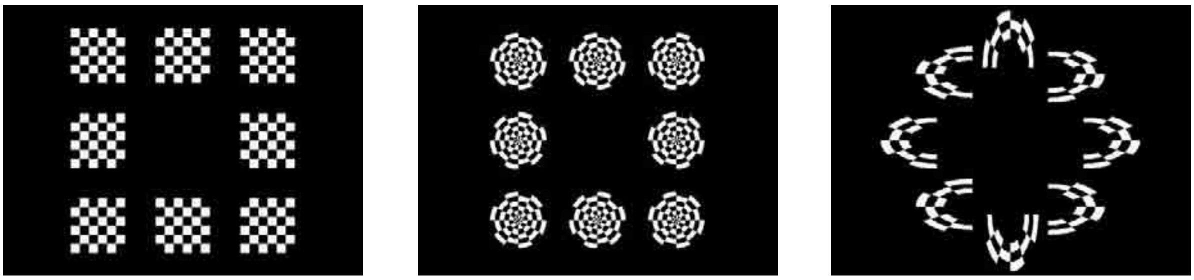


Fig. 32. Neutral 8-command SSVEP-BCI stimulus designs using reversing checkerboard-type patterns.

Fig. 33. Multi-command BCI platform based on affective-face SSVEP - user control of a multi-joint robotic arm device (iARM). As the user attends a selected command stimulus on the screen, the recognized BCI command is executed to control a complex movement of the robotic arm (such as delivering a bottle/can/soft box with tissue paper, or serving a coffee cup drink to the lips of a disabled user).

The subjects directed their attention to a selected video to evoke an affective-SSVEP response and a corresponding movement of the robotic arm (Fig. 33). The computer display used for this BCI task was more compact (17” notebook PC).

6.2.4. Online SSVEP-BCI Analysis and User-Interface Modules

The BCI analysis module in these experiments was based on signal energy measures, as described in detail in Chapter 4 (Bakardjian et al., 2010). The affective-face SSVEP-BCI platform consisted of the following main modules: 6-channel EEG data acquisition (Biosemi, Biosemi Inc, the Netherlands), an analysis (signal processing and evaluation) unit, a stimulus-control user interface, and a neurofeedback multi-joint robotic arm executive device (iARM, Exact Dynamics Inc, The Netherlands).

6.3. Results

6.3.1. Multi-command SSVEP-BCI Using Emotional-Face Video Stimuli

The mean command delay was measured for all 5 types of stimuli used in the previous affective-face SSVEP experiment, for 10Hz flicker. The BCI delay was defined as the time between issuing a request for a specific command till the time this command was recognized from the user's EEG by the signal analysis module. In agreement with the results of the previous experiments, the affective SSVEP responses were faster (Fig. 34) and exhibited less transient properties than in emotion-free checkerboards or blurred video. The mean BCI delay for commands using emotional face stimuli was 2.7s, while the mean neutral delay was 3.4s. The mean BCI success rates were 99% for emotional face stimuli, and 98% for their blurred versions and for checkerboards.

Overall, the 8-command BCI information transfer rate was boosted to 64 bits/min for emotional face stimuli, as compared to 50 bits/min for neutral stimuli. In addition to increased reliability, the BCI users reported reduced fatigue over long-term exposure to flicker, and enhanced ability to maintain their visual attention on the task.

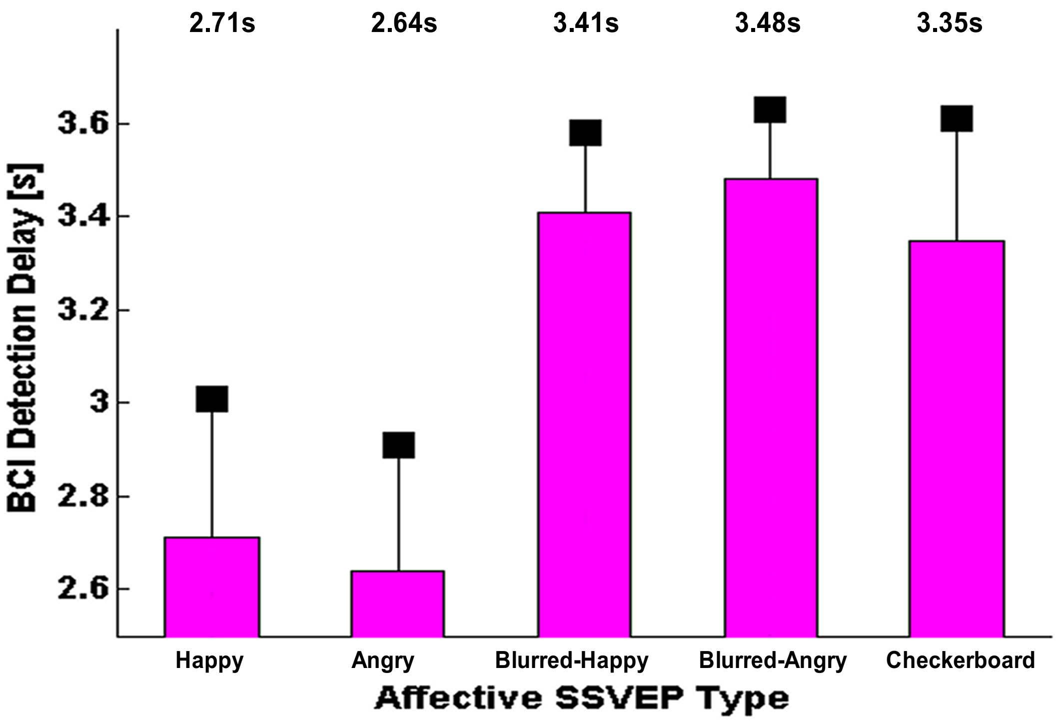


Fig. 34. BCI command delays for affective-face video and neutral SSVEP. Emotions in the visual stimuli boosted substantially the speed of command recognition through enhancing the SSVEP detection signal-to-noise ratio.

6.3.2. Overall Behavioral Measures for the User Emotional Experience

After each experiment, the participants responded to a few straightforward questions about their subjective emotional experiences. In that way, behavioral measures were also available for analysis, in addition to the brain responses. The information requested in the behavioural questionnaire included a self-estimate of the participant's emotionality, and the degree to which they felt similar emotions (an empathic match) as they observed the actors depicting joy or anger.

The results (Fig. 35) showed that the degree of admitted personal emotionality as a trait (on a scale from 1 to 10) for all subjects was 6.3 ± 2.1. The degree to which they identified with the depicted positive emotion (from 1 to 10) was 7 ± 1.9, while for the negative emotion the score was 5.7 ± 2.2. The higher behavioural scores for positive emotion were in line with the results obtained using EEG measures. All subjects also stated that they did not experience any emotions while viewing the blurred video stimuli and the checkerboard.

