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The Berlin Brain-Computer Interface (BBCI) – towards a new communication channel for online control in gaming applications

Roman Krepki · Benjamin Blankertz · Gabriel Curio · Klaus-Robert Müller

Abstract The investigation of innovative Human-Computer Interfaces (HCI) provides a challenge for future multimedia research and development. Brain-Computer Interfaces (BCI) exploit the ability of human communication and control bypassing the classical neuromuscular communication channels. In general, BCIs offer a possibility of communication for people with severe neuromuscular disorders, such as Amyotrophic Lateral Sclerosis (ALS) or spinal cord injury. Beyond medical applications, a BCI conjunction with exciting multimedia applications, e.g., a dexterity game, could define a new level of control possibilities also for healthy customers decoding information directly from the user's brain, as reflected in electroencephalographic (EEG) signals which are recorded non-invasively from user's scalp. This contribution introduces the Berlin Brain–Computer Interface (BBCI) and presents setups where the user is provided with intuitive control strategies in plausible gaming applications that use biofeedback. Yet at its beginning, BBCI thus adds a new dimension in multimedia research by offering the user an additional and independent

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communication channel based on brain activity only. First successful experiments already yielded inspiring proofs-of-concept. A diversity of multimedia application models, say computer games, and their specific intuitive control strategies, as well as various Virtual Reality (VR) scenarios are now open for BCI research aiming at a further speed up of user adaptation and increase of learning success and transfer bit rates.

Keywords Brain-Computer Interface · Electroencephalography · Digital Signal Processing · Machine Learning · Biofeedback · Human-Computer Interaction · Brain-gaming

1 Introduction

In the seven decades since Berger's original publication [1] the electroencephalogram (EEG) has been used mainly to evaluate neurological disorders and to investigate brain function. Besides, people have also speculated that it could be used to decipher thoughts or intents, such that a person will be able to control devices directly by her/his brain activity, bypassing the normal channels of peripheral nerves and muscles. However, due to the large amount of data to be analyzed within limited time, it could attract serious scientific attention only in the last decade, promoted by the rapid development in computer hardware and software engineering. As nowadays it is possible to distribute tasks of a complex system over different computers communicating with each other and to process acquired data in a parallel manner and in real time.

Currently, modern multimedia technologies[1] address only a subset of I/O channels humans use for communication. Those demand mainly motor (joystick, pedal), visual (graphics, animation) and acoustic (music, speech) senses. Recent research tries to include also olfaction [11], tactile sensation [10, 13], interpretation of facial emotions [18] and gestures [19]. Since all these information streams pass its own interface (hand/skin, eye, ear, nose, muscles) yet indirectly converge or emerge in the brain, the investigation of a direct communication channel between the application and the human brain should be of high interest to multimedia researchers [8]. In addition brain waves include information about the user condition, like involvement into mental task solving, stress or the workload level that otherwise can be measured only by monitoring the user's behavior. Moreover, controlling a device with the own brain activity can allow for faster reaction times, since intentions of movements can be recognized as movement preparations before the action is intrinsically initiated.

The present study proposes the extension of information types currently available to multimedia technology by brain waves and presents setups where the user is capable of controlling a computer application by this new type of media. In Section 2 we give a short introduction in state-of-the-art in BCI. Then, in Section 3, we introduce a novel communication channel that can be used in Human-Computer Interfaces (HCI) and a correspondingly new technique for information retrieval directly from the brain. This is followed by a demonstration of a set of multimedia applications used as biofeedback, in Section 4. Section 5 concludes with a discussion on future disposition of Brain-Computer Interfaces (BCI) in the field of control, multimedia and gaming.

[1] The term of "multimedia technology" is defined as a conjunction of hardware and software systems that are capable of acquiring and processing the user's input or of providing the user with the information via several human communication channels.

2 State of the Art in BCI

A recent review on BCI defines a *Brain-Computer Interface* as *a system for controlling a device, e.g., computer, wheelchair or a neuroprosthesis by human intentions, which does not depend on the brain's normal output pathways of peripheral nerves and muscles* [26].

There are several non-invasive methods of monitoring brain activity encompassing positron emission tomography (PET), functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG) or electroencephalography (EEG) techniques, which all have advantages and shortcomings. Notably alone EEG yields data that is easily recorded with comparatively inexpensive equipment, is rather well studied and provides high temporal resolution. Thus it outperforms remaining techniques as an excellent candidate for BCI.

EEG-based BCI systems can be subdivided into several groups according to the electrophysiological signals they use. Visual evoked potentials (VEP) define a *dependent* BCI, i.e., they depend on oculomotor control of gaze direction. Sutter [23] described a Brain Response Interface (BRI) applying it as a keyboard interface: by selecting a symbol from a set of 64 proposed in an 8×8 array by focusing on it volunteers were able to type 10–12 words per minute. Symbols were changing their color or flashing with a certain frequency, which induces a distinct spatiotemporal pattern in the visual cortex of the user's brain. However, this method requires stable control over oculomotor muscles, needed for focusing a letter. Moreover, it relies on intact neural pathways carrying information presented on the computer screen into the user's primary visual cortex.

BCI systems, which do not rely on any muscular activity, are defined to be *independent*. For example, a subject waiting for the occurrence of a rare stimulus on the background of a series of standard stimuli evokes a Positive peak over parietal cortex about 300 ms (P300) after appearance. Donchin and Smith [7] presented a P300-based BCI used for typing of ca. five letters per minute. However those techniques remain limited to letter selection paradigms, and the like.

In Albany, New York, Jonathan Wolpaw et al. [25] directs the development of a BCI system that lets the user steer a cursor by oscillatory brain activity into one of two or four possible targets. In the first training sessions most of the subjects use some kind of motor imagery which are then, during further feedback sessions, replaced by adapted strategies. Well-trained users achieve hit rates of over 90% in the two-targets setup. However, each selection typically takes 4 to 5 s.

