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Hardware/Software Components and Applications of BCIs

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1. Introduction

Human-Computer interfaces can use different signals from the body in order to control external devices. Beside muscle activity (EMG-Electromyogram), eye movements (EOG-Electrooculogram) and respiration also brain activity (EEG-Electroencephalogram) can be used as input signal. EEG-based brain-computer interface (BCI) systems are realized either with (i) slow cortical potentials, (ii) the P300 response, (iii) steady-state visual evoked potentials (SSVEP) or (iv) motor imagery.

Potential shift of the scalp EEG over 0.5 – 10 s are called slow cortical potentials (SCPs). Reduced cortical activation goes ahead with positive SCPs, while negative SCPs are associated with movement and other functions involving cortical activation (Birbaumer, 2000). People are able to learn how to control these potentials, hence it is possible to use them for BCIs as Birbaumer and his colleagues did (Birbaumer, 2000, Elbert, 1980). The main disadvantage of this method is the extensive training time to learn how to control the SCPs. Users need to train in several 1-2 h sessions/week over weeks or months.

The P300 wave was first discovered by Sutton (Sutton, 1965). It elicits when an unlikely event occurs randomly between events with high probability. In the EEG signal the P300 appears as a positive wave about 300 ms after stimulus onset. Its main usage in BCIs is for spelling devices, but one can also use it for control tasks (for example games (Finkea, 2009) or navigation (e.g. to move a computer-mouse (Citi, 2008))). When using P300 as a spelling device, a matrix of characters is shown to the subject. Now the rows and columns (or in some paradigms the single characters) of the matrix are flashing in random order, while the person concentrates only on the character he/she wants to spell. For better concentration, it is recommended to count how many times the character flashes. Every time the desired character flashes, a P300 wave occurs. As the detection of one single event would be imprecise, more than one trial (flashing of each character) has to be carried out to achieve a proper accuracy.

Krusiński et al. (Krusiński, 2006) evaluated different classification techniques for the P300 speller, wherein the stepwise linear discriminant analysis (SWLDA) and the Fisher's linear discriminant analysis provided the best overall performance and implementation characteristics. A recent study (Guger 2009), performed on 100 subjects, revealed an average accuracy level of 91.1%, with a spelling time of 28.8 s for one single character. Each character was selected out of a matrix of 36 characters.

Steady state visual evoked potentials (SSVEP)-based BCIs use several stationary flashing sources (e.g. flickering LEDs, or phase-reversing checkerboards), each of them flashing with another constant frequency. When a person gazes at one of these sources, the specific frequency component will increase in the measured EEG, over the occipital lobe. Hence, when using different light sources, each of them representing a predefined command, the person gives this command by gazing onto the source. The classification is either done by FFT-based spectrum comparison, preferably including also the harmonics (Müller-Putz, 2005), or via the canonical correlation analysis (CCA) (Lin, 2006). A third possibility is via the minimum energy approach which was published by O. Friman et al. in 2007 (Friman, 2007) and requires no training.

Typical SSVEP applications are made for navigation, for example Middendorf et al. (Middendorf, 2000) used SSVEPs to control the roll position of a flight simulator. The number of classes varies between two and eight, although Gao et al. (Gao, 2003) established an experiment with even 48 targets. Bakardijan et al. (Bakardijan, 2010) investigated SSVEP responses for frequencies between 5 and 84 Hz to find the strongest response between 5.6 Hz and 15.3 Hz peaking at 12 Hz. With their frequency-optimized-eight-command BCI they achieved a mean success rate of 98 % and an information transfer rate (ITR) of 50 bits/min. Bin et al. (Bin, 2009) reports of a six-target BCI with an average accuracy of 95.3% and an information transfer rate of 58 ± 9.6 bits/min.

Although most SSVEP-based BCIs work with gaze shifting towards a source, recent studies (Allison, 2009, Zhang, 2010) proofed that only selective attention onto a pattern alone is sufficient for control. The latter paper achieved an overall classification accuracy of $72.6 \pm 16.1\%$ after 3 training days. Therefore also severely disabled people, who are not able to move their eyes, can control an SSVEP-based BCI.

When subjects perform or only imagine motor tasks, an event related desynchronization (ERD) (Pfurtscheller & Neuper, 1997) and an event related synchronization (ERS) is detectable by changes of EEG rhythms on electrodes close to the respective sensorimotor areas. The ERD is indicated by a decrease of power in the upper alpha band and lower beta band, starting 2 seconds before movement onset on the contra lateral hemisphere and becomes bilaterally symmetrical immediately before execution of movement (Pfurtscheller, 1999). An ERS appears either after termination of the movement, or simultaneously to the ERD, but in other areas of the cortex. The decrease/increase is always measured in comparison to the power in a reference interval, for example a few seconds before the movement occurs. For classification there are several approaches used. The simplest one is by calculating the bandpower in a specific frequency band and consecutive discrimination via a Fisher linear discriminant analysis. Other classification strategies are support vector machines (SVM) (Solis-Escalante, 2008), principal component analysis (PCA) (Vallabhaneni, 2004), or common spatial patterns (CSP) (Guger, 2003)

2. Components and signals

For BCI experiments the subject or the patient is connected via electrodes or sensors to a biosignal amplifier and a data acquisition unit (DAQ board) containing the analog-to-digital conversion (as shown in Figure 1). Then the data are passed to the real-time system to perform the feature extraction and classification. Important is that the real-time system

works fast enough to present feedback to the subject via a stimulation unit. The feedback represents the BCI output and allows the subject to learn the BCI control faster. For system update and data collection a central control unit managing several systems is of advantage.

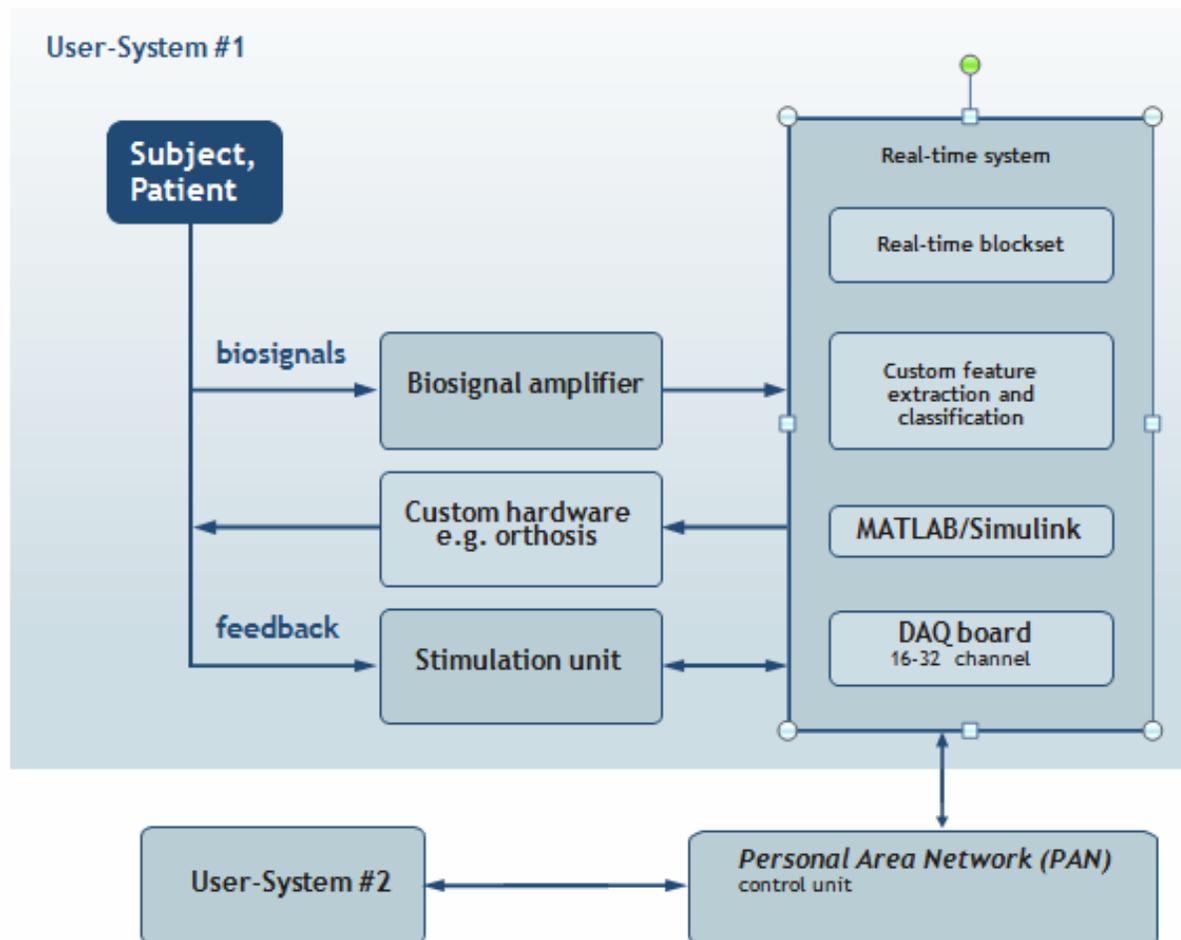


Fig. 1. BCI components to run real-time experiments

2.1 Electrodes

For EEG measurements normally single disk electrodes made of gold or Ag/AgCl are used (see Figure 2). Gold electrodes are maintenance free and have a good frequency response for EEG, EMG or ECG measurements. For DC derivations with EEG frequencies below 0.1 Hz Ag/AgCl electrodes perform better than gold electrodes. Passive electrodes consist only of the disk material and are connected with the electrode cable and a 1.5 mm medical connector to the biosignal amplifier. Active electrodes have a pre-amplifier with gain 1-10 inside the electrode which makes the electrode less sensitive to environmental noise such as power line interference and cable movements. Because of this fact, active electrodes also work if the electrode-skin impedance is higher than for passive electrodes (should be below 10 kOhm). Active electrodes have system connectors to supply the electronic components with power. Fig.A, Fig.B and Fig.C show EEG electrodes that can be fitted into EEG caps, Fig.D shows an ECG/EMG electrode which is placed close to the muscle/heart. Electrodes of type A and D can also be used for EOG recordings.