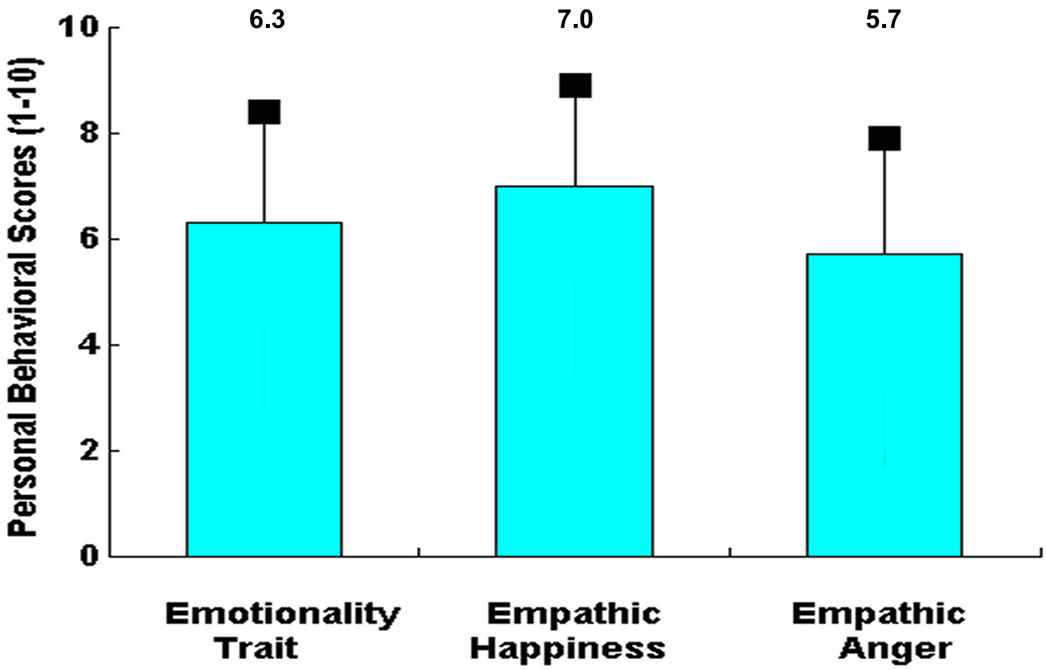


Fig. 35. Behavioral measures (self-estimate) in affective-face SSVEP experiments. The participants estimated the following scores (on a scale from 0 to 10): their degree of personal emotionality as a trait (left), the degree to which they felt happiness while watching the actor video (middle), and the degree to which they felt anger together with the actor (right). In this passive emotional approach, empathizing with happiness was more successful than with anger, for most participants.

Chapter 7:

CONCLUSIONS

The research described in this thesis aimed to solve several essential problems in the wider field of SSVEP-based Brain-Computer Interfaces. Overall, five types of EEG experiments were performed to obtain the necessary brain data:

1) 6-sec SSVEP stimulation with increasing frequency using a very small checkerboard in order to measure the frequency response curve for this type of stimuli (offline processing, Chapter 3)
2) 15-sec SSVEP stimulation at 3 frequencies using very small checkerboards to study the actual onset response dynamics (offline processing, Chapter 3)
3) BCI evaluation using 8 independent small checkerboards reversing at 8 frequencies (online processing, Chapter 4)
4) 30-sec SSVEP stimulation at 5 frequencies using 5 different video stimuli (happy and angry emotional faces, their blurred versions and checkerboards) to study the potential optimization effects of emotional-face contents (offline processing, Chapter 5)
5) BCI evaluation using 5 stimuli (happy and angry emotional faces, their blurred versions and checkerboards) to study the effects of emotional-face contents (online processing, Chapter 6).

Furthermore, the signal processing approaches in this work involved the following main methods of analysis:

1) ICA/BSS artifact rejection (offline and online, Chapters 3, 4, 5, 6, Appendix A)
2) Bandpass-based SSVEP feature extraction (offline and online, Chapters 3, 4, 5 and 6)
3) Normalized quadrature amplitude demodulation envelopes of the SSVEP brain response (offline, Chapter 3)
4) Normalized phase-locking value variability (PLVV) and wavelet-transformed energy variability (WTV) (offline, Chapter 5)
5) Statistical evaluation using two-factor analysis of variance (Chapters 3 and 5)
6) Other methods - inter-trial reproducibility analysis using cross-cumulant measures in single trials, area analysis, time-frequency decompositions using wavelet bases (Chapter 5).

The research described in this thesis has given successful proof, by using both signal processing techniques and neurophysiological experiments, for reaching the following general conclusions.

7.1. Conclusions – Properties of SSVEP Using Small Checkerboard Stimuli

Chapter 3 described an investigation of basic SSVEP properties such as the frequency characteristics and the time dynamics of the brain responses to small reversing checkerboard patterns. This knowledge was used in subsequent experiments to optimize the performance of SSVEP-based BCI systems. Specifically, the following conclusions were reached about SSVEP properties:

1) **SSVEP stimulus size**: Very small checkerboard stimuli, with diameter of 2.5° arc (size comparable to the fovea), elicited measurable and consistent SSVEP responses. Such small stimuli are necessary to minimize visual occlusion and free up useful screen space for executive purposes in applications such as multi-command BCI.

2) **SSVEP frequency response curve – optimal frequency range**: The frequency responses of the brain were measured for 32 discrete SSVEP stimulation frequencies from 5.1 Hz to 84.0 Hz using EEG data. The frequency stimulation range 5.6 – 15.3 Hz was found to be optimal for small patterned stimuli based on z-score analysis of the normalized brain responses.

3) **SSVEP frequency response curve – local maxima**: The maximal response to small-checkerboard SSVEP stimulation was elicited for 12Hz. Overall, local maxima in the frequency response were observed at 5.6 Hz, 8 Hz (7.6-8.8 Hz), 12 Hz, 15.3 Hz, and 28 Hz, with an additional small local enhancement at 42 Hz. For higher stimulation frequencies the brain responses deteriorated gradually. The highest inter-subject variability was observed at 9.9 Hz (which corresponds to individual differences in the intrinsic alpha-band activity).

The results for small-checkerboard reversal were in partial agreement with previous reports using different stimuli. Srinivasan (Srinivasan et al., 2006) showed that random-dot patterns elicited occipital response peaks at 12 Hz, as well as 8 Hz. Koch (Koch et al., 2006) experimented with red flash stimulation using goggles and found EEG response peaks for 11 Hz, and also for 5 Hz flicker. Furthermore, corroborating the findings described in this thesis, a study using transcranial magnetic stimulation (TMS) demonstrated strongest suppression of the brain's flash response when the lag between the stimulus and the magnetic pulse was 80-100 ms (Amassian et al., 1989).

4) **SSVEP time dynamics – onset and peak markers**: The first measurable SSVEP local maxima after the start of stimulation were observed at 1.5-2.5 s in single trials (~1.5 s

delay for 14 Hz, ~2 s for 8 Hz, and ~2.5 s for 28 Hz), as the SSVEP activity gradually increased after stimulation onset. In almost all trials, the SSVEP largest maxima were usually delayed by several seconds after the first peak. Before the first maxima, the earliest initial SSVEP onset delays (estimated according to individual baseline activity) were measured starting from 0.5 s after stimulation start. The SSVEP onset delays were also considerably frequency-dependent, with the largest mean delays observed for the highest measured frequency (28 Hz).