Physiologically meaningful signal features can be extracted from various frequency bands of recorded EEG, e.g., Pfurtscheller [20] reports that μ- and/or β-rhythm amplitudes serve as effective input for a BCI. Movement preparation, followed by execution or even only motor imagination is usually accompanied by a power decrease in certain frequency bands, labeled as Event-Related Desynchronization (ERD), in contrast, their increase after a movement indicates relaxation and is due to a synchronization in firing rates of large

Table 1 Frequency bands

Band	Frequency (Hz)	Occur while/indicate
δ	0.5–3.5	Movement preparation
θ	3.5–8	Memory
α (μ)	8–13	Relaxation, sensory idling
β	13–22	Motor idling
γ	22–40	Feature binding

populations of cortical neurons (ERS). Table 1 summarizes frequency bands and neurophysiological features they are assumed to encode. Please note, that marginal frequency values are highly subject specific.

Slow Cortical Potentials (SCP) are voltage shifts generated in cortex lasting over 0.5–10 s. Slow negativation is usually associated with cortical activation used to implement a movement or to accomplish a task, whereas positive shifts indicate cortical relaxation [2]. Further studies showed that it is possible to learn SCP control. Consequently, it was used to control movements of an object on a computer screen in a BCI referred to as Thought Translation Device (TTD) [3]. After repeated training sessions over months, through which patients achieve accuracies over 75% they are switched to a letter support program, which allows selection of up to three letters per minute.

Using information recorded invasively from an animal brain Nicolelis and Chapin [17] report a BCI able to control a robot. Four arrays of fine microwires penetrate the animal's scull and connect to different regions inside the motor cortex. A robotic arm remotely connected over the Internet implements roughly the same trajectory as the owl monkey gripping for food. Granted, this invasive technology allows the extraction of signals with fine spatial and temporal resolution, since each microelectrode integrates firing rates of few dozens of neighboring neurons. However, to make a BCI attractive to an everyday user it should be non-invasive, fast mounted and leave no marks.

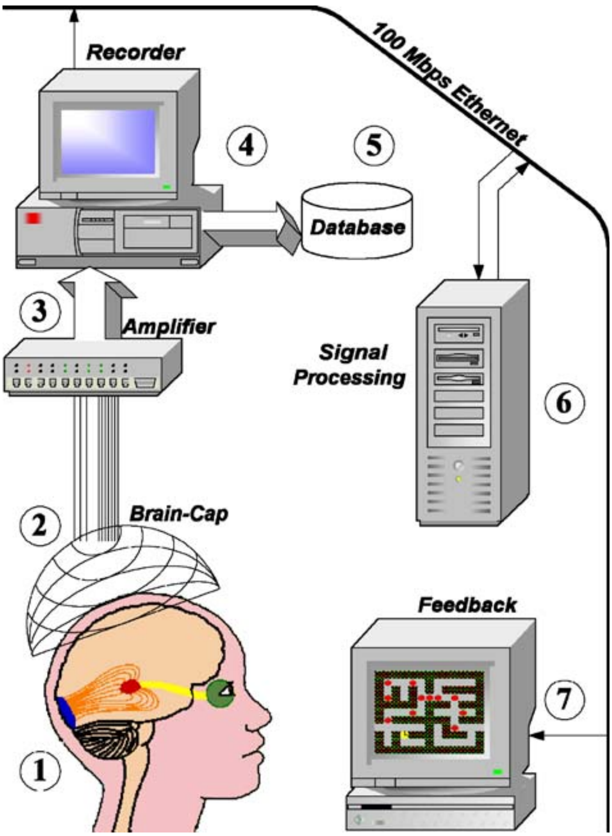


Fig. 1 Distributed design of BBCI

3 The Berlin brain–computer interface

This section presents an independent non-invasive EEG-based online-BCI, developed at Fraunhofer FIRST and the Neurophysics Group of the Free University of Berlin, that overcomes limitations mentioned above. The enormous amount of data to be processed in a limited time forced the distribution of processing tasks over several computers communicating via client–server interfaces, cf. Fig. 1. Moreover, this distributed concept allows advantageous replacement of single modules according to particular communication protocols.

The volunteer user (1) is facing a computer screen. A drapery brain-cap (2) furnished with 128 electrodes is put on her/his head. Four flat cables of 32 wires each, connect the cap with four amplifiers (3), which also perform an A/D-conversion and transmit the acquired EEG at sampling rate of 5 kHz and accuracy of 16 bits via a fiber optic cable to the recorder PC (4). The recorder performs some predefined simple preprocessing operations, i.e., subsampling to 1 kHz, optional low/high/band-pass or notch filters, and stores the data in raw format for later offline analysis into the database (5). Additionally it acts as Remote Data Access server (RDA) which allows up to ten client connections and serves one data block each 40 ms. A second computer (6) runs a corresponding client, which performs, after data acquisition, some preprocessing steps for feature selection (details in Section 3.4) in a parallel manner: for detection and determination of user action two separate non-blocking threads were employed, followed each, after a synchronization step, by a classification step of the current acquired data block (details in Section 3.5).

Finally, a combiner joins the two classifier results and produces a control command. Figure 2 illustrates the parallel approach of data processing. The online classifier (6) acts as a server for various feedback clients (7) and serves each 40 ms the control command produced by the combiner. The feedback client is a multimedia application that runs on a separate computer and acquires the control commands produced by the combiner module of the data processing server. It is conceived to rely on simple control, e.g., left/right movements, which may be expressed by a small command set, and should give the user a feeling of being inside the simulation. Currently we employed simple computer games like Pacman or Tele-Tennis, however other more sophisticated and challenging multimedia applications are conceivable.