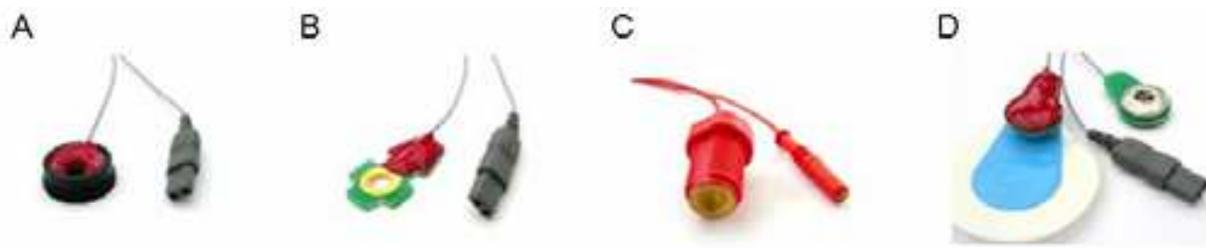


Fig. 2. Electrodes for EEG, ECG, EOG,... measurements. A: Active single electrode with multi-pole connector; B: active gold electrode with multi-pole connector; C: screw-able passive gold electrode to adjust location; D: active ECG electrode with disposable Ag/AgCl electrode

EEG electrodes are normally distributed on the scalp according to the international 10-20 electrode system. Therefore, the distance from the Inion to the Nasion is first measured. Then, electrode Cz on the vertex of the cap is shifted exactly to 50 % of this distance, as indicated in Figure 3A. Figure 3B shows a cap with 64 positions. The cap uses screwable single electrodes to adjust the depth and optimize electrode impedance. Each electrode has a 1.5 mm safety connector which can be directly connected to the biosignal amplifier. Active electrodes have system connectors to supply the electronic components with power. There are two main advantages of a single electrode system: (i) if one electrode breaks down it can be removed immediately and (ii) every electrode montage can be realized easily. The disadvantage is that all electrodes must be connected separately each time. Hence, caps are also available with integrated electrodes. All the electrodes are combined in one ribbon cable that can be directly connected to system connectors of the amplifiers. The main disadvantage is the inflexibility of the montage, and the whole cap must be removed if one electrode breaks down.

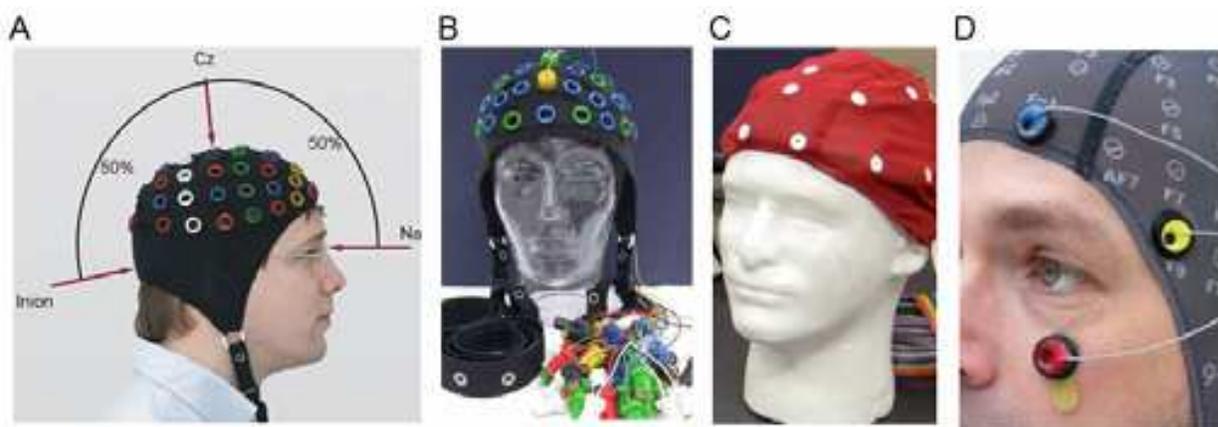


Fig. 3. Electrode caps. A: Electrode positioning according to the 10/20 electrode system. B: Electrode cap with screwable single passive or active electrodes. C: Electrode cap with build-in electrodes with a specific montage. D: Electrode cap with active electrodes

Active electrodes avoid or reduce artifacts and signal noise resulting from high impedance between the electrode(s) and the skin (e.g. 50/60 Hz coupling, artifacts caused by electrode or cable movements, distorted signals or background noise). Figure 4 shows a comparison of active and passive electrodes. Active electrodes were mounted on positions F1 (channel 1), C1 (channel 2), O1 (channel 3) with g.GAMMAgel (no abrasion) and passive electrodes were

mounted on positions F2 (channel 4), C2 (channel 5) and O2 (channel 6) with abrasive gel. Active and passive electrodes are located next to each other to allow a better comparison. The ground electrode was located on position FPz. The active electrodes were referenced against the right ear. The passive electrodes are referenced against the left ear. Five conditions were compared: (i) eye movements, (ii) biting, (iii) cable artefacts, (iv) active head movements by the person himself and (v) passive head movements done by a second person.

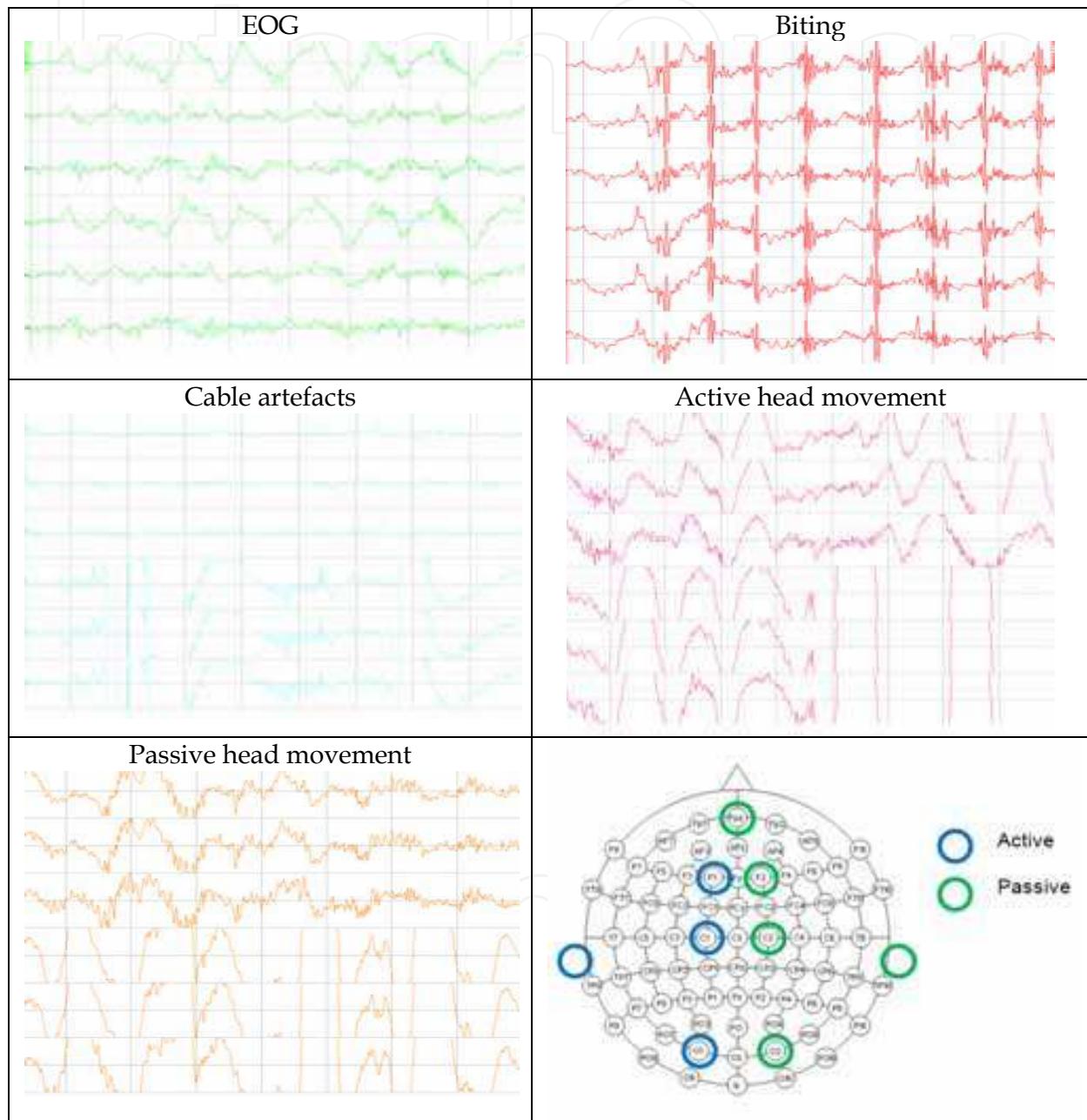


Fig. 4. Comparison of active and passive electrodes. The first three channels in each plot are recorded with active electrodes, the last three channels with passive electrodes

EYE MOVEMENTS -The channels closer to the eyes (1 and 4) show higher EOG artefacts than central and occipital channels. Both passive and active electrodes show a similar EOG contamination which is also clear because both pick up the same source signal.