The proper understanding of the time delays of the SSVEP peak response to small checkerboard stimuli is essential in evaluating the inherent time-delay limitations of SSVEP-based BCI commands, and in overcoming these limitations by new methods. The relatively long SSVEP peak time delays, as observed in the narrow-band filtered data, may be accountable by attentional switching mechanisms which could cause delays of up to 0.6-0.8 s between cue onset and SSVEP facilitation (Müller et al., 1998).

5) **SSVEP time dynamics – optimal frequency:** Among the three investigated reversal frequencies in these experiments, 8 Hz (LF), 14 Hz (MF), and 28 Hz (HF), the 14 Hz response was the strongest in average and its first peak was the fastest (except for one subject who exhibited an 8 Hz preference). This result is in agreement with finding 2).

6) **SSVEP time dynamics – non-stationarity:** The dynamics of extended SSVEP responses (15 s in duration) were found to be essentially non-stationary, especially for higher stimulation frequencies (28 Hz). Recent EEG studies often examine relatively short-term SSVEP oscillations or otherwise ignore the oscillation envelope changes, which could be substantial at higher frequencies. Also, slow SSVEP envelope modulations with a period of roughly 2-3 s were observed in the data (Fig. 6), which may be due either to natural fluctuations in attention, or to inhibition feedback in order to prevent fatigue and preserve concentration, or possibly due to another unknown mechanism.

7) **Influence of brain sensor locations on SSVEP response quality:** SSVEP measurements at three scalp locations (occipital, parieto-temporal and frontal) showed that the SSVEP responses are available, but decline in quality with increasing distance from the occipital cortex. In addition, occipital sensor locations ensured the highest inter-trial reproducibility. 14 Hz responses were most reproducible when 8 Hz, 14 Hz, and 28 Hz were compared. The non-stationary SSVEP activity envelope was more transient and the shape of the responses was less predictable with repetition at the suboptimal parieto-temporal and frontal sensor locations for all studied stimulation frequencies. In that way, SSVEP measurements at non-occipital sites can be used for new, more practical SSVEP-BCI designs, but at the cost of reduced SSVEP signal quality.

Overall, it is concluded that the optimization of the experimental stimulus parameters in order to evoke a maximal visual brain response is essential due to possible substantial differences in the brain responses. SSVEP stimulus optimization enables higher efficiency for any SSVEP application, including the 8-command BCI system presented in this thesis.

7.2. Conclusions - Multi-command SSVEP-BCI SSVEP Using Small Checkerboard Stimuli

The design and evaluation of an 8-command SSVEP-based BCI system using visual stimuli with optimized brain responses lead to the following conclusions:

1) **SSVEP-BCI – overall evaluation:** The BCI system reached a mean command success rate of 98 % and mean command recognition delay of 3.4 ± 0.7 s, with information transfer rates of 50 bits/min, as the performance of the 8-command BCI system was measured in evaluation mode (using voice request-responses)

2) **SSVEP-BCI – optimal frequency range:** The highest possible BCI information transfer rates and robustness for the proposed paradigm were achieved for very small checkerboard SSVEP patterns reversing in the optimized 6.0 - 16.8 Hz range.

3) **SSVEP-BCI – effect of close proximity and large number of stimuli:** It is feasible to deploy a large number of small-checkerboard SSVEP patterns in close proximity to each other without substantial brain response interference. Close aggregation, small size and rapid movement of the 8 reversing patterns did not affect BCI performance negatively, and users were able to attend successfully to each selected pattern. The small size of the patterns and their attachment to the moving controllable object served to reduce the time and distraction from large eye movements necessary for patterns for example fixed to the edges of the screen (Trejo et al., 2006). This maximally robust mode of aggregated stimulation improved user performance and reduced fatigue by scaling down the demands on visual attention, especially over longer periods of operation.

4) **SSVEP-BCI – movement of SSVEP stimuli:** It is feasible to acquire reliable SSVEP responses from fast moving flickering/reversing visual patterns, in a novel dynamic paradigm for pattern SSVEP BCI (control of a moving object)

5) **SSVEP-BCI – non-occipital sensor locations:** It is feasible to use sub-optimal temporal or pre-frontal sensor locations on the scalp for new SSVEP-BCI designs with dry electrodes (without the need for application of EEG gel)

Since it is basically advantageous for BCI to use as small number of sensors as possible, SSVEP-based BCI systems employ mainly optimal electrode locations over the medial occipital (Lalor et al., 2004) or parieto-occipital cortex (Wang et al., 2006). However, in practical BCI applications it may be desirable to attach the brain sensors effortlessly, quickly and without the necessity for wet EEG gel. Hairless scalp locations such as the forehead and around the ears could meet these requirements if the feasibility of this approach could be demonstrated. That is why the performance of the SSVEP-based BCI was compared for 3 sensor locations – occipital, parieto-temporal, and frontal, in an extension of the neurophysiological SSVEP results in Chapter 3. As expected, the occipital locations facilitated optimal visual cortical responses, enabling the highest mean success rate (98 %) and the shortest mean time delay (3.4 s) necessary for the online analysis algorithm to capture reliably the user's intent. The hairless inferior parieto-temporal (near ears) and frontal (on forehead) electrode locations, which are more convenient for practical daily application, also enabled identification of the SSVEP response onset, however at the cost of increasingly reduced quality with greater distance from the visual cortex. The success rate was 81 % (delay 4.0 ± 1.2 s) for parieto-temporal locations, and 74 % (delay 4.3 ± 1.5 s) for frontal sensors.

6) **SSVEP-BCI – SSVEP non-stationarity:** On the basis of the results in Chapter 3, it is recommended for SSVEP-based BCI designs always to take into account the highly non-stationary and frequency-dependent nature of the SSVEP responses by using adaptive feature extraction, as well as stimuli with optimal characteristics capable of evoking the strongest single-trial brain responses possible.

7) **SSVEP-BCI – user training:** There were no observable changes in the SSVEP-BCI performance as novice users acquired better expertise in operating the BCI system, apart from a very short testing during the initial introduction to the task.

Overall, it is concluded that SSVEP-based BCI systems can achieve excellent reliability even for a high number of commands and little or no user training, if optimal stimulus parameters are used, and if proper inter-subject normalization measures are taken by the online analysis algorithm. It is feasible for practical adaptive BCI systems to utilize a large number of small checkerboard stimuli in close proximity to each other, as well as moving SSVEP stimuli. SSVEP-BCI is possible also when using only a few active sensors in suboptimal but hairless scalp locations, for example, mounted on a cap headband or incorporated in a sunglasses frame.

