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A brain–computer interface (BCI) for the locked-in: comparison of different EEG classifications for the thought translation device

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Abstract

Objective: The Thought Translation Device (TTD) for brain–computer interaction was developed to enable totally paralyzed patients to communicate. Patients learn to regulate slow cortical potentials (SCPs) voluntarily with feedback training to select letters. This study reports the comparison of different methods of electroencephalographic (EEG) analysis to improve spelling accuracy with the TTD on a data set of 6650 trials of a severely paralyzed patient.

Methods: Selections of letters occurred by exceeding a certain SCP amplitude threshold. To enhance the patient's control of an additional event-related cortical potential, a filter with two filter characteristics ('mixed filter') was developed and applied on-line. To improve performance off-line the criterion for threshold-related decisions was varied. Different types of discriminant analysis were applied to the EEG data set as well as on wavelet transformed EEG data.

Results: The mixed filter condition increased the patients' performance on-line compared to the SCP filter alone. A threshold, based on the ratio between required selections and rejections, resulted in a further improvement off-line. Discriminant analysis of both time-series SCP data and wavelet transformed data increased the patient's correct response rate off-line.

Conclusions: It is possible to communicate with event-related potentials using the mixed filter feedback method. As wavelet transformed data cannot be fed back on-line before the end of a trial, they are applicable only if immediate feedback is not necessary for a brain–computer interface (BCI). For future BCIs, wavelet transformed data should serve for BCIs without immediate feedback. A stepwise wavelet transformation would even allow immediate feedback.

Keywords: Brain–computer interface; Slow cortical potentials; Discriminant analysis; Wavelet transform; Classification of brain states

1. Introduction

Some neurological diseases such as amyotrophic lateral sclerosis (ALS), Guillain–Barré syndrome or subcortical stroke may lead to severe or complete motor paralysis. During the final stages of ALS, some artificially respirated patients are no longer able to communicate because even eye movements become unreliable and exhausting or impossible. Nevertheless, in most cases, cognitive and sensory functions remain intact and patients are aware of their environment (Norris, 1992). The Thought Translation Device (TTD) was developed to communicate with these locked-in patients (Birbaumer et al., 1999; Kübler et al., 1999). Comparable systems using oscillatory brain activity, particular the mu-rhythm of the sensorimotor cortex were developed by Pfurtscheller et al. (1993) and Wolpaw et al. (2000).

The TTD consists of a computer program (TTD software) developed by our group (Hinterberger, 1999), which reads data from an electroencephalographic (EEG)-amplifier system, performs on-line processing and provides feedback of the processed signal. The feedback signal is classified and serves as a response code for letter selection with the Language Support Program (LSP), which is a sub-module of the TTD. The EEG data are stored and can be later used for off-line simulations using different parameter settings in the TTD in replay mode (for details see Hinterberger, 1999). The TTD provides feedback of slow cortical potentials (SCPs). SCPs are potential shifts of the

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electrical brain activity lasting from several hundred milliseconds up to several seconds. They reflect the level of excitability of the underlying cortical areas (Rockstroh et al., 1989). There are several reasons for using the SCPs to control the TTD. SCPs are detectable in every human brain, even if the motor periphery is completely disconnected from the central nervous system (Kübler et al., 1998). In addition, the neurophysiological basis of SCPs and the operant learning rules for the acquisition of voluntary control of SCPs are well understood (Birbaumer et al., 1990).

Subjects can learn to self-regulate their SCPs by producing either cortical positivity or negativity according to the task requirement (Birbaumer et al., 1981; Birbaumer, 1984, 1998). To train subjects in SCP self-regulation, feedback of SCP amplitude shifts is provided by a graphic signal on a computer screen, immediately rewarding the SCP shifts in the requested direction (operant conditioning). To use the trials as a response signal, the negative or positive potential shifts have to be classified into a binary response, e.g. yes/no or accept/reject. Patients can respond to questions or select sentences, words or letters with the LSP (Birbaumer et al., 1999; Perelmouter et al., 1999, Hinterberger et al., 2001, Kaiser et al., 2001). The higher the correct response rate, the higher is the speed of communication.

There are at least two strategies to improve patients' correct response rate. First, with respect to patients, operant reinforcement schedules can be adapted to the individual patient in order to obtain a more precise differentiation in the brain signal (Birbaumer et al., 1999; Kübler et al., 2001). The second strategy, and the focus of this study, involves the processing and analysis of the EEG signal. Of specific interest are the ways a trial is defined, what constitutes a correct or incorrect response, and how the shape of the EEG signal over time can be adapted or modified to promote performance.

2. Methods

2.1. Subject

Data were collected from a severely paralyzed 46 year-old male patient, diagnosed with ALS in 1989. Since 1993, he has been artificially ventilated and fed. His motor abilities are reduced to two small facial muscle movements and weak eye movements which are exhausting and unreliable for extensive communication over longer time periods. There is progressive loss of this remaining motor control, and therefore, preventive training is necessary. The patient was trained to communicate with the TTD two to three times a week for two years prior to data collection. After one year of training, the patient was able to write messages using the TTD. Training was realized at the patient's home, while he sat in his wheelchair in front of a notebook monitor.

2.2. EEG recording

The EEG was recorded from Cz, Fz and Pz according to the international 10–20 system. One electrode at the patient's forehead served as a reference. In addition, vertical electrooculogram (EOG) was recorded from electrodes placed above and below the left eye. Artifacts due to eye movement or eye blinks were corrected on-line and off-line as described in Kotchoubey et al. (1996). Eight millimeter Ag/AgCl electrodes were applied with Elefix electrode creme. Electrode impedance was kept below 5 kOhms. The EEG was amplified using an EEG8 amplifier system (Contact Precision Instruments Inc.) and acquired with the TTD software with a sampling rate of 256 S/s. The low-pass filter was set to 40 Hz and the high-pass filter to 0.1 Hz. Although the EEG was recorded with a bandwidth of 40 Hz, the software applied a low-pass filter at 1 Hz to detect the SCP signal. This low-pass filter was achieved by using a moving average window of 500 ms, updated 16 times a second.

2.3. Feedback design

The TTD provided feedback of SCP amplitude shifts at the vertex (Cz) in a rhythmic, time-locked manner. One training day consisted of 10–20 runs. Each run comprised 80–100 trials with no inter-trial intervals. Each trial was divided into a 2 s passive preparation phase (where the required task was indicated, but no feedback was provided) and a 2 s active phase in which the patient should apply his cognitive response strategy. The beginning of the preparation phase was indicated by a short high-pitched tone of 1200 Hz, whereas the active phase was introduced by a clearly distinguishable low-pitched tone of 500 Hz indicating that the patient now had to apply his mental strategy to perform the response. At the top and the bottom of the screen, a rectangle was shown to indicate the task requirement: From the beginning of each trial, one rectangle was highlighted indicating the direction into which the cursor should be moved during the active phase. When the cursor reached the lower rectangle, it indicated that the SCP had exceeded the threshold level required for a selection response. This will be referred to as the threshold method. A cursor movement that exceeded the threshold level was rewarded at the end of each trial by a smiling face and by blinking of the rectangle. The position of the feedback cursor during the feedback period (Fig. 1) was determined by the current SCP amplitude compared to a baseline recorded 500 ms prior to the low-pitched tone. Negative cortical potential shifts moved the graphic feedback cursor (a yellow 'ball') upward; positive shifts moved the cursor downward. Depending on the patients' individual EEG response, SCP feedback was given in a suitable time window during the active phase to achieve a high hit rate and avoid false alarms. In the present study, the feedback