BITING - Biting produces an EMG contamination almost equally on all channels and there is no difference between active and passive electrodes because both pick up the same source signal.

CABLE ARTEFACTS - Cable artefacts are produced by touching or shaking the cables. The active electrodes are almost unaffected while the passive electrodes show large movement artefacts.

ACTIVE HEAD MOVEMENTS - Active head movements produce fewer artefacts with active electrodes compared to passive ones. Artefacts for both electrodes can occur because of skin-electrode movements. Passive electrodes are mostly affected by the cable movements initiated by the head movements.

PASSIVE HEAD MOVEMENTS - Passive head movements have lower accelerations than active head movements and therefore the artefacts are smaller and mostly visible with passive electrodes.

2.2 Biosignal amplifier

One of the key components of a physiological recording and analysis system is the biosignal amplifier. Figure 5 illustrates g.USBamp and a block diagram of the amplifier.

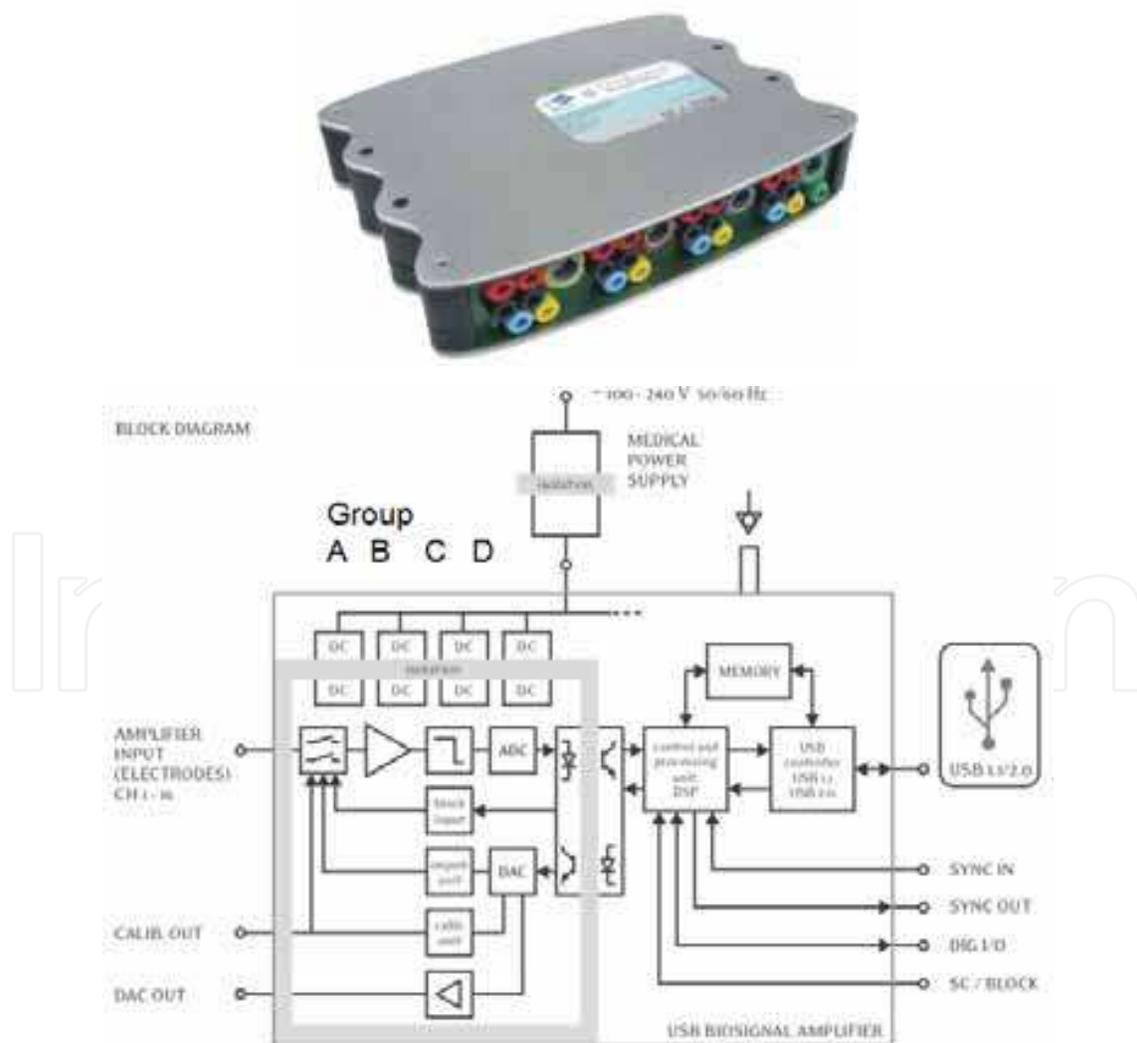


Fig. 5. Biosignal amplifier and block diagram

This device has 16 input channels, which are connected over software controllable switches to the internal amplifier stages and anti-aliasing filters before the signals are digitized with sixteen 24 Bit ADCs. The device is also equipped with digital to analog converters (DAC) enabling the generation of different signals like sinusoidal waves, which can be sent to the inputs of the amplifiers for system testing and calibration. Additionally, the impedance of each electrode can be checked by applying a small current to the individual electrodes and measuring the voltage drops. All these components are part of the so-called applied part of the device, as a subject or patient is in contact to this part of the device via the electrodes. All following parts of the device are separated via optical links from the subject/patient.

The digitized signals are passed to a digital signal processor (DSP) for further processing. The DSP performs an over-sampling of the biosignal data, band pass filtering, Notch filtering to suppress the power line interference and calculates bipolar derivations. These processing stages eliminate unwanted noise from the signal, which helps to ensure accurate and reliable classification. Then the pre-processed data are sent to a controller which transmits the data via USB 2.0 to the PC. One important feature of the amplifier is the over-sampling capability. Each ADC is sampling the data at 2.4 MHz. Then the samples are averaged to the desired sampling frequency of e.g. 128 Hz. Here a total of 19.200 samples are averaged, which improves the signal to noise ratio by the square root of $19.200 = 138,6$ times.

For EEG or ECoG (Electrocorticogram) recordings with many channels, multiple devices can be synchronized. One common synchronization signal is utilized for all ADCs, yielding a perfect non delayed acquisition of all connected amplifiers. This is especially important for evoked potential recordings or recordings with many EEG channels. If only one ADC with a specific conversion time is used for many channels, then a time lag between the first channel and the last channel could be the result (e.g. 100 channels * 10 μ s = 1 ms). Important is also that biosignal acquisition systems provide trigger inputs and outputs to log external events in synchrony to the data or to send trigger information to other external devices such as a visual flash lamp. Digital outputs can also be used to control external devices such as a prosthetic hand or a wheelchair. An advantage here is to scan the digital inputs together with the biosignals to avoid time-shifts between events and physiological data. A medical power supply that works with 230 or 110 V is required for physiological recording systems that are used mainly in the lab. For mobile applications like the controlling a wheelchair, amplifiers which run on battery power are also useful.

For invasive recordings, only devices with an applied part of type CF are allowed. For EEG measurements, both BF and CF type devices can be used. The difference here is the maximum allowed leakage current. Leakage current refers to electric current that is lost from the hardware, and could be dangerous for people or equipment. For both systems, the character F indicates that the applied part is isolated from the other parts of the amplifier. This isolation is typically done based on opto-couplers or isolation amplifiers. For a BF device, the ground leakage current and the patient leakage current must be $\leq 100 \mu$ A according to the medical device requirements, such as IEC 60601 or EN 60601. These refer to widely recognized standards that specify details of how much leakage current is allowed, among other details. For a CF device, the rules are more stringent. The ground leakage current can also be $\leq 100 \mu$ A, but the patient leakage current must be $\leq 10 \mu$ A only.

The next important feature is the number of electrodes used. For slow wave approaches or oscillations in the alpha and beta range and P300 systems, a total of 1-8 EEG channels are sufficient (Birbaumer, 2000, Krusienski, 2006, Guger, 2003). BCIs that use spatial filtering,

such as common spatial pattern (CSP), require more channels (16-128) (Ramoser, 2000). For ECoG recordings, 64-128 channel montages are typically used (Leuthardt, 2004). Therefore, stack-able systems might be advantageous because they can extend the functionality with future applications. A stack-able e.g. 64-channel system can also be split into four 16-channels systems if required for some experiments.

The signal type (EEG, ECoG, evoked potentials - EP, EMG, EOG) also influences the necessary sampling frequency and bandwidth of the amplifier. For EEG signals, sampling frequencies of 256 Hz with a bandwidth of 0.5 - 100 Hz are typically used (Guger, 2001). For ECoG recordings, sampling frequencies of 512 or 1200 Hz are applied with a bandwidth of 0.5 - 500 Hz (Leuthardt, 2004). A special case are slow waves, where a lower cut - off frequency of 0.01 Hz is needed (Birbaumer, 2000). For P300 based systems, a bandwidth of 0.1 - 30 Hz is typically used (Sellers, 2006). Notch filters are used to suppress the 50 Hz or 60 Hz power line interference. A notch filter is typically a narrow band-stop filter having a very high order. Digital filtering has the advantage that every filter type (Butterworth, Bessel, etc), filter order, and cut-off frequency can be realized. Analog filters inside the amplifier are predefined and can therefore not be changed. The high input range of g.USBamp of ± 250 mV combined with a 24-bit converter (resolution of 29 nV) allows measuring all types of biosignals (EMG, ECG, EOG, EPs, EEG, ECoG) without changing the amplification factor of the device.