7.3. Conclusions – Properties of SSVEP Using Emotional-Face Video Stimuli

In Chapter 5, some essential brain response properties were studied for SSVEP flicker using emotionally-charged (Caucasian female) face video stimuli. The emotional face stimuli were compared to their blurred versions to remove the contents (De Cesarei and Codispoti, 2008), as well as to reversing checkerboards. The aim of these experiments was to evaluate this novel type of SSVEP stimuli for a subsequent application to BCI. The following conclusions were reached about emotional-face SSVEP properties:

1) **Emotional-Face SSVEP – effect of stimulus type:** SSVEP activity (averaged over flicker frequency) was statistically significantly dependent on stimulus type

2) **Emotional-Face SSVEP – effect of emotion/faces:** Affective face video SSVEP stimuli provided significantly stronger SSVEP responses than their corresponding emotionally-neutral blurred versions

3) **Emotional-Face SSVEP – no effect of emotional valence:** No significant differences in the occipital SSVEP responses were detected due only to emotional valence differences (happiness vs. anger)

4) **Emotional-Face SSVEP – no effect of inter-subject variability:** Furthermore, there were also no statistically significant differences between the SSVEP responses of individual subjects for all experimental conditions.

5) **Emotional-Face SSVEP – effect of frequency:** A frequency response curve was constructed for 5 SSVEP stimulation frequencies (5 - 12 Hz). The average SSVEP activity was strongest for 10Hz flicker when averaged over all stimulus types.

6) **Emotional-Face SSVEP – behavioural measures:** At the end of each experiment the subjects evaluated their degree of empathy (on a scale of 1 to 10) with the observed emotional faces. In general, they identified themselves slightly better with joyful faces than with angry ones (7 ± 1.9 for joy vs. 5.7 ± 2.2 for anger). A measure of self-estimated personal emotionality (also on a scale from 1 to 10) showed that the eight Japanese subjects were only moderately emotional (6.3 ± 2.1), which also indicates the relevance of cultural influences on affect.

7) **Emotional-Face SSVEP – effect on attention and fatigue:** The subjects also reported substantially higher level of attention (interest) for affective-face stimuli, as well as higher resistance to fatigue after long-term SSVEP exposure.

8) **Emotional-Face SSVEP – phase-based and energy-based algorithms for SSVEP onset detection and evaluation:** Novel single-trial phase-locking value variability (PLVV) and wavelet-transformed energy variability (WTV) measures were used in this offline analysis. The phase-based PLVV measure was found to be a more sensitive and fast indicator of SSVEP lock-in than the oscillation energy increase WTV measure. However, it was also observed that phase-resets at the flicker frequency may infrequently occur also due to other (background) brain events. It is concluded that an optimal SSVEP detection mechanism would be based on a parallel implementation of both phase-locking and energy variability tools in order to offer best results in terms of signal sensitivity, elimination of competing brain transients in the critical SSVEP frequency bands, and lower inter-subject variability.

Overall, it is concluded that the emotional-face contents in SSVEP stimuli were able to enhance the visual flicker responses of the brain, an effect which can be applied for optimized SSVEP-BCI systems.

7.4. Conclusions – Multi-command SSVEP-BCI SSVEP Using Emotional-Face Video Stimuli

On the basis of the findings of the previous neurophysiological experiments, happy and angry face video stimuli, as well as their blurred versions, and reversing checkerboards, were used to evaluate the hypothesis that affective-face video content of the SSVEP stimuli is able to optimize further the performance of a SSVEP-BCI systems. The following further conclusions were reached:

1) **Emotional-Face SSVEP-BCI – evaluation:** BCI command detection for 10 Hz flicker was ~20 % faster for affective-face SSVEP than for content-free blurred video or for neutral checkerboard stimuli (mean BCI delay 2.7s vs. 3.4s; mean BCI success rate 99% vs. 98%). When using affective-face stimuli, a higher mean BCI information transfer rates (ITR) of 64 bits/min was achieved, as compared to 50 bits/min for the neutral stimuli.

2) **Emotional-Face SSVEP-BCI – SSVEP non-stationarity over time:** Flicker stimulation using emotional face videos resulted in more stable and reliable band-pass SSVEP measures over time, in spite of the inherent non-stationarity of the brain's flicker response.

3) **Emotional-Face SSVEP-BCI – multi-command attention load and fatigue:** All users reported that their experience was enhanced by the affective-face video content as motivation (Lang, 1995) was sustained at higher levels (Kleih et al., 2010; Campanella et al., 2010) during switching of the attention focus between the different affective face stimuli. As

a result, BCI users also reported reduced long-term fatigue and frustration (according to the NASA TLX Frustration Scale).

4) **Emotional-Face SSVEP-BCI – executive devices requiring high reliability:** The optimized performance of the affective-face video SSVEP brain responses allowed the 8-command SSVEP-BCI system to control smoothly a multi-joint robotic arm with pre-programmed complex movements, targeted mainly for disabled users confined daily to wheelchair or bed settings.

Overall, it is concluded that it is advantageous to employ emotional-face video stimuli in SSVEP-based practical applications such as BCI.

7.5. Remaining Open Problems

The results achieved in this work also expose a number of open, unresolved problems in the research fields of SSVEP-BCI and SSVEP. Some of these problems may even be described as 'fundamental' since they would require a new theory or a new level of understanding of the relevant brain mechanisms. Undoubtedly, efforts from many research groups will present the solutions which are still not evident.

Some of the questions that may be raised are as follows (in order of presentation of the relevant topics in the thesis):

7.5.1. Open Problems - Steady-State Visual Evoked Potentials (SSVEP)

1) **SSVEP - frequency response curves and stimulus shapes:** The brain responses to SSVEP stimulation are very dependent on various stimulus parameters, since the visual system is highly sensitive to all details of the visual scene. When estimating the basic SSVEP

frequency response curve, currently there is no single answer as to its shape, and what are the 'optimal' stimulation frequencies. Especially important is the dependency of the frequency response on the stimulus size, shape and pattern composition. For example, SSVEP stimulation using large white stimuli has a different frequency response than SSVEP with very small checkerboards, or natural content such as emotional faces. It is imperative that researchers should understand the objective laws of this stimulus dependency in visual cortical processing, so that informed decisions can be made in SSVEP applications without the need for empirical measurements for each used stimulus shape. Until then, a research database of known SSVEP frequency responses could contribute substantially to the better comparison between various studies, similarly to other knowledge mapping efforts (Bohland et al., 2009).

2) **SSVEP – time dynamics problems caused by inherent SSVEP non-stationarities, attention:** Even though a human subject can clearly perceive an uninterrupted train of SSVEP flicker, most often the EEG brain responses are highly unstable and changing over the time span of several seconds. This phenomenon is probably due to the imperfection of the recording equipment, as well as the continuous interference between simultaneous brain-processes generating competing EEG output signals in the SSVEP stimulation band. It will be highly beneficial to create a new way of recording more stationary SSVEP signals with clear onsets and offsets synchronized with the stimuli.

3) **SSVEP – signal extraction methods:** A multitude of SSVEP signal extraction methods exists depending on research goals and requirements. The creation of a systematic taxonomy of SSVEP extraction algorithms, with their strengths and weaknesses, would enable more efficient SSVEP research and better comparisons between studies.