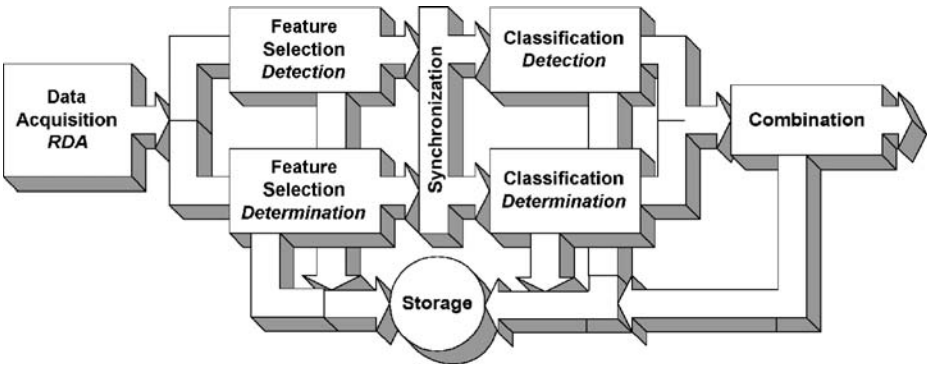


Fig. 2 Parallel manner of data processing

3.1 Data acquisition

We recorded brain activity with multi-channel EEG amplifiers (BrainVision™, Munich) using 128 channels from the cap with Ag/AgCl Electrodes (∅ of the contact region is 5 mm). Additionally, surface electromyogram (EMG) signals, which detect muscle activity at both forearms, as well as horizontal and vertical electrooculogram (EOG) signals, which reflect eye movements, were recorded. All signals were band-pass filtered between 0.05 and 200 Hz and sampled at 1,000 Hz. For online analysis, the data signals were then subsampled to 100 Hz to minimize the data processing effort.

The labels of electrodes are composed of some letters and a number. The letters refer to anatomical structures (Anterior, Frontal, Parietal, Occipital, Temporal lobes and Central sulcus), while the numbers denote sagittal (anterior–posterior) lines. Odd numbers correspond to the left hemisphere, while even numbers to the right; small ‘z’ marks electrodes on the central sagittal line. Labels with one or two capital letters correspond to the 64 electrodes of

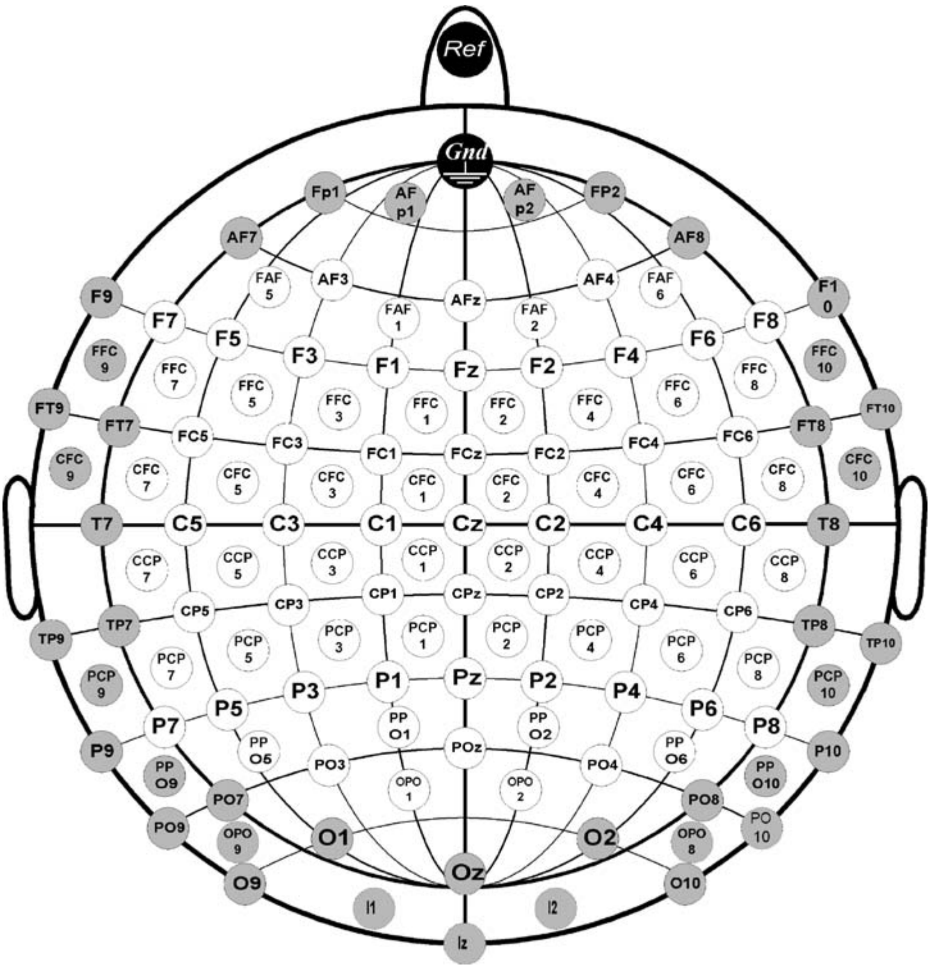


Fig. 3 Locations of electrodes and labels of corresponding channels

the extended international 10–20 system [22] while labels with three capital letters were composed from the neighboring electrode labels and denote additional channels in a 128-channel setup. EEG activity is measured against the reference electrode (*Ref*) mounted on the nasion, while the ground electrode (*Gnd*) is mounted on the forehead. Locations of the electrodes and corresponding labels are illustrated in Fig. 3.

The voltage measured by the electrodes is very low and fluctuates rapidly within the range of ±300 μV. Electrical noise from the surrounding environment (mainly 50 Hz, respectively 60 Hz, power outlet frequency) interferes with the data via connecting wires, which act in this setup as small "antennas". To assure low impedances between the electrodes and the scalp (desired below 5 kΩ), electrolyte gel is filled into each electrode before experiments start.

3.2 Task and its neurophysiology

We let our subjects (all without neurological deficits) take a binary (left- or right-hand) decision coupled to a motor output, i.e., self-paced typewriting on a computer keyboard. Using multi-channel scalp EEG recordings, we analyze the single-trial differential potential distributions of the Lateralized Readiness Potentials (LRP/Bereitschaftspotential) preceding voluntary (left or right hand) index or pinky finger movements over the corresponding (respectively, right or left) primary motor cortex, which is contralateral to the executing hand. As we study brain signals from healthy subjects executing real movements, our paradigm requires a capability to predict the laterality of imminent hand movements prior to any EMG activity to exclude a possible confound with afferent feedback from muscle and joint receptors contingent upon an executed movement.