2.3 Real-time processing environment

Physiological recording systems are constructed under different operating systems (OS) and programming environments. Windows is currently the most widely distributed platform, but there are also implementations under Windows Mobile, Linux and Mac OS. C++, LabVIEW (National Instruments Corp., Austin, TX, USA) and MATLAB (The MathWorks Inc., Natick, USA) are mostly used as programming languages. C++ implementations have the advantages that no underlying software package is needed when the software should be distributed, and allow a very flexible system design. Therefore, a C++ Application Program Interface (API) was developed that allows the integration of the amplifiers with all features into programs running under Windows or Windows Mobile. The main disadvantage is the longer development time. The BCI2000 software package was developed with the C API (Schalk, 2004).

Under the MATLAB environment, several specialized toolboxes such as signal processing, statistics, wavelets, and neural networks are available, which are highly useful components for a BCI system. Signal processing algorithms are needed for feature extraction, classification methods are needed to separate biosignal patterns into distinct classes, and statistical functions are needed e.g. for performing group studies. Therefore, a MATLAB API was also developed, which is seamlessly integrated into the Data Acquisition Toolbox. This allows direct control of the amplification unit from the MATLAB command window to capture the biosignal data in real-time and to write user specific m-files for the data processing. Furthermore, standard MATLAB toolboxes can be used for processing, as well as self-written programs. The MATLAB processing engine is based upon highly optimized matrix operations, allowing very high processing speed. Such a processing speed is very difficult to realize with self-written C code.

Beside the MATLAB and C API it is also useful to have a rapid prototyping environment that allows to create different BCI experiments rapidly. Such an environment was designed under

Simulink and allows the real-time processing of EEG data. The following BCI experiments were realized with this “Highspeed On-line Processing for Simulink” software package.

2.3.1 Motor imagery

To train a user to control a BCI with motor imagery a training paradigm is necessary that is synchronized with the EEG data acquisition and real-time analysis. Therefore the subject is seated in front of the computer screen where the paradigm is shown. The user has the task to wait until an arrow pointing either to the right or left side of the screen occurs (using bipolar EEG derivation around C3 and C4). The direction of the arrow instructs the subject to imagine a right or left hand movement for 3 seconds. Then, after some delay, the next arrow appears. The direction of the arrows is randomly chosen, and about 40-200 trials are typically used for further processing. The EEG data, together with the time points of the appearance of the arrows on the screen, are loaded for off-line analysis to calculate a subject-specific weight vector (WV) which is used for the feedback experiment.

A Simulink model for the real-time analysis of the EEG patterns is shown in Figure 5. Here ‘g.USBamp’ represents the device driver reading data from the biosignal amplifier into Simulink. Then the data is converted to ‘double’ precision format and connected to a ‘Scope’ for raw data visualization and to a ‘To File’ block to store the data in MATLAB format. Each EEG channel is further connected to 2 ‘Bandpower’ blocks to calculate the power in the alpha and beta frequency range (both ranges were identified with the ERD/ERS and spectral analysis). The outputs of the band-power calculation are connected to the ‘BCI System’, i.e. the real-time LDA implementation which multiplies the features with the weight vector WV. The ‘Paradigm’ block is responsible for the presentation of the experimental paradigm in this case the control of the arrows on the screen and the feedback.

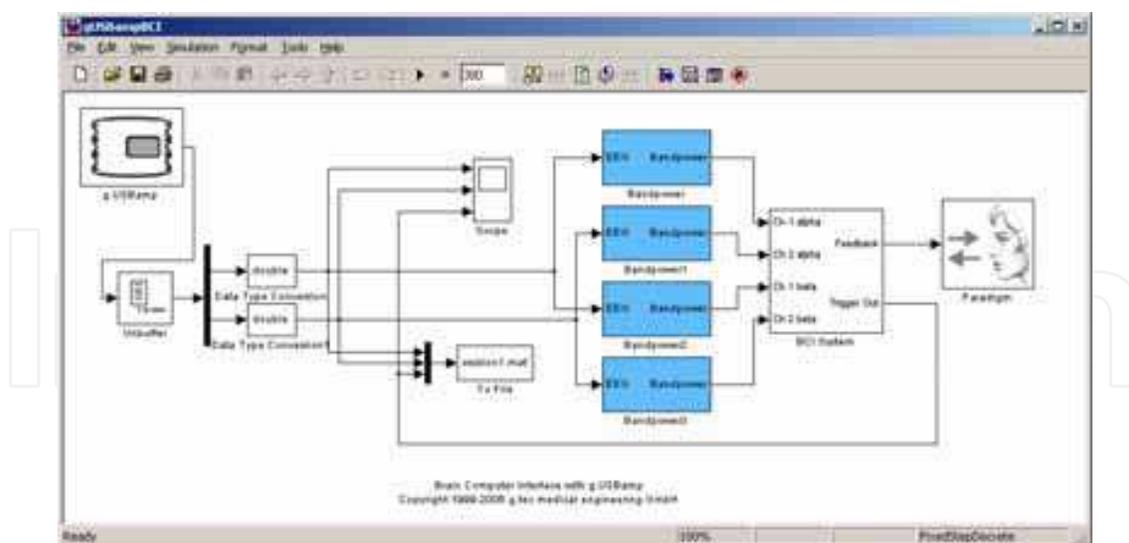


Fig. 5. Simulink model for the real-time feature extraction, classification and paradigm presentation

2.3.2. P300

A P300 spelling device can be based on a 6 x 6 matrix of different characters displayed on a computer screen. The row/column speller flashes a whole row or a whole column of

characters at once in a random order as shown in Figure 6. The single character speller flashes only one single character at an instant in time. This yields of course to different communication rates; with a 6 x 6 matrix, the row/column approach increases speed by a factor of 6. The underlying phenomenon of a P300 speller is the P300 component of the EEG, which is seen if an attended and relatively uncommon event occurs. The subject must concentrate on a specific letter he/she wants to write (Sellers, 2006, Guger, 2009). When the character flashes on, the P300 is induced and the maximum in the EEG amplitude is reached typically 300 ms after the flash onset. Several repetitions are needed to perform EEG data averaging to increase the signal to noise ratio and accuracy of the system. The P300 signal response is more pronounced in the single character speller than in the row/column speller and therefore easier to detect (Guger, 2009).

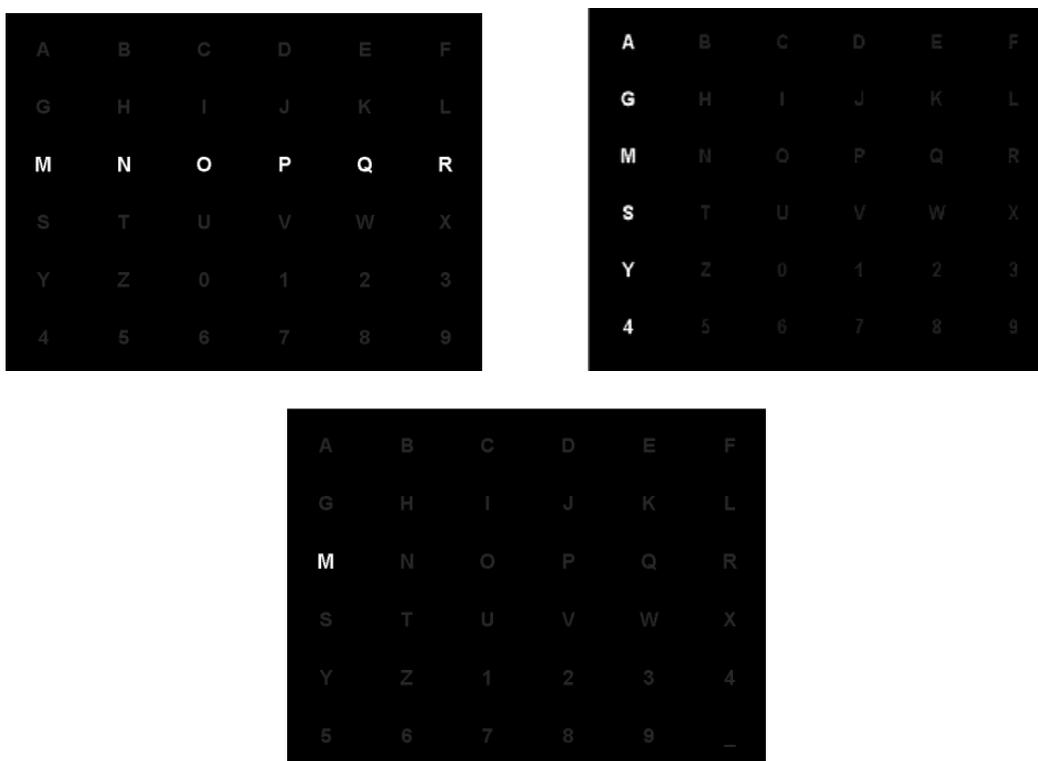


Fig. 6. Left, mid panels: row/column speller. Right panel: single character speller

For training, EEG data are acquired from the subject while the subject focuses on the appearance of specific letters in the copy spelling mode (positions Fz, Cz, Pz, Oz, P3, P4, PO7, PO8). In this mode, an arbitrary word like LUCAS is presented on the monitor. First, the subject counts whenever the L flashes. Each row, column, or character flashes for e.g. 100ms per flash. Then the subject counts the U until it flashes 15 times, and so on. These data, together with the timing information of each flashing event, are then loaded for off-line analysis. Then, the EEG data elicited by each flashing event are extracted within a specific interval length and divided into sub-segments. The EEG data of each segment are averaged and sent to a step-wise linear discriminant analysis (LDA). The LDA is trained to separate the target characters, i.e. the characters the subject was concentrating on (15 flashes x 5 characters), from all other events (15 x 36 - 15 x 5). This yields again a subject specific weight vector WV for the real-time experiments. It is very interesting for this approach that the LDA is trained only on 5 characters representing 5 classes and not on all 36 classes. This

driving commands (0-stop, 1-forward, 2-right, 3-backward, 4-left) and sends them to the robot, which moves and gives the feedback to the user.