7.5.2. Open Problems - SSVEP-Based Brain-Computer Interfaces

1) **SSVEP-BCI – reduction of online command delays:** The mean time delay for BCI commands in this work was ~3.4 s for small checkerboard stimuli and ~2.7 s for affective-face video stimuli. Some previous SSVEP-BCI studies referred to delays of up to 7 s (Trejo et al., 2006). EEG experiments described in Chapter 3 were specifically targeted at determining the time dynamics limits and causes of such delays due to inherent brain response properties. As a result, the more sensitive phase-locking approach (offline) in Chapter 5 is a promising alternative to classical FFT-based or band-energy-based SSVEP estimation methods. Nevertheless, there is a clear need for online signal processing methods which are able to detect reliably and without substantial delay the onset of even very weak SSVEP responses such as those triggered by the small checkerboard stimuli used in this work.

2) **SSVEP-BCI – visual sensory channel occupancy problem:** By design, the SSVEP-based BCI paradigms require not only user's full attention, but also the complete engagement of the visual system, processing the user-selected external SSVEP stimuli to generate new BCI commands. This constitutes a disadvantage for this type of multi-command BCI in situations when the operator needs to use the visual field to control devices or observe the results of the most recent BCI neurofeedback (executive device). To reduce this problem to a minimum, the design in Chapter 4 of this thesis addressed it directly by decreasing the stimulus sizes to a minimum to avoid visual occlusion as much as possible. Nevertheless, new approaches may be necessary, such as using reliably covert attention (Müller and Hillyard, 2000) to peripheral SSVEP stimuli.

3) **SSVEP-BCI – sensors type and location problems:** Current SSVEP-BCI systems use mostly electroencephalography (EEG) for data acquisition due to the compact size and

low price of the devices. However, there is an essential problem in relation to that recording mode which is preventing a more wide-spread use of BCI systems for daily application. EEG sensors normally require the usage of conductive electrode gel to provide an acceptable signal-to-noise ratio for the acquired brain signals. This gel could dry out within a few hours of usage, and needs to be washed away at the end of the experiments. Recognizing this problem, recently new types of 'dry' electrodes without the need for connecting gel are being developed (Taheri et al., 1994; Searle et al., 2000; Fonseca et al., 2007), and increasingly made available by equipment manufacturers. Yet, a reliable and casual connection for such contactless electrodes may still require their preferred application on a hairless surface of the scalp, such as the forehead, or behind the ears. Again, experiments in Chapter 4 specifically investigated the feasibility of using such brain locations for SSVEP-BCI, and found it acceptable, although with decreased performance. Still, this problem persists, and new signal processing approaches are necessary to deal with weaker and more non-stationary SSVEP signals from non-visual brain locations, as well as potentially less reliable 'dry' electrodes, sweat and movement artifacts, and other factors interfering with an optimal BCI performance.

7.5.3. Open Problems – Affective-face video SSVEP and Brain-Computer Interfaces Based on Stimuli with Emotional or Cognitive Content

1) **Affective-face video SSVEP stimuli – origins of the emotion-vision interaction:** While SSVEP brain responses to simple visual stimuli (Regan, 1966), such as white squares or checkerboards, have predominantly visual components, including cognitive or emotional content in the stimuli, as well as enhancing the experience by natural video sequences, may increase substantially the complexity and non-linearity of the brain responses. The work presented in Chapter 5 of this thesis has demonstrated an enhancement of the oscillatory

visual activity due to emotional faces. However, the precise mechanisms of such response gain still remain to be investigated. One feasible hypothesis is that activity in the visual cortex corresponding to SSVEP is being boosted through a complex feedforward-feedback network connecting the primary visual cortex, the extrastriate visual cortex, the inferotemporal visual cortex, the amygdala, prefrontal brain areas, and the insula. A proposed model of these emotion-vision interactions, based on corroborating research reports, is shown in Fig. 36. According to this model, most essential for the observed boosting effect are the feedback connections from emotion-processing areas such as the amygdala and the prefrontal areas to the inferotemporal visual cortex, and back to other visual areas from there. Reportedly, the amygdala has also direct feedback connections to visual areas V1, V2, and V4 (Amaral et al., 2003), as shown in the connectivity model as well. It should be also mentioned here that additional brain processing (not shown in the model) of the affective face video stimuli presented in Chapters 5 and 6 of this thesis also occurs in the fusiform area responsible for face analysis, while the MT/V5 cortical area responds to the visual motion component of the video stimuli.