The basic BBCI idea is focusing on control applications, such as "virtual keyboard typing", that can be conceived as potentially resulting from a natural sequence of motor intention, followed by preparation and completing by the execution. Accordingly, our neurophysiological approach aims to capture EEG indices of preparation for an immediately upcoming motor action.

At present, we exploit the LRP, i.e., a slow negative EEG shift, which develops over the activated motor cortex during a period of about 1 s prior to the actual movement onset; it is assumed to reflect mainly the growing neuronal activation (apical dendritic polarization) in a large ensemble of pyramidal cells. Previous studies [6, 12] showed that in most subjects the spatial scalp distribution of the averaged LRP correlates consistently with the moving hand (focus of brain activity is contralateral to the performing hand).

The upper part of Fig. 4 shows Laplace filtered EEG around the left and right hand motor cortices (electrodes C3 and C4) within a time range of [−450:200] ms relative to the key tap, averaged selectively for left-hand vs right-hand taps. The gray bars indicate a 100-ms baseline correction. The lateralization of LRP is clearly specific for left resp. right finger movements. Potential maps show the scalp topographies of the LRP averaged over time windows (upper) before movement preparation and (lower) when LPR reaches its maximum negativation, again averaged over left-hand and right-hand taps separately. Bold crosses mark electrode positions C3 and C4.

We would like to emphasize that the paradigm is shaped presently for fast classifications in normally behaving subjects and thus could open interesting perspectives for a BCI assistance of action control in time-critical behavioral contexts. Notably, also a possible transfer to BCI control by paralyzed patients appears worthwhile to be studied further because these patients were shown to retain the capability to generate LRPs with partially modified scalp topographies [9].

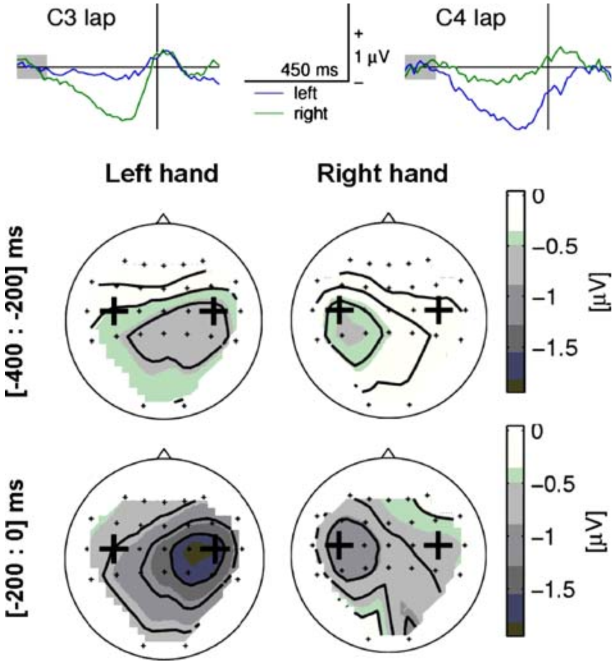


Fig. 4 Averaged lateralized readiness potentials (LRPs)

3.3 Training procedure

The guiding motto of BBCI is: "*Let the machines learn!*", thus the user should require only a minimum of training for operating it. The training procedure described here serves for "teaching the machine" and adjusting its model parameters to better match the user and his brain signal's properties. During the training procedure we acquire example EEG from the user while performing a certain task, e.g., execution or imagination of left- vs right-hand movement of the index or pinky fingers. The user is instructed to sit comfortably and, as far as possible, to omit any muscular artifacts, like biting, gulping, yawning, moving the head, arms, legs or the whole body. These would induce electromyographic (EMG) noise activity that interferes with EEG signals, such that the signal-to-noise ratio (SNR) converges to zero. Eye movements are to be minimized for the same reason. To prevent possible (involuntarily) cheating, e.g., producing eye movements correlated with performed tasks, vertical and horizontal electrooculograms (EOG) are recorded, which can be used for artifact correction, i.e., cleaning up EEG signals of interfering EOG by weighted subtraction.

The training is performed in three to four sessions, each of about 7 min, as illustrated in Fig. 5. Tasks are performed for a period of 6 min repeatedly with an interval of 0.5–2 s. All training sessions may be performed in two experimental kinds: (1) imagined, i.e., queried, (2) executed, i.e., self-paced. In the executed task experiment we acquire response markers via keyboard, while the user determines himself which task to perform next. During the imagined task experiment a visual cue indicates the task, which has to be executed on the

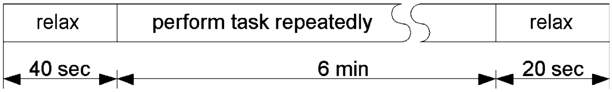


Fig. 5 Setup of a training session

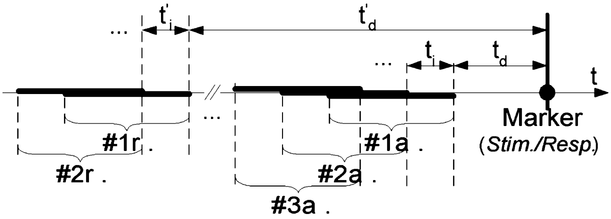


Fig. 6 Selection procedure for training samples

next auditory beat produced by a digital metronome. Both stimuli place corresponding markers into the data, stored with a timestamp. To train the learning machine and adjust its parameters, we select time series of EEG activity acquired within a certain time region before the marker, which gives the training sample its label.