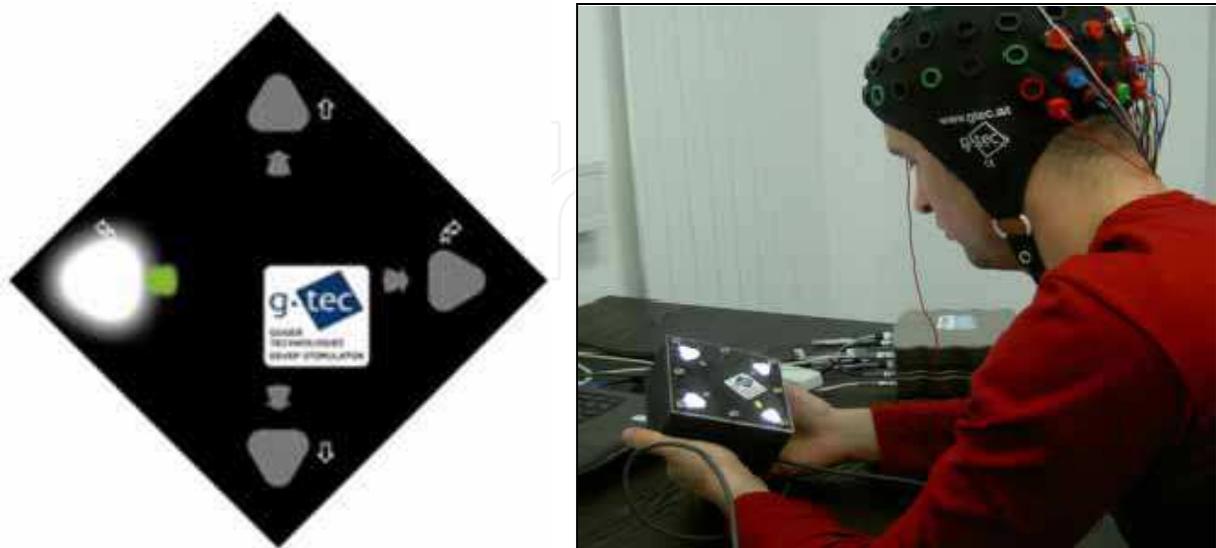


Fig. 8. SSVEP stimulation box and EEG recording

The four LEDs are flickering with different frequencies (10, 11, 12 and 13 Hz). These frequencies have been chosen in preceding off-line tests and showed good performance for the test subjects and are also known from literature to give good accuracy (Friman, 2007). During training the subject has to look at each of the LEDs for several seconds which are controlled by the paradigm. Beside the EEG data also the instruction at which LED the user should look at is logged to harddisk.

All the components of the BCI system are shown in Figure 9. EEG data are recorded with a sampling rate of 256 Hz with the g.USBamp block. Then in the Preprocessing block Laplacian derivations are performed. Each Laplacian derivation is composed of one center signal X_C and an arbitrary number $n > 1$ of side signals $X_{S,i}, i = 1, \dots, n$ which are arranged symmetrically around the center signal. These signals are then combined to a new signal $Y_j = n \cdot X_c - (X_{S,1} + \dots + X_{S,n})$ where j is the index of the derivation.

Two different methods are used to calculate features of the EEG data. One is the minimum energy approach (ME) (Friman, 2007) which requires no training. This algorithm is fed with raw EEG-data channels since it selects the best combination of channels by itself. First of all the EEG-data gets "cleaned" of potential SSVEP-signals. After that operation the signals contain just the unwanted noise. Now a weight vector is generated, which has the property of combining the channels in a way, that the outcome has minimal energy. Now SSVEP detection is done utilizing a test statistic which calculates the ratio between the signal with an estimated SSVEP-response and the signal where no visual stimulus is present. This is done for all stimulation frequencies and all EEG-channels. The output of this classifier is the index of the frequency with the highest signal/noise ratio.

As second method a Fast Fourier Transformation (FFT) and linear discriminant analysis (LDA) using the Laplacian derivations is used. First of all the incoming data gets transformed to the frequency spectrum with a 1024-point FFT. A feature vector is extracted by taking the values of the stimulation frequencies and their 1st and 2nd harmonics. With

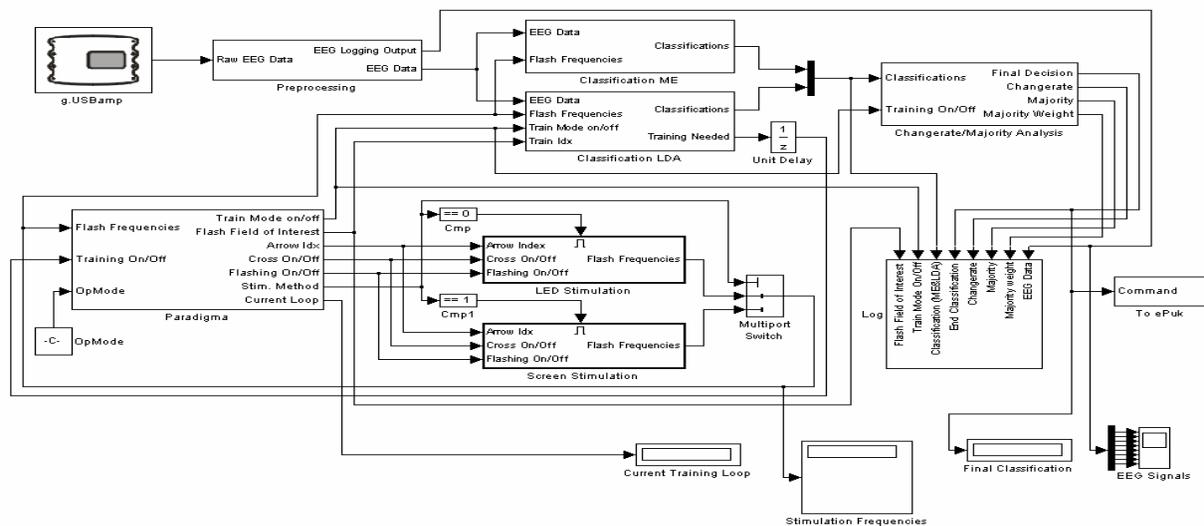


Fig. 9. SSVEP Simulink model. g.USBamp, Preprocessing, Classification ME (Minimum Energy)/LDA and Changerate/Majority Analysis blocks perform the real-time analysis of the EEG data. The block Paradigm controls the training sequence of the LED Stimulation. Beside LEDs also the computer screen can be used as stimulation unit. Furthermore EEG data is visualized and stored

these feature vectors a weight/bias vector must be generated for each user in a training procedure. When the training was completed successfully the LDA classifier can then be used to classify new feature vectors to one of the stimulation frequency indices. In the model used for the experiments described in this paper four ME classification units and four FFT+LDA classification units were used with different EEG channels as inputs.

The last step is a procedure called change rate/majority weight analysis. By having multiple classification units configured with slightly different input data there will be in general random classification results on noise input. This effect is used on one side to produce a zero decision when the outputs of the classifiers are changing heavily and are very different. On the other side a low change rate and a high majority weight (the number of classifications of the different algorithms which are pointing in the same direction) can be used to strengthen the robustness of the decision. Calculation is made on the last second. Default thresholds of 0.25 for change rate and 0.75 (1 - all outputs are pointing into the same direction) for majority weight were used.

The first step of the procedure is to look at the change rate. If it is above the threshold the procedure returns a final classification result of 0 which corresponds to a stop command. Otherwise, if it is below the threshold the next step is to look at the majority weight. If this is above the threshold the majority is taken as final result, otherwise the final output is again 0. The final classification is then sent to external device such as a robot.

3. Accuracies achieved with different BCI principles

Results are presented of 81 subjects who tested a P300 based system, of 99 subjects who tested a motor imagery based BCI system and of 3 subjects who tested a SSVEP based system.

The subjects participating in the P300 study had to spell a 5 character word with only 5 minutes of training. EEG data were acquired to train the system while the subject looked at

a 36 character matrix to spell the word WATER. During the real-time phase of the experiment, the subject spelled the word LUCAS.

For the P300 system 72.8 % were able to spell with 100 % accuracy and less than 3 % did not spell any character correctly as shown in Table 1 (Guger, 2009). Interesting is also that the Row-Column Speller reached a higher mean accuracy compared to the single character speller which produces higher P300 responses. This can be explained by the longer selection time per character for the SC speller.

Classification Accuracy [%]	Row-Column Speller: Percentage of sessions (N=81)	Single Character Speller: Percentage of Sessions (N=38)
100	72.8	55.3
80-100	88.9	76.3
60-79	6.2	10.6
40-59	3.7	7.9
20-39	0.0	2.6
0-19	1.2	2.6
Average Accuracy of all subjects	91.0	82.0
Mean of subjects who participated in RC and SC (N=19)	85.3	77.9

Table 1. Classification accuracy for P300 experiments

The subjects participating in the motor imagery study had to move 40 times a cursor to the right or left side of the computer monitor. Training and classifier calculation were performed with 40 imaginations of left and right hand movement initiated by an arrow pointing to the left and right side.

For motor imagery 6.2 % achieved an accuracy above 90 % and 6.7 % performed with almost random classification accuracy between 50-59 % as shown in Table 2 (Guger, 2003).