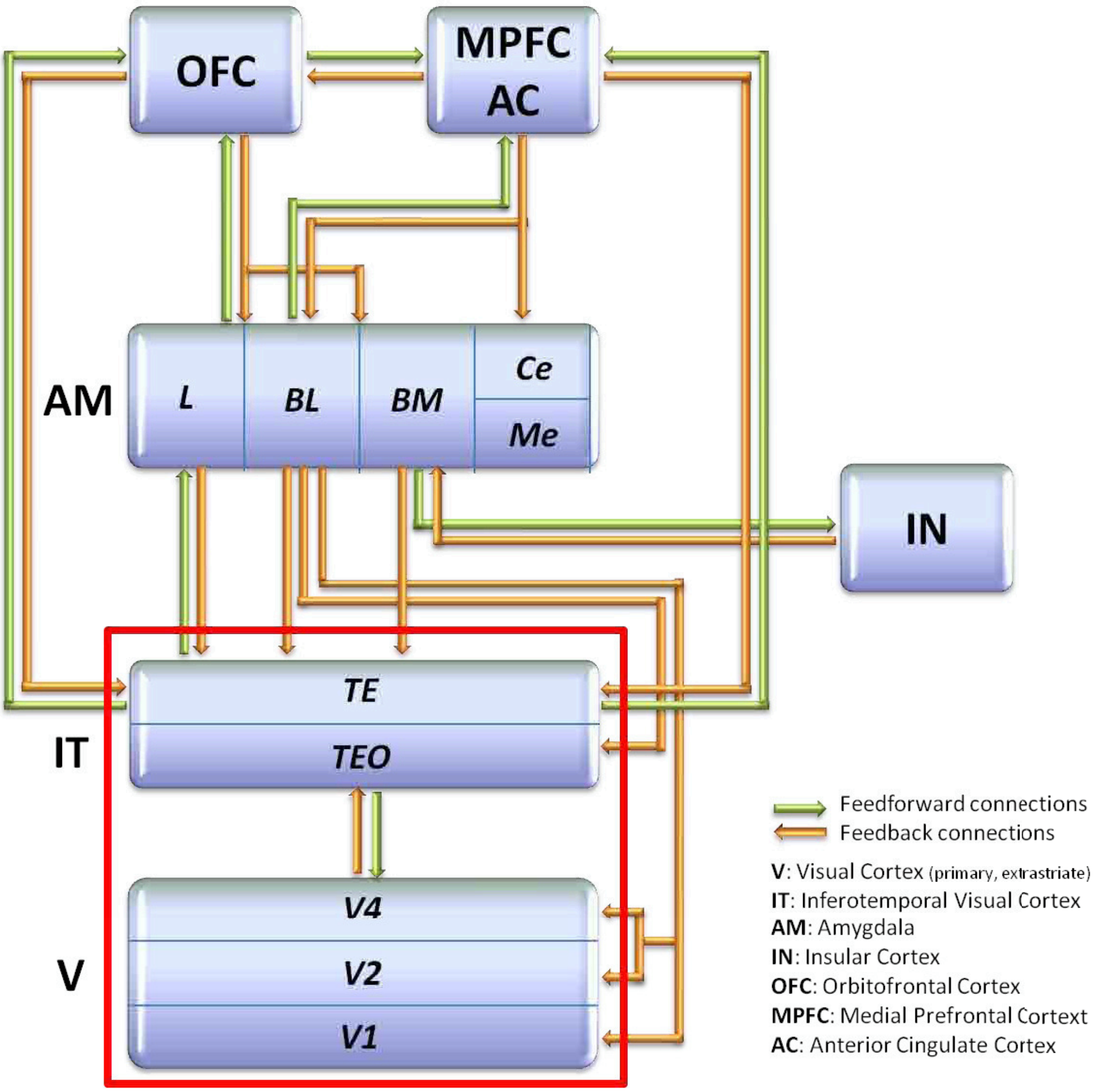


Fig. 36. A proposed model of emotion-vision interactions. The model includes feedforward-feedback connections between the primary visual cortex (V1), the extrastriate visual cortex (V2, V4), the inferotemporal visual cortex (IT), the amygdala (AM), prefrontal brain areas (OFC,MPFC,AC), and the insula (IN). Feedback connections from the amygdala and the prefrontal cortex to visual areas allow affective gating of visual input.

Ref: (Amaral and Price, 1984; Stefanacci and Amaral, 2002; Amaral et al., 2003; Freese and Amaral, 2005; Freese and Amaral, 2006; Sabatinelli et al., 2009; Rolls, 2009; Ghashghaei and Barbas, 2002; Höistad and Barbas, 2008; Barbas, 2007a; Barbas, 2007b; Barbas et al., 2010)

2) **Affective-face video SSVEP – Emotion-attention interactions:** The exact relationship between emotion processing and attentional processes has still not been completely clarified, and conclusions from different studies are rather controversial. Nevertheless, there is evidence that while in coarse affective-face tasks attention is not essential for producing emotional responses, in more demanding tasks attention modulates the processing of emotional stimuli (Pessoa, 2005). For example, briefly presented emotional faces do not automatically capture visual attention (Koster et al., 2007), however, beauty has been found to activate the same parietal regions which are associated with spatial attention (Kawabata and Zeki, 2004). Furthermore, emotional cues that signal reward or danger are able to capture attention preferentially (Lang et al., 1997; Vogt et al., 2008). In that way, visual attention may also play a substantial role in the emotion-vision interactions proposed in Fig. 36, recruiting other brain areas. The exact sources behind the SSVEP enhancement for emotional-face stimuli still remain to be investigated.

3) **Affective-face video SSVEP-BCI – individual variability:** While the work presented in Chapter 5 has shown that SSVEP responses were enhanced by emotional-face content, there may be additional sources of inter-subject variability due to differing cultural perceptions, mood swings, as well as the presence of negative emotions for some anxiety-prone users. Keeping the affective arousal moderately low may partially address this problem (as it was done here) but it may also reduce the effectiveness of the presented novel emotional-cognitive approach for the optimization of SSVEP-BCI paradigms.

7.6. Possible Future Directions for SSVEP-BCI

Brain technologies such as BCI have a strong potential to serve society. Some of the possible future directions for the SSVEP-based BCI designs presented in this thesis are:

1) Robust **Hybrid BCI** systems (Pfurtscheller et al., 2010a,b) using integration of 3 or more independent BCI types (such as SSVEP-BCI, motor-imagery BCI, P300-BCI and others). Easy switching between systems for users who have difficulties with a particular BCI type; Enhanced usage of commands when 2 or more BCI type are used simultaneously

2) Robust SSVEP-BCI systems with **more than 20 independent commands**, which would work reliably for most home users

3) New online SSVEP-BCI algorithms to detect reliably SSVEP activity immediately at stimulation onset

4) New error-resistant SSVEP-BCI designs to **minimize false-positive commands** even outside the laboratory, as the brain may use the same frequencies as the SSVEP flicker for other activities

5) Non-invasive remote control of appliances in intelligent **e-homes** (electronic homes) with BCI control capabilities. SSVEP-BCI-based e-homes would feature numerous small LCD screens each corresponding to a single BCI stimulus and command. This concept is conditional on the development of remote sensors to measure the brain activity from a distance

6) Robust SSVEP-BCI **robotic prosthesis limbs** (using either small portable screen(s) or e-home-based)

7) Effective SSVEP-based **diagnostic probes** for hospitals, clinics, or nursing homes for diagnosis of neuropathological conditions.

7.7. A Few Final Words

Unraveling the ‘mysterious’ brings great satisfaction to the inquiring mind (to paraphrase Einstein). I hope that with the work described in this thesis I can help use a few of the mysteries of the brain for the benefit of society. Reliable multi-command Brain-Computer Interfaces with designs such as the ones described in this thesis hold the promise of making life better for those disabled individuals who need our help the most. Finally, I would be greatly satisfied if the presented results would inspire others to continue from where this work has ended.

Appendix A:

INDEPENDENT COMPONENT ANALYSIS (ICA)

This appendix describes details of the Independent Component Analysis (ICA) method and the more general case of Blind Source Separation (BSS). The specific properties of the three ICA/BSS algorithms used in this thesis are given at the end of Appendix A.

A.1. Introduction

The main objective of the ICA/BSS procedure is to separate multi-channel input data into source components. When this 'unmixing' process is performed without any a-priori knowledge of the properties of the input signals, then it is called 'blind source separation' (BSS). BSS is a wider term for a second-order statistics (SOS) procedure which guarantees only that the sources will be spatio-temporally uncorrelated (independence is not required). The estimated sources would generally have low complexity and best linear predictability. Independent Component Analysis (ICA) represents a subset of BSS methods which include criteria for statistical independence as its objective is to find such a transformation for which the output signals (components) would be maximally independent. Since ICA/BSS performance may depend on several factors such as the specific algorithm, number of input channels, length of the input data, level of interfering 'noise', and so on, one essential problem in ICA/BSS pre-processing of EEG data is the challenge in evaluating and selecting the necessary components automatically. Several methods exist which are either based on the single-trial properties of the signal (Cichocki et al., ICALAB Toolboxes) (see also below), as well as the multi-trial structure of the data (Bakardjian, 2004b).

A.2. Independent Component Analysis (ICA)

ICA is a process which can extracts from exploratory (observed) input data represented by the m-dimensional vector $x(t)$ ($t = 1,2,\ldots,N$) a new set of statistically independent components represented by the n-dimensional vector

$$y(t) = Wx(t). \tag{17}$$

These components correspond to estimates of hidden or latent variables in the data called sometimes sources. This process assumes that a time series $x(t)$ has an embedded mixing process of the form

$$x(t) = As(t), \tag{18}$$

where A denotes an unknown mixing matrix and $s(t)$ is a vector representing unknown hidden (latent) variables or sources. ICA can be considered as a demixing or a decomposition process which is able to recover the original sources, i.e.,

$$y(t) = \hat{s}(t), \tag{19}$$

through the linear transformation $y(t) = Wx(t)$. The fact that two random variables are uncorrelated does not also imply that they are independent. This fact is lost in using other methods such as Principal Component Analysis (PCA). The ICA approach seeks to find such independent directions through maximization of a suitable cost function called sometimes contrast function which is a measure of statistical independence. Such functions can be maximized or minimized using various optimization methods, including artificial neural networks.