We search for event markers in the acquired data and examine each for affiliation to one of the classes of interest. Each class covers its own sample-selection parameter set *SSP* := ({*mrk*}, *n*, t_d, t_i), where a set of marker labels *mrk* identifies the affiliation of markers to classes, *n* gives the number of training samples to be selected from the data, t_d and t_i are time constants indicating the delay and inter-sample interval. Beside the classes indicating *Action*, e.g., implementation or imagination of a task accomplishment, which in Fig. 6 provide samples 1a, 2a and 3a, an additional class indicating *Rest* is introduced. This provides in an analog manner training samples 1r and 2r, that are used together with *Action*-samples for *detection* of task accomplishment, though we use action samples only, for the *determination* of which task has been completed. For sample selection in the training

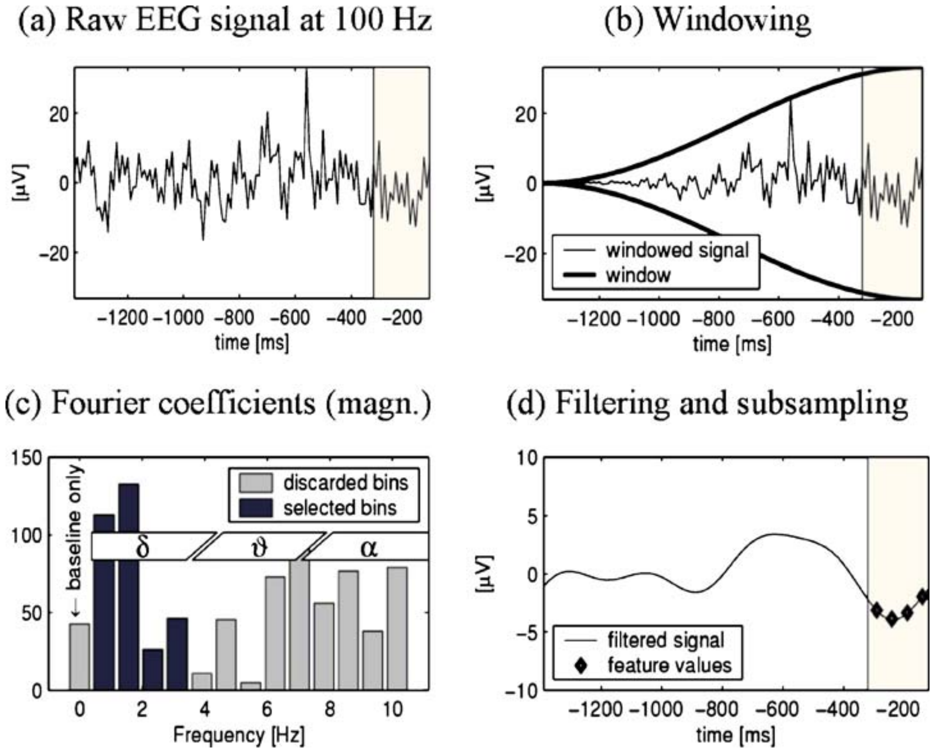


Fig. 7 Pre-processing procedure

procedure, negative time constants are preferred, positive are allowed, however they make sense for online analysis only in a limited subset of experimental setups.

Special attention must be paid in fast-pace experiments to the issue that samples of the *Rest* class do not intersect with *Action* class samples of the preceding event marker, as they should not include any information about action.

3.4 Preprocessing and feature selection

To extract relevant spatiotemporal features of slow brain potentials we subsample signals from all or a subset of all available channels and take them as high-dimensional feature vectors. We apply a special treatment because in pre-movement trials most information is expected to appear at the end of the given interval.

Starting point of the procedure are epochs of 128 data points (width of a sample window) of raw EEG data, corresponding to 1280 ms as depicted in Fig. 7a for one channel from −1400 ms to −120 ms (t_{d}) relative to the timestamp of the desired event marker. To emphasize the late signal content, we first multiply the signal by a one-sided cosine function (1), as shown in Fig. 7b.

$$\forall n = 0, \ldots, 127 : w(n) := 0.5 \cdot \left(1 - \cos\left({}^{n\pi}\!/_{128}\right)\right) \tag{1}$$

A Fast Fourier Transformation (FFT) filtering technique is applied to the windowed signal. From the complex-valued FFT coefficients all are discarded but the ones in the pass-band (including the negative frequencies, which are not shown), cf. Fig. 7c. Transforming the selected bins back into the time domain gives the smoothed signal of which the last 200 ms are subsampled at 20 Hz by calculating means of consecutive non-overlapping intervals, each of five values, resulting in four feature components per channel, cf. Fig. 7d.

3.5 Classification

The Lateralized Readiness Potential (LRP) features are superpositions of task-related and many task-unrelated signal components. The mean of the distribution across trials is the non-oscillatory task-related component, ideally the same for all trials. The covariance matrix depends only on task-unrelated components. Our analysis showed that the distribution of Event-Related Potential (ERP) features is indeed normal. The important observation here is, that the covariance matrices of both classes (left/right movements) look very much alike [5].

A basic result from the theory of pattern recognition, says that Fisher's Discriminant (FD) gives the classifier with minimum probability of misclassifications for known normal distributions with equal covariance matrices [24]. As was pointed out in the previous paragraph the classes of LRP features can be assumed to obey such distributions. Because the true distribution parameters are unknown, means and covariance matrices have to be estimated from training data. This is prone to errors since we have only a limited amount of training data at our disposal. To overcome this problem it is common to regularize the estimation of the covariance matrix. In the mathematical programming approach [15] the following quadratic optimization has to be solved in order to calculate the Regularized Fisher's Discriminant (RFD) w from data x_k and labels $y_k \in \{-1, 1\}$ (k=1, ..., K):

$$\min_{w,b,\xi} {}^{1}\!/_{2}\|w\|_2^2 + {}^{C}\!/_{K}\|\xi\|_2^2 \quad \text{subject to} \quad \mathrm{y_k}\left(\mathrm{w^T x_k + b}\right) = 1 - \xi_{\mathrm{k}} \quad \text{for } \mathrm{k} = 1, \ldots, \mathrm{K} \tag{2}$$

where $\|\cdot\|_2$ denotes the ℓ_2 norm $\left(\|w\|_2^2 = w^T w\right)$, ξ are slack variables. C is a hyper-parameter, which has to be chosen appropriately, say, by cross-validation strategies. There is a more efficient way to calculate the RFD, but this formulation has the advantage, that other useful variants can be derived from it [15, 16]. For example, using the ℓ_1 norm in the regularizing term enforces sparse discrimination vectors. Other regularized discriminative classifiers like support vector machines (SVM) or linear programming machines appear to be equally suited for the task [4].