Classification accuracy [%]	Percentage of subjects (N=99)
90-100	6.2
80-89	13.0
70-79	32.1
60-69	42.0
50-59	6.7
	100

Table 2. Classification accuracy for motor imagery

The subject using the SSVEP based system had to control a robot to a desired location by making 12 choices. The difference to the motor imagery and P300 experiments is that with SSVEP a continuous control signal was realized. For motor imagery and P300 at a specific time point the classification was performed, while for SSVEP the classification was done continuously every 250 ms. As shown in Table 3 subject 1 had an overall error rate of 9.5%. The error rate consisted of no decisions and wrong classes. A fraction of 28.3% of the error rate were wrong classifications. An error of 9.5% seems to be high, but it includes also the

breaks between the stimulations. In total 1088 classifications were made during one run and consisted of the following periods: 20 sec pause at the beginning + 3 times 15 seconds LED stimulation + 7 seconds pause after each stimulation. This was repeated 4 times for each LED and gives in total 1088 classification time points. Out of the 1088 decisions only 28 wrong classifications were made during the whole experiment including the breaks. No decisions were only made for 71.7 % of the 9.5 % errors.

Subject	Error [%]	No decision [%]	Wrong class [%]
S1	9.5	71.7	28.3
S2	23.5	92.7	7.3
S3	18.9	75.0	25.0
Mean	17.3	79.8	20.2

Table 3. Classification accuracy for SSVEP

Table 4 compares the 3 BCI principles. As mentioned before, motor imagery and the P300 speller performed the classification at one specific time point and had 6.2 and 72.8 % of the users with more than 90 % accuracy. In contrast the SSVEP BCI classified every 250 ms continuously. If the SSVEP BCI makes the decision only at a certain time point all subjects reached more than 90 % accuracy. It must be noted that for the P300 system the random classification accuracy is 1/36, for the motor imagery system it is 1/2 and for SSVEP it is 1/5. The training time and the montage time of the electrodes was almost equal for P300, motor imagery and SSVEP.

	Motor imagery	P300 speller	SSVEP
Population with 90-100% accuracy	6.2%	72.8%	100%
Training time [min]	6 min	5 min	5 min
Number of electrodes	5	9	9
Random classification accuracy [%]	50 %	1/36	1/5
Decision time for one character	60 s	45 s with 15 flashes	0.25 s

Table 4. Comparison of motor imagery, P300 speller and SSVEP

This study shows that high spelling accuracy can be achieved with the P300 BCI system using approximately five minutes of training data for a large number of non-disabled subjects. The large differences in accuracy between the motor imagery and P300/SSVEP suggest that with limited amount of training data the P300 based BCI is superior to the motor imagery BCI. Overall, these results are very encouraging and a similar study should be conducted with subjects who have ALS to determine if their accuracy levels are similar. Summarizing it can be said that a P300 based system is suitable for spelling applications, but also e.g. for Smart Home control with several controllable devices. The motor imagery and SSVEP based systems are suitable if a continuous control signal is needed.

4. Applications

4.1 Twitter

One growing application area of BCIs is the control of social environments that allow the user to participate like a healthy person in daily live activities. Therefore 2 frequently used social networks - Twitter and Second Life - were interfaced to the BCI.

Twitter (Twitter Inc.) is a social network that enables the user to send and read messages. The messages are limited to 140 characters and are displayed in the authors profile page. Messages can be sent via the Twitter website or via smart phones or SMS (Short Message Service). Twitter provides also an application programming interface to send and receive SMS. Figure 10 shows an UML diagram of the actions required to use the service Twitter. The standard P300 spelling matrix with 6 x 6 characters was redesigned to cover all the necessary actions for Twitter. Therefore the first two lines contain now the commands to operate the service and the remaining characters are used for spelling itself. The matrix contains now 6 x 9 = 54 characters instead of 36.

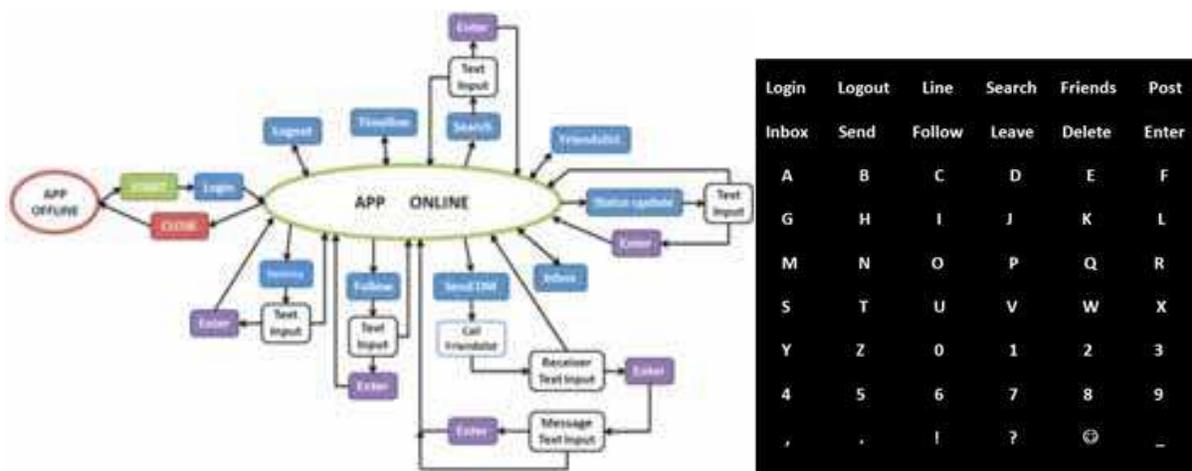


Fig. 9. UML diagram of service Twitter

To interface the BCI system with Twitter the API functions according to Table 5 were used.

BCI command	Description	Twitter API function
Login	Performs authentication	Login account verify credentials
Logout	Logout from Twitter	Logout
Line	Get the 20 newest messages of the user and of friends	Status home timeline
Search	Search for other twitter users	Search
Friends	Get list of friends	Status friendslist
Post	Update user status	Status update
Inbox	Get 20 newest messages from inbox	Direct messages
Send	Send twitter message	Direct direct messages
Follow	Add a friend	Friendships/create
Leave	Cancel a friendship	Friendships/destroy

Table 5. API function for service Twitter

Initially the subject was trained with 10 training characters to calculate a weight vector for testing the Twitter-BCI. Then another user was asking questions via Twitter and the BCI User had to answer one questions on each day. Therefore in total the BCI User had to use the interface on 9 different days and selected between 6 and 36 characters each day. Interesting is to compare the beginning with the end of the study. The first session lasted 11:09 min and the user spelled 13 characters, but made 3 mistakes. The user had the instruction to correct any mistake and this yielded to an average of 51 seconds selection time per character. In comparison in the last session the user spelled 27 characters in 6:38 min with only 1 mistake and an average selection time of 15 seconds per minute. Also the number of flashes per character was reduced from 8 to only 3 flashes to increase the speed.

Tweets	Charac.	Duration [mm:ss]	Errors	Flashes	Time per character [s]
Friend: Which kind of Brain-Computer Interface do you use?					
BCI: P300 GTEC BCI	13	00:11:09	3	8	51
Friend: Are you using the g.GAMMASys?					
BCI: Exactly!	7	00:06:18	1	8	54
Friend: Active or passive electrodes? For explanation: the active system avoids or reduces artefacts and signal noise.					
BCI: Active electrodes	17	00:06:10	0	5	22
Friend: The mounting of the active system is very comfortable. You do not need to prepare the skin first, do you?					
BCI: you are absolutely right	24	00:08:55	1	5	22
Friend: How many electrodes are needed to run the BCI?					
BCI: For P300 we usually use 8 electrodes	36	00:14:21	2	5	24
Friend: What amplifier are you using for the Brain-Computer Interface?					
BCI: g.MOBILab+	10	00:04:42	1	5	28
Friend: How long does it take to code the software for the BCI for TWITTER?					
BCI: 3 Weeks	7	00:03:13	1	4	28
Friend: How many characters are you able to write within a minute?					
BCI: 3 TO 4	6	00:03:15	0	5	33
Friend: Did you get faster in writing during this period?					
BCI: Yes, from 2 to 4 characters	27	00:06:38	1	3	15

Table 6. Questions and text input with the BCI system, errors and speed

4.2 Second Life (SL)

Second Life is a free 3D online virtual world developed by the American company Linden Lab. It was launched on June 23, 2003. In September 2008 Linden Lab announced that there were 15 million registered accounts whereas on average 60 000 users are online at the same time. The free client Software "Second Life Viewer" and an account are necessary to participate.

One of the main activities in Second Life is socializing with other so-called residents whereas every resident represents a person of the real world (see Figure 10). Furthermore it is possible to hold business meetings, to take photographs and make movies, to attend courses,...Communication takes place via text chat, voice chat and gestures.

For ALS or locked-in patients Second Life allows them to participate like any other user.



Fig. 10. Screenshot of Second Life

The P300 BCI system was interfaced with a Second Life (SL) controller implemented as a C++ S-function. Important is to run the BCI system and SL on separate computers to have enough performance.

To control Second Life three masks were developed: i) the main mask as shown in Figure 11 which has 31 characters, (ii) the mask for chatting (55 characters) and a mask (iii) for searching (40 characters).

Each of our symbols on the P300 mask represents actually a specific key, key combination or sequence of keys of a keyboard and therefore a specific function in Second Life. If now a certain symbol is selected, Second Life is notified to execute this individual action with keyboard events.

An important component of the Second Life matrix is the stand-by character on top right position as BCI systems are designed for disabled persons who cannot switch-on or switch-off the system on their own. If the user selects the character twice in a row the BCI system is switched off until the character is selected again twice. This makes it quite unlikely that a decision is made without attending to the BCI system.