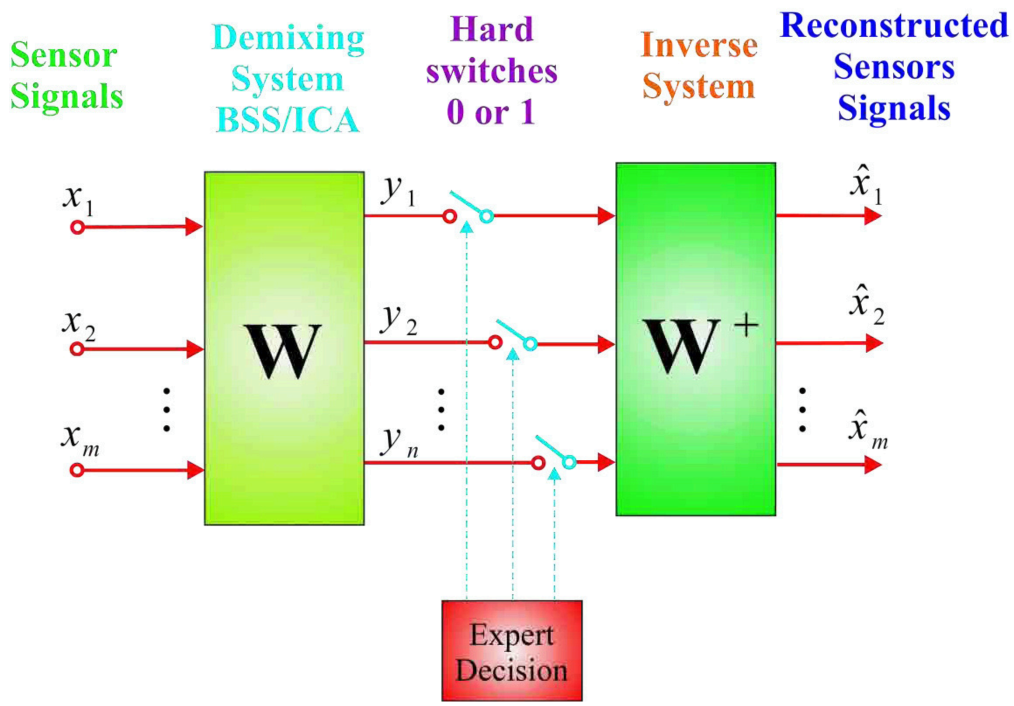


Fig. 37. Block diagram of the ICA/BSS component / artifact rejection procedure. After the input EEG signals are decomposed into independent-components / blind-sources, an automatic 'switch' procedures estimates which ones are artifacts. Only the remaining 'clean' components/ sources are reconstructed back to sensor / EEG space.

A.3. Algorithms for ICA

Independent component analysis (Fig. 37) can be considered an extension of the principal component analysis (PCA) method. In PCA, the input data $x(t)$ is decorrelated to find the components that are maximally uncorrelated according to second-order statistics. PCA gives orthogonalized and normalized outputs according to the second-order statistics by minimizing the second-order moments. The principal components can still be dependent however. The problem of independent component analysis or blind source separation of sources mixed instantaneously, can be defined as follows. Let's assume that we have available to us a set of multivariate time series $\{x_i(t)\}$ $(1,2,\ldots,m)$. We assume also that these time series, for example corresponding to individual EEG electrodes, are the result of an unknown mixing process defined by the following relationship:

$$x_i(t) = \sum_{j=1}^{n} a_{ij} s_j(t) \qquad (i = 1,2,\ldots,m) \tag{20}$$

or equivalently in compact matrix form $x(t) = A\, s(t)$ $(t=1,2,\ldots,N)$, where A is an unknown mixing matrix sized m by n, and $s(t) = [s_1(t),s_2(t),\ldots,s_n(t)]^T$ are hidden (latent) components called the sources. We seek to estimate the unknown sources $s_j(t)$ using only the observed data vector $x(t) = [x_1(t),x_2(t),\ldots,x_m(t)]^T$. The problem is to find a demixing or separating matrix W such that $y(t) = Wx(t)$ estimates the hidden independent components. It is possible that there could be a different numbers of sensors than sources, that is, A may not be square. If it is assumed that the number of sources (hidden components) is the same as the number of time series or observed inputs n, then A is a square (n by n) matrix. If $W = A^{-1}$, then $y(t) = s(t)$, and perfect separation occurs. In practice, the optimal y will be some permutated and scaled version of s, since it is only possible to find W such that $WA = PD$ where P is a permutation matrix and D is a diagonal scaling matrix. In general, the ICA of a random vector $x(t)$ is obtained by finding a n by m, (with $m \geq n$), full rank separating (transformation) matrix W such that the output signal vector $y(t) = [y_1(t),y_2(t),\ldots,y_n(t)]^T$ (independent components) estimated by $y(t) = Wx(t)$, are as independent as possible. Compared with the principal component analysis (PCA), which removes second-order correlations from observed signals, ICA further removes higher-order dependencies. Statistical independence of random variables is a more general concept than decorrelation. In general, we can state that random variables $y_i(t)$ and $y_j(t)$ are statistically independent if knowledge of the values of $y_i(t)$ provides no information about the values of $y_j(t)$.

Mathematically, the independence of $y_i(t)$ and $y_j(t)$ can be expressed by the relationship $p(y_i,y_j) = p(y_i)p(y_j)$, where $p(y)$ denotes the joint probability density function (pdf) of the random variable y. This means that the signals are independent if their joint probability density function can be factorized into marginal distributions.

A.4. Deflation and filtered reconstruction of multidimensional data

After extracting the independent components or performing blind separation of signals (from the mixture), we can examine the effects of discarding some non-significant components by reconstructing the observed EEG data from the remaining components. This procedure is called deflation or reconstruction, and allows us to remove unnecessary (or undesirable) components that are hidden in the mixture (superimposed or overlapped EEG data). In other words, the deflation procedure (Fig. 37, right side) allows us to extract and remove one or more components (or estimated sources) from the mixture data $x(t)$.

The deflation procedure is carried out in two steps. In the first step, the selected algorithm estimates the demixing (separating or decomposition) matrix W and then performs the decomposition of the data observations into the independent components $y(t) = Wx(t)$. In the second step, the deflation algorithm eliminates one or more components from the vector $y(t)$ and then performs the back-propagation

$$x_r(t) = W^{\dagger} y_r(t), \tag{21}$$

where $x_r(t)$ is a vector of reconstructed input (exploratory) data $x(t)$, $W^{\dagger} = \hat{A}$ is a generalized pseudo inverse matrix of the estimated demixing matrix W, and $y_r(t)$ is the vector obtained from the vector of independent components $y(t)$ after removal of all the undesirable components (i.e., by replacing them with zeros). In the special case, when the number of sources is equal to the number of observations (and the number of outputs), we can use the standard inverse matrix W^{-1} instead of the pseudo-inverse $W^{\dagger}$.