3.6 Biofeedback

Finally, a multimedia application, running on a separate computer, receives combined results of the classification via an asynchronous client–server interface and acquires them in a temporal queue. It examines the queue repeatedly for stationary signals persisting for a certain time length, i.e., a Command Activation Term (CAT) and emits the command, corresponding to the class label of the classification result (left/right/rest). After a command has been emitted, it then falls into “relaxation” for a certain time period, i.e., Command Relaxation Term (CRT), which should be at least as long as the CAT. During this period combiner outputs remain being collected in the queue, but further command emissions are suppressed. This procedure, for three classes: left (black), right (gray) and rest (dashed) is illustrated in Fig. 8. Here the combiner yields the class label (denoted as color of bars) and the fuzzy values $\widetilde{P}_{\max} = \max_i \widetilde{P}_i$ of the most likely recognized class (depicted as amplitude) distributed over time at a frequency of 25 Hz. CAT is set to 10 periods (400 ms), and CRT is set to 14 periods (560 ms).

This flexible setup allows individual adjustments for the user and the control strategy of the biofeedback application: (1) long CAT, helps to avoid false-positively emitted commands; (2) short CAT, allows fast emission of commands, i.e., before the real movement is executed; (3) intraindividually adjusted CRT prevents erroneous, respectively allows volitional successive emissions of the last command. These parameters depend strongly on the user and should be set initially to values calculated from the results of the application of trained classifier to the training data. At starting point CAT_0 may be set to the median length of the stable signal containing a marker of the same action class, and CRT_0 to a value larger than CAT_0 by twice the amount of the standard deviation of the distribution of lengths of stable signals. The values of CAT and CRT should then be adjusted according to the user’s demand.

The underlying multimedia application should be intuitive, simply to understand, and the control strategy should give the user a feeling of natural acting, however it should require a small (at present: binary) control set of commands, i.e., left-turn/right-turn, avoid fast animation and high-contrast changes to prevent or minimize spoiling of data affected by artifacts, e.g., brisk eye-, head- or body movements. An issue of particular importance for a fast

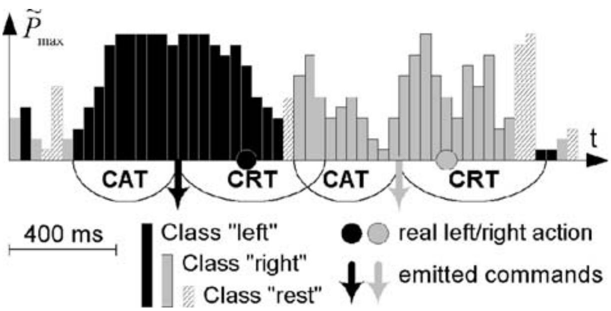


Fig. 8 Time structure of command emission queue

pacing of control commands is a “natural mapping” of the action required in the multimedia, Virtual Reality (VR) or gaming scenario to the “action space” of the human operator, which is coded in egocentric coordinates. To this end the on-screen environmental perspective must continuously represent the viewing direction of the human operator, so that, e.g., a selection of the option of right-turn can be addressed by the intention to move the right hand and vice versa.

4 Results

To enable the classifier training, we initially let the user execute or imagine the task accomplishment repeatedly. For real movements, which can be monitored the user may perform tasks “self-paced”. For imagined movements (in paralyzed patients) the lateralization of each action (left/right) is queried by an auditory and/or visual cue. We extract training samples, preprocess each as described in Sections 3.3 and 3.4, calculate a set of optimal classifiers on a selection of 90% of the markers and test each on remaining 10%. This cross-validation procedure is repeated ten times with all non-overlapping test sets.

By calculating, then, means of training and test errors, we obtain a measure for effectiveness of a particular classifier model. A test error essentially higher than the training error would indicate that the model is too complex for the given data, such that the risk of over-training is high due to bad generalization ability.

Notably, test errors of the cross-validation procedure depend on the choice of the delay time t_d in the pre-processing procedure. Obviously classification is ambiguous for large values of t_d and mostly correct for $t_d=0$. Figure 9 shows the cross-validation test error of classification of EEG single trials as a function of t_d for a single subject performing in a self-paced experiment with 30 taps per minute.

The right ordinate enumerates the number of communicated bits per minute that can be extracted from the classification results. Compared to the errors of classification based on EMG (upper curve), which mirrors the muscle activity in the forearms, the EEG approach yields superior classification results already 120 ms prior to the actual movement execution and retains its higher performance, as classifications after the hit marker is present are not interesting any more. This phenomenon is neurophysiologically evident, because the decision about lateralization of movement has to be met in the brain firstly, followed by the preparation of cortical neurons and emission of the command down to the spinal cord, peripheral nerves and to the effector muscles spending at least 60–80 ms.