Fig. 11. BCI mask to walk forward/backward, turn left/right, slide left/right, climb, teleport home, show map, turn around, activate/deactivate running mode, start/stop flying, decline, activate/deactivate mouselook view, enter search mask, take snapshot, start chat, quit and stand-by



Fig. 12. IntendiX running on the laptop and active electrodes

4.3 intendiX

intendiX® is designed to be installed and operated by caregivers or the patient's family at home. The system consists of active EEG electrodes to avoid abrasion of the skin, a portable

biosignal amplifier and a laptop or netbook running the software under Windows (see Figure 12). The electrodes are integrated into the cap to allow a fast and easy montage of the intendiX equipment.

The intendiX software allows viewing the raw EEG to inspect data quality, but indicates automatically to the unexperienced user if the data quality on a specific channel is bad. If the system is started up for the first time, a user training has to be performed. Therefore usually 5-10 training characters are entered and the user has to copy the characters. The EEG data is used to calculate the user specific weight vector which is stored for later usage. Then the software switches automatically into the spelling mode and the user can spell freely. The input screen is shown in Figure 13.

The user can perform different actions: (i) copy the spelled text into an Editor, (ii) copy the text into an email, (iii) send the text via text-to-speech facilities to the loud speakers, (vi) print the text or (v) send the text via UDP to another computer. For all these services a specific icon exists.

The number of flashes for each classification can be selected by the user or the user can also use a statistical approach that detects automatically the required number of flashes and if the user is working with the BCI system. The later one has the advantage that no characters are selected if the user is not looking at the matrix or does not want to use the speller.

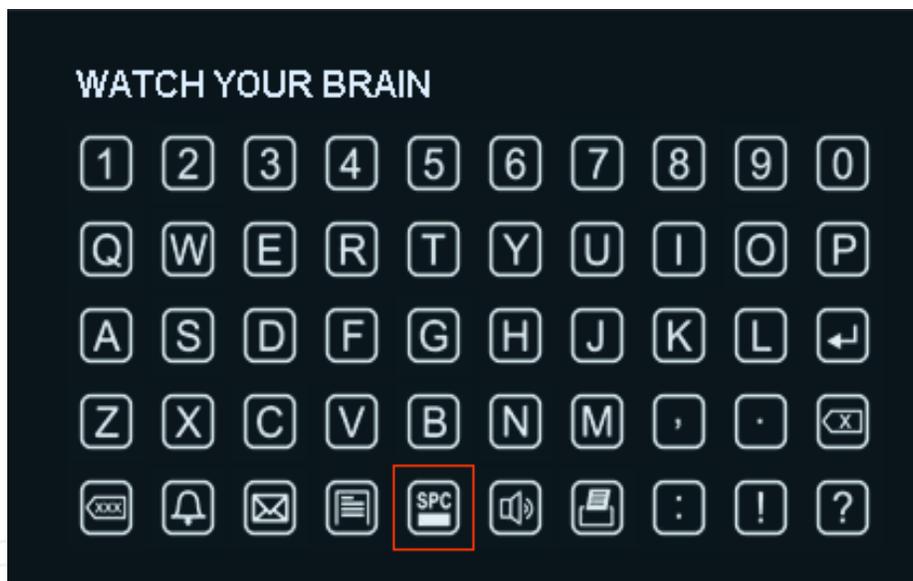


Fig. 13. User interface with 50 characters and computer keyboard like layout

4.4 SM4All – smart home control with BCI

Beside virtual worlds BCI systems can also be used to control real environments. Therefore smart homes are developed that allow independent living for handicapped people. Within an European Union project called SM4All (www.sm4all-project.eu) a middleware platform is developed that allows to control multiple domotic devices with a BCI system.

The SM4All system consists of three layers as shown in Figure 12:

1. The Pervasive Layer gives access to the hardware infrastructure. Different devices and sensors can communicate with the layer (lights, washing machine, doors, temperature sensors, ...) and the embedded software on top of them make services available to the composition layer.

2. The Composition Layer consists of all the components needed to automatically satisfy user needs. It contains the user profile and context manager that prepares the home and user interface according to certain states of the house. Services are described in the repository.
3. The User Layer provides the interface for controlling the house either with a web-interface on a computer or with the BCI system.

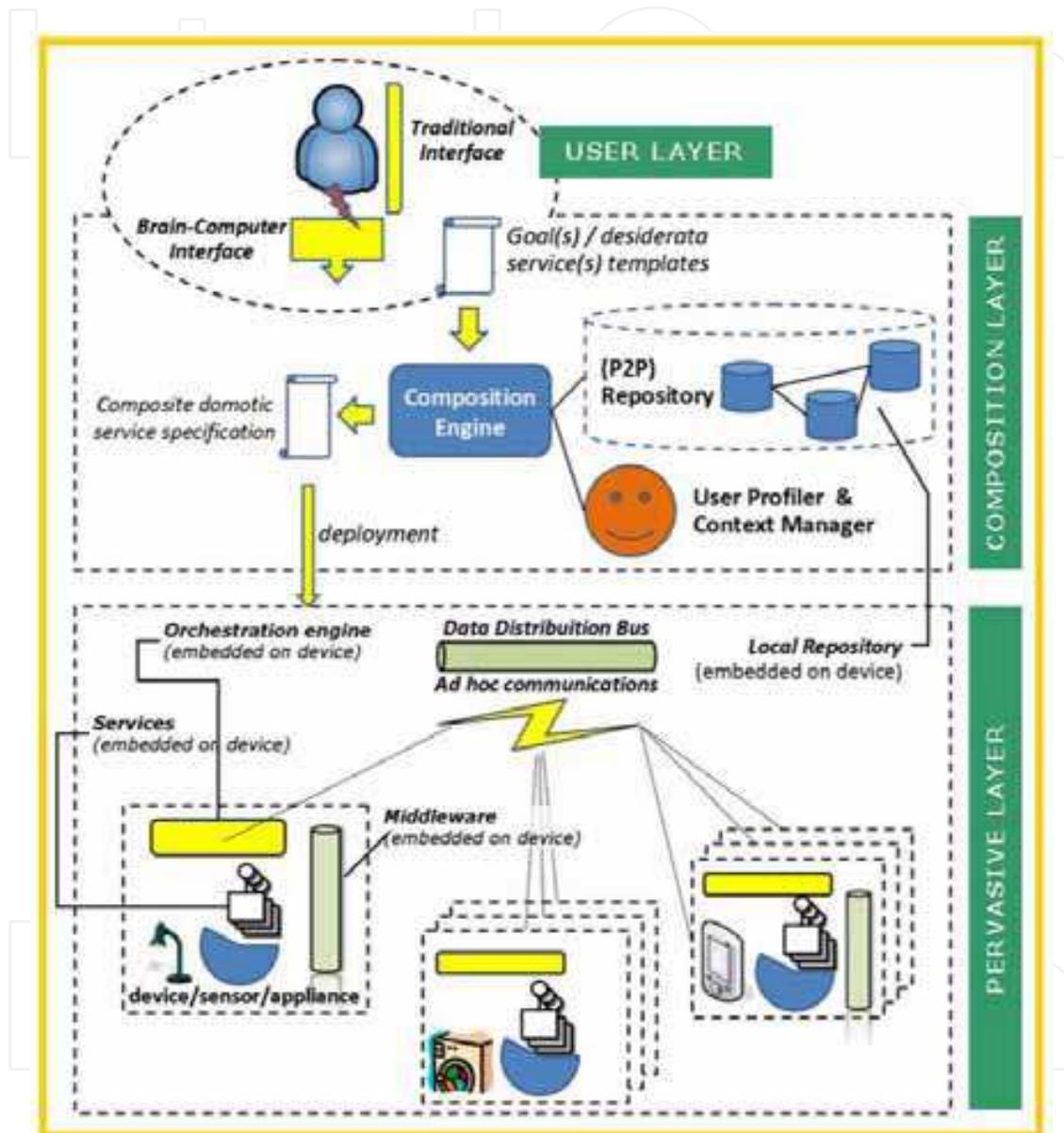


Fig. 12. The SM4ALL architecture

Between the Composition Layer and the User Interface is the abstract adaptive interface (AAI) that extracts all currently available actions for certain services for the user interface as shown in Figure 13. All available services are shown in the user interface and are ordered according to the priority of the service. The user can now simply click with the mouse on the web-interface or can use the P300 BCI system to initiate an action. Both transmit the command via SOAP messages to the SM4All system and therefore from any computer with internet connection the house can be controlled.



Fig. 13. BCI interface and web interface

A light is for example 1 service with 2 actions because it can be switched on and off. Therefore the control icon allows either to switch on or off the light. Figure 14 shows the service TV. The TV can be in several different states and the arrows between represent the actions that must be selectable with the web-interface or BCI system.