In block data format, the reconstruction procedure can be described as

$$X_r = W^{\dagger} Y_r \ , \tag{22}$$

where $X_r = [x_r(1), x_r(2), \ldots, x_r(N)]$ is the reconstructed (filtered) exploratory data, and $Y_r = [y_r(1), y_r(2), \ldots, y_r(N)]$ is the reduced set (selected or filtered) of the significant independent components. In the deflation procedure, we can eliminate undesirable components by discarding some of the components which represent, for example noise, artifacts or random interference.

The selection of a meaningful and useful subset of input variables is a difficult task. Procedures such as factor analysis (FA) and principal components analysis (PCA) have been widely used in this area. Both have been shown to have significant limitations. Independent Component Analysis (ICA) enables the extraction of independent components (ICs) from a set of multivariable observed (e.g. EEG data) $x(t)$. ICA is a process which statistically reduces a possibly very multidimensional complex data set into sub-components which are statistically independent. This procedure reduces the number of explanatory variables by condensing the set of information to a much smaller set of significant ICs. These ICs are expected to capture most of the useful information regarding the underlying events that form the basis for the indexes. Removal of some ICs representing the random processes, on-going activity of the brain or noise from the set of the recorded data makes it much easier to identify real relationships between the dominant ICs and the dependent variable. Since properly estimated ICs are statistically independent from each other, they can be used to create a new set of explanatory variables in order to investigate brain signal relationships much more efficiently than it would be possible with the unprocessed data.

A.5. The AMUSE algorithm for ICA/BSS (Chapters 4, 6)

Probably one of the simplest ICA and blind source separation procedures is the AMUSE algorithm (Tong et al., 1991). The AMUSE algorithm belongs to the group of second-order-statistics spatio-temporal decorrelation blind source separation algorithms. The AMUSE algorithm can be described as consisting of two consecutive PCA or SVD (singular value decomposition) blocks: First, PCA/SVD is applied to the input data; and second, SVD is applied to the time-delayed covariance matrix of the output of the previous stage. In the first step, a standard or robust pre-whitening (sphering) is applied as a linear transformation

$$z(t) = Qx(t), \tag{23}$$

where $Q = R_x^{-\frac{1}{2}}$ is a pre-whitening matrix of the standard covariance matrix defined as

$$R_x = E\{x(t)x^T(t)\} \cong XX^T/N \tag{24}$$

where *E* means expectation operator and *x*(*t*) is a vector of observed data for time instant *t*. Next, SVD is applied to a time-delayed covariance matrix of the pre-whitened data:

$$R_z = E\{z(t)z^T\,(t-1)\} = U\Sigma V^T\ , \tag{25}$$

where Σ is a diagonal matrix with decreasing singular values and *U*, *V* are matrices of eigenvectors. Then, the demixing (separating) matrix is estimated as

$$W = \hat{A}^{-1} = U^T Q. \tag{26}$$

The components extracted by the AMUSE are ordered according to decreasing singular values of the time-delayed covariance matrix. As in PCA and unlike many other ICA algorithms, all components estimated by AMUSE are uniquely defined (i.e., any run of algorithms on the same data will always produce the same components) and consistently ranked according to increasing complexity of components (decreasing linear predictaibility).

The high speed and inherent complexity ranking of the components gives the AMUSE algorithm an advantage which is so far unsurpassed for online BCI applications.

A.6. The SOBI algorithm for ICA/BSS (Chapter 3)

A natural extension of AMUSE is the Robust Second Order Blind Identification (SOBI) (Belouchrani et a., 1997) with Joint Approximate Diagonalization (JAD) (Cardoso and Souloumiac, 1996), which estimates the matrix $\underline{U}$ more robustly in respect to noise. In the SOBI algorithm the unitary matrix $\underline{U}$ performs approximate jointly diagonalization of many time delayed covariance matrices

$$R_z(\tau) = E\{z(t)z^T\,(t-\tau)\} \qquad (\tau = 1,2,\dots,P)\,, \tag{27}$$

where typically P is 100 for noisy data.

The source components obtained by SOBI were subjected to automatic ranking, based on Hoyer sparsity measures, in order to remove any subjectivity in the artifact component selection procedure. Algorithms like AMUSE and SOBI exploit only second order statistics (SOS) information by using time-delayed covariance matrices, and they cannot be considered to perform ICA. Nevertheless, BSS algorithms are generally better able to estimate the original source (component) signals even if they are not completely mutually statistically independent, which is often the case with multi-channel EEG data.

A.7. The UNICA algorithm for ICA/BSS (Chapter 5)

The advantages of the Unbiased Quasi-Newton Algorithm for ICA (UNICA) algorithm (Cruces et al., 2000) consist mainly in its reliable separation of ocular independent components by performing unbiased ICA in the presence of strongly correlated Gaussian noise in the mixture. UNICA performs quasi-Newton iteration for the estimation of the mixing system with a minimum variance distortion response criterion which eliminates from the outputs the interfering components and all the noise that is outside the extracted signal subspace. UNICA was selected for offline pre-processing of the data after evaluation of more than 20 ICA algorithms (Cichocki et al., ICALAB Toolboxes) based on distinctive time-frequency signatures showing: 1) minimal number of components containing undesirable eye-blinking artifacts; 2) lack of other signals in the artifact components.

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Invited Talks *(in chronological order)*

1. Steady-State Visual Evoked Responses As A Reliable Tool For Online Brain-Machine Interfaces, BSI-TOYOTA Collaboration Center Seminar, BSI, RIKEN, Wako, Japan, Mar.25, 2008.

2. An EEG-Based Brain-Computer Interface with Multiple SSVEP Commands, Università Politecnica delle Marche, Ancona, Italy, Mar.28, 2007.

3. Real-time multi-command EEG-based Brain-Computer Interface platform, Round Table "EEG signal processing: applications in BCI systems", Fondazione Santa Lucia, Rome, Italy, Mar.7, 2007.

4. Electroencephalography (EEG): From Artifact Removal To Emotion Recognition, EMAC Series Seminar, Kyushu University, Feb.22, 2007.

5. A Real-Time Brain-Computer Interface with Multiple Commands Using Blind Source Separation for Artifact Removal, Frontier Medilac Seminar, Research Center for Frontier Medical Engineering, Chiba University, Nov.27, 2006.

6. Real-time multi-command EEG-based Brain-Computer Interface platform, Hot Topic Talk at the 9th Retreat of the Brain Science Institute, The Institute of Physical and Chemical Research, Oegawa, Konan-cho, Saitama, Japan, Oct.31, 2006.

7. Measurement of Weak Electrical Signals from the Human Brain, Riken-Denso Industry Fusion Seminar, Brain Science Institute, RIKEN, Wako, Japan, Oct.11, 2006.

8. Driver Satisfaction Enhancement by Adaptive Brain Response Optimization, Riken-Subaru Collaboration Seminar, Brain Science Institute, RIKEN, Wako, Japan, May.14, 2004.

9. Crossmodal interplay of auditory and visual cortical responses revealed by single-trial wavelet-packet-enhanced ICA, Brain Science Institute, RIKEN, Wako, Japan, October 15, 2003.