Initially we implemented a very simple visual biofeedback application to provide the user with a first feeling of her/his intentions: a thick black cross is moving over a

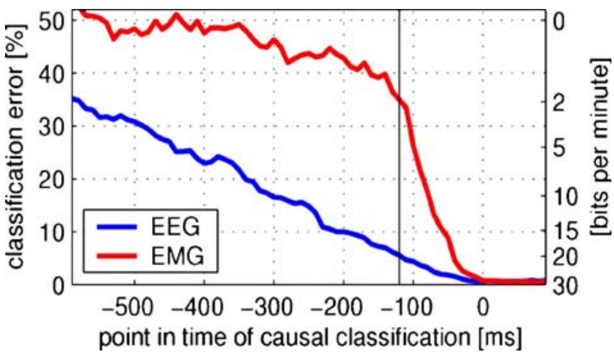


Fig. 9 Classification test errors based on EEG/EMG

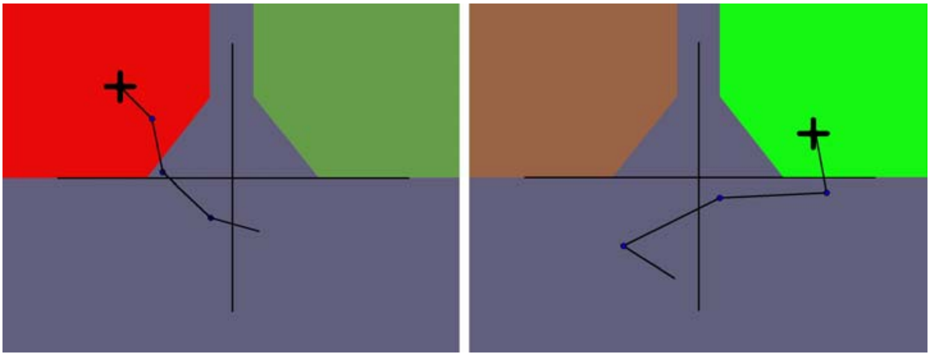


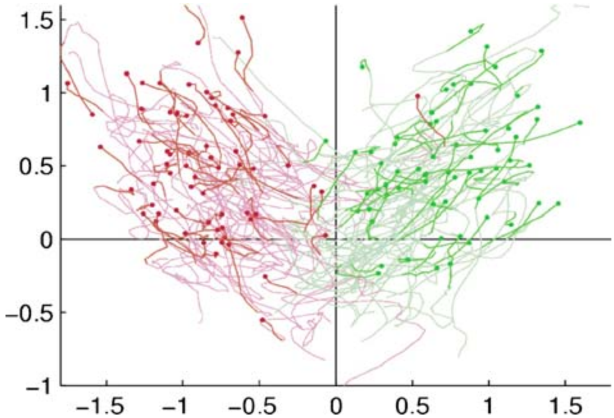
Fig. 10 Feedback “Jumping Cross” with history tail

full-screened window containing a thin fixation cross in the center and two target fields (dark red—in the upper left corner, and dark green—in the upper right corner, indicating left-hand and right-hand movements, respectively). The ordinate of the “jumping cross” reflects the normalized decision of the movement detection classifier (“up” indicating action vs. “down” indicating rest), i.e., that the missile jumps in the upper half of the screen on upcoming “action”. The abscissa provides the natural mapping of the determination classifier result (left vs. right). The “jumping-cross” trails a history tail of four points (data drawn at 40 ms intervals). The single action trial is indicated as correctly completed, when (1) the screen freezes on occurrence of an event marker, i.e., after an actual movement is performed and when (2) the corresponding lateralization field, the cross is actually located in, is highlighted. Figure 10 illustrates two typical left and right single-trial events.

A series of single trials acquired over the whole experiment (here: 64 left and 64 right trials) may be represented in an instructive summary plot, cf. Fig. 11. Here, crosses were replaced, for clarity, by bold dots and the history tails are painted bold for the three most recent periods and thin for another four preceding periods. The axes represent the classification results of the determination and detection classifiers, respectively. It can be recognized at a single glance, that the majority of trials have been classified correctly.

Finally, the well-known Pacman video game has been adapted to serve as biofeedback, cf. left part of Fig. 12. The idea is to combine the information, available

Fig. 11 Accumulated feedback trials



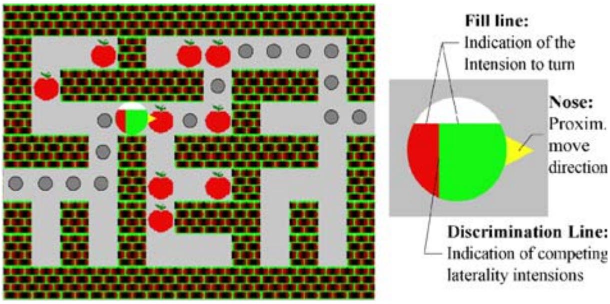


Fig. 12 Feedback "Brain Pacman" and the head filling strategy for indication of user's upcoming intentions

from the "jumping-cross" feedback with an aim–gain inventively in a gaming application. A random labyrinth is generated in a full-screened window, which has exactly one way from the entry (in the left wall) to the exit (in the right wall), which is the shortest path and is marked with gray track marks. The player may also decide to run the Pacman through the rest of the maze, e.g., to receive additional credits for harvesting the apples.

As control strategy we use the following approach: The Pacman makes one step each 1.5–2 s and moves always straight ahead until it reaches a wall or receives a turn command. The direction, in which the Pacman is intended to make the next step is pointed by its yellow nose. Initially the Pacman's head is completely white and fills with red and green color from bottom up as the player's intention to turn rises, i.e., the detection classifier yields "action" results. A vertical line discriminating the two filling colors, i.e., intention to turn left (red) vs right (green) is placed according to the result of the determination