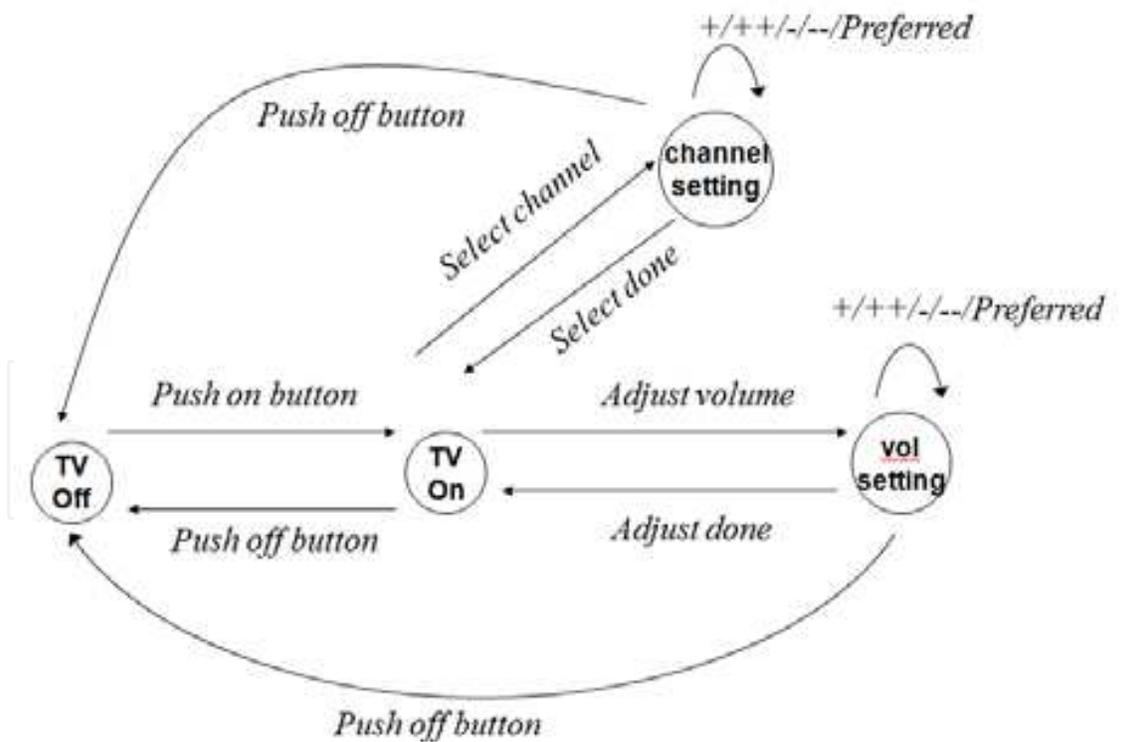


Fig. 14. Description of service TV with several actions

In future the SM4all system will be able to control many different domotic devices from different manufacturers and this makes it simple for handicapped people to have access to them and to life independent.

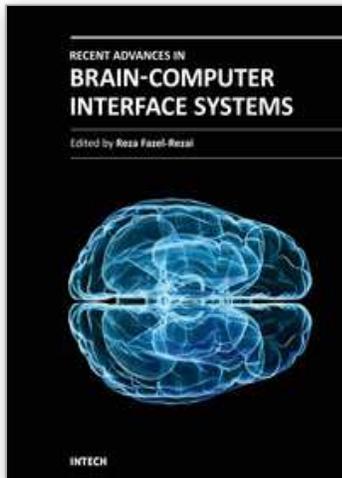
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6. References

- Allison, B. Z., McFarland, J., D., Schalk, G., Zheng, S. D., M., J. M., et al. (2008). Towards an independent brain-computer interface using steady state visual evoked potentials. *Clin Neurophysiol*, 399-408.
- Bakardjian, H., Tanaka, T., & Cichocki, A. (2010). Optimization of SSVEP brain responses with application to eight-command Brain-Computer Interface. *Neurosci. Lett.*, 34-8.
- Bin, G., Gao, X., Yan, Z., Hong, B., & Gao, S. (2009). An online multi-channel SSVEP-based brain-computer interface using a canonical correlation analysis method. *Journal of Neural Engineering*, 6pp.
- Birbaumer, N., Kubler, A., Ghanayim, N., Hinterberger, T., Perelmouter, J., Kaiser, J., Iversen, I., Kotchoubey, B., Neumann, N., Flor, H. (2000). The thought translation device (TTD) for completely paralyzed patients. *IEEE Trans.Rehabil.Eng*, 8(2): p. 190-193.
- Citi, L., Poli, R., Cinel, C., & Sepulveda, F. (2008). P300-based BCI mouse with genetically-optimized analogue control. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 51-61.
- Elbert T, Rockstroh B, Lutzenberger W, Birbaumer N. Biofeedback of slow cortical potentials. *Electroenceph clin Neurophysiol* 1980;48:293-301.
- Finkea, A., Lenhardt, A., & Ritter, H. (2009). The MindGame: a P300-based brain-computer interface game. *Neural Networks*, 1329-1333.
- Friman, O., Volosyak, I., Graser, A.: Multiple channel detection of Steady-State Visual Evoked Potentials for brain-Computer interfaces. *IEEE Transactions on Biomedical Engineering*, 54, 742--750, (2007).
- Gao, X., Xu, D., Cheng, M., & S., G. (2003). A BCI-Based Environmental Controller for the Motion-Disabled. *IEEE Trans. Neural Sys. and Rehab. Eng.*, 137-140.
- Guger, C., Ramoser, H., and Pfurtscheller, G. (2000). Real-time EEG analysis with subject-specific spatial patterns for a Brain Computer Interface (BCI). *IEEE Trans Neural Syst Rehabil Eng.*, 8: p. 447-456.
- Guger, C., Schlögl, A., Neuper, C., Walterspacher, D., Strein, T., and Pfurtscheller, G. (2001) Rapid prototyping of an EEG-based brain-computer interface (BCI). *IEEE Trans. Rehab. Engng.*, vol. 9 (1): p. 49-58.
- Guger, C., Edlinger, G., Harkam, W., Niedermayer, O., and Pfurtscheller, G. (2003). How many people are able to operate an EEG-based brain computer interface? *IEEE Trans. Rehab. Engng.*, vol. 11: p. 145-147.
- Guger, C., Daban, S., Sellers, E., Holzner, C., Krausz, G., Carabalona, R., et al. (2009). How many people are able to control a P300-based brain-computer interface (BCI)? *Neuroscience Letters*, 94-98.
- Krusienski, D.J., Sellers, E.W., Cabestaing, F., Bayouth, S., McFarland, D.J., Vaughan, T.M., and Wolpaw, J.R. (2006). A comparison of classification techniques for the P300 Speller. *J.Neural Eng*, 3(4): p. 299-305.

- Leuthardt, E.C., Schalk, G., Wolpaw, J.R., Ojemann, J.G., and Moran, D.W. (2004). A brain-computer interface using electrocorticographic signals in humans. *J. Neural Eng.*, 1: p. 63-71.
- Lin Z., Zhang C., Wu W., & X., G. (2006). Frequency recognition based on canonical correlation analysis for SSVEP-based BCIs. *IEEE Trans Biomed Eng.* , 2610-2614.
- Middendorf, M., McMillan, G., Calhoun, G., & Jones, K. S. (2000). Brain-computer interfaces based on the steady-state visual-evoked response. *IEEE Transactions on Rehabilitation Engineering* , 211-214.
- Muller-Putz, G.R., Scherer, R., Brauneis, C., and Pfurtscheller, G. (2005). Steady-state visual evoked potential (SSVEP)-based communication: impact of harmonic frequency components. *J. Neural Eng.*, 2(4): p. 123-130.
- Pfurtscheller, G., Neuper, C., Flotzinger, D., and Pregenzer, M. (1997). EEG-based discrimination between imagination of right and left hand movement. *Electroenceph. clin. Neurophysiol.*, 103: p. 642-651.
- Pfurtscheller, G., Neuper, C., Guger, C., Obermaier, B., Pregenzer, M., Ramoser, H., and Schlögl, A. (2000). Current trends in Graz brain-computer interface (BCI) research. *IEEE Trans. Rehab. Engng.*, vol. 8: p. 216-219.
- Schalk G, McFarland DJ, Hinterberger T, Birbaumer N, Wolpaw JR. BCI2000: a general-purpose brain-computer interface (BCI) system. *IEEE Trans Biomed Eng.* 2004 Jun;51(6):1034-43.
- Sellers, E.W., Krusienski, D.J., McFarland, D.J., Vaughan, T.M., and Wolpaw, J.R. (2006). A P300 event-related potential brain-computer interface (BCI): the effects of matrix size and inter stimulus interval on performance. *Biol. Psychol.*, 73(3): p. 242-252.
- Sellers, E.W., and Donchin, E. (2006). A P300-based brain-computer interface: initial tests by ALS patients. *Clin. Neurophysiol.*, 117(3): p. 538-548.
- Sutton, S., Braren, M., Zubin, J., & John, E. R. (1965). Evoked-Potential Correlates of Stimulus Uncertainty. *Science* , 1187-1188.
- Thulasidas, M., Cuntai, G., and Jiankang, W. (2006). Robust classification of EEG signal for brain-computer interface. *IEEE Trans Neural Syst Rehabil Eng.*, 14(1): p. 24-29.
- Vallabhaneni, A., "Motor imagery task classification for brain computer interface applications using spatiotemporal principle component analysis". *Neurol Res.* 2004 Apr ;26 (3):282-7 15142321 Cit:5
- Waldhauser, M. (2006). Offline and online processing of evoked potentials. Master thesis, FH Linz.
- Wolpaw J. R., Birbaumer N., McFarland D.J., Pfurtscheller G., Vaughan T. M. (2002). Brain-computer interfaces for communication and control", *Clinical Neurophysiology*, Volume 113, Issue 6, Pages 767-791.
- Zhang, D., Maye, A., Gao, X., B., H., Engel, A. K., & Gao, S. (2010). An independent brain-computer interface using covert non-spatial visual selective attention. *J Neural Eng.*, 16010. Epub 2010 Jan 19.



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Brain Computer Interface (BCI) technology provides a direct electronic interface and can convey messages and commands directly from the human brain to a computer. BCI technology involves monitoring conscious brain electrical activity via electroencephalogram (EEG) signals and detecting characteristics of EEG patterns via digital signal processing algorithms that the user generates to communicate. It has the potential to enable the physically disabled to perform many activities, thus improving their quality of life and productivity, allowing them more independence and reducing social costs. The challenge with BCI, however, is to extract the relevant patterns from the EEG signals produced by the brain each second. Recently, there has been a great progress in the development of novel paradigms for EEG signal recording, advanced methods for processing them, new applications for BCI systems and complete software and hardware packages used for BCI applications. In this book a few recent advances in these areas are discussed.

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