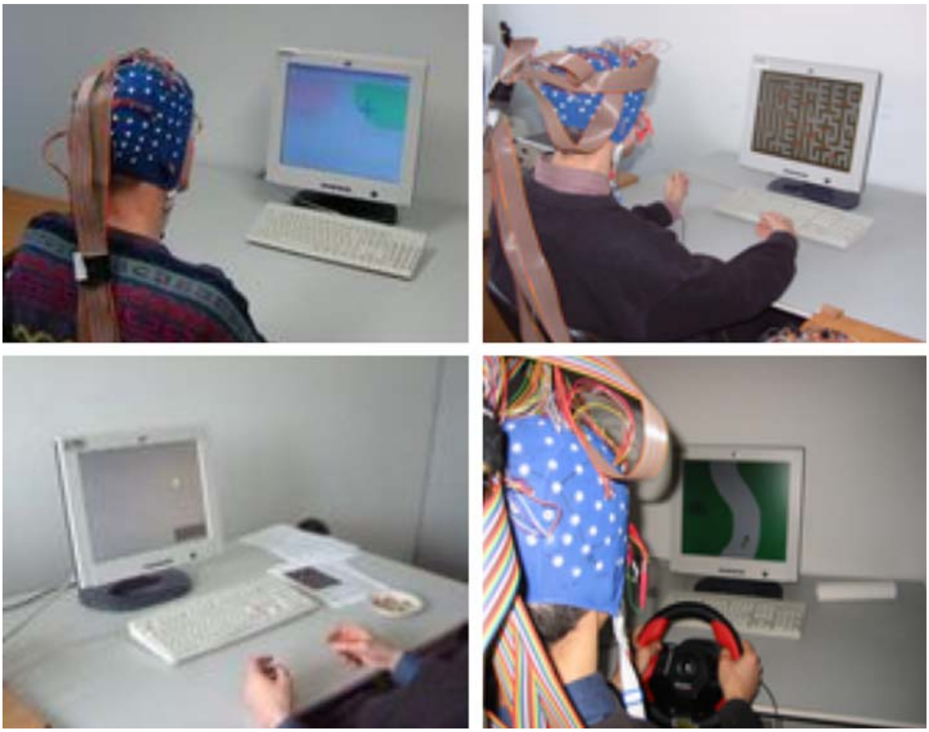


Fig. 13 Users of BBCI incorporating various feedback scenarios

classifier, cf. right part of Fig. 12. Effectively, the intersection of the fill level and the discrimination line matches the position of the "jumping cross", with the inverted sign of the abscissa. Such that, if the player intends to steer the Pacman to the right, this should fill the Pacman's head green for at least the CAT. After a turn, the Pacman does not accept any further commands for at least CRT. User is acquiring credits for harvesting apples, for making steps on the grey path marks, and loosing credits in each step while bashing against the wall. The simulation is finished when the Pacman reaches the exit of the labyrinth.

A healthy subject will be able to navigate the Pacman through the presented labyrinth within 40 sec (20 steps, each of 2 sec) using a conventional keyboard or a mouse, however, the "*fun factor*" of navigating the Pacman just by intentions of the own brain turned out to be very appealing. Although it takes much longer to move through the maze by the power of thoughts alone, it is highly interesting that when immersed into the BCI game scenario the user has sometimes the feeling that the Pacman moves in the correct direction though the user was consciously not aware of his decision, sometimes consciously not even ready for a decision.

Summarizing the variety of feedback modules implemented for the use with BBCI, besides the "Jumping Cross" and the "Brain-Pacman" scenarios presented above in more detail, it offers currently a "Brain-Pong" scenario, which is based on a well-known single-player Tele-Tennis video game, cf. bottom left part of Fig. 13. Moreover, a "Brain-Speller" utility (not shown here) may provide a handicapped person with a communication capability. We are currently working on a "Brain-Driver" scenario, shown in the lower right part of Fig. 13, and on a "Brain-Tetris", which will exploit the usage of a third class of imagined movements, e.g., moving a block to the left–left hand movement, vs moving it to the right–right hand movement, vs rotate it by 90° feet movement, while the block is falling down the screen autonomously.

5 Conclusion and outlook

Brain-Computer Interfaces have traditionally been conceived and used in assistance systems for the disabled [3, 25, 26]. We have shown in this contribution that our BBCI explores also the interesting path towards multimedia applications, exemplified here as brain-gaming.

While most BCIs (except VEP or P300-based) require extensive training (>200 h) from their users, it is one distinctive feature of the BBCI that it employs advanced signal processing and machine learning technology for training the computer rather than the human subject, such that the user can start "communicating" without extensive prior training. The particular focus of the present paper was to introduce appropriate as well as appealing biofeedback signals that allow a user, who has taken a "cold-start" to explore and improve his individual possibilities to use the BBCI communication channel.

There are several aspects for further improvement of BBCI: so far we have used a paradigm, where the user actually implements a movement, i.e., typing with the left or right fingers. In ongoing research we transfer this paradigm to assistance systems where a disabled person still has movement intentions and their respective neural correlate, but no means for an actual movement.

Generally, the question of an ideal biofeedback signal for BCI will find new answers appropriate for each new application. The current study showed clearly, that a biofeedback in a gaming scenario, such as Pacman can be realized very naturally and by work successfully. Eventually, this biofeedback can make the user adapt to the classification engine and vice versa the classification engine might experience it simpler to classify correctly in the course of mutual adaptation. Another issue with pioneering appeal is the thrilling possibility that, because the BBCI bypasses the conduction delays from brain to muscles, it could speed up the initiation of actions in competitive, dual-player scenarios.

Let us finally discuss how much information we can expect to transmit in such a new BCI channel. Invasive technologies can achieve bit-rates that are high enough for, e.g., online 3D robot control (as already discussed before) [18], but require hundreds of microelectrodes implanted into the brain's cortex, which appears as an unlikely condition for healthy subjects. For non-invasive techniques our own earlier studies have shown that in a pseudo-online idealized evaluation—i.e., data are recorded and analyzed later as if online—record bit-rates of up to 50 bits per minute are achievable [5]. In spelling tasks that are truly online with biofeedback, single subjects can reach a level of two to three letters per minute [21, 25, 3]. At first sight, this might appear rather slow for a communication device, as other communication devices, e.g., a computer mouse can achieve 300–350 bits per minute [14]. Yet, one should realize that a BCI communication channel is largely independent of other channels and offers a unique feature of ultra fast action emissions for each single reaction trial.

In conclusion, we discussed state-of-the-art BCI research and presented recent results that could be achieved by providing multimedia, i.e., gaming feedback to a BCI user. Future research will further explore this direction towards more natural feedback modi, appropriate and plausible control strategies and user adaptation ultimately using brain signals for control in Virtual Reality (VR) environments [27].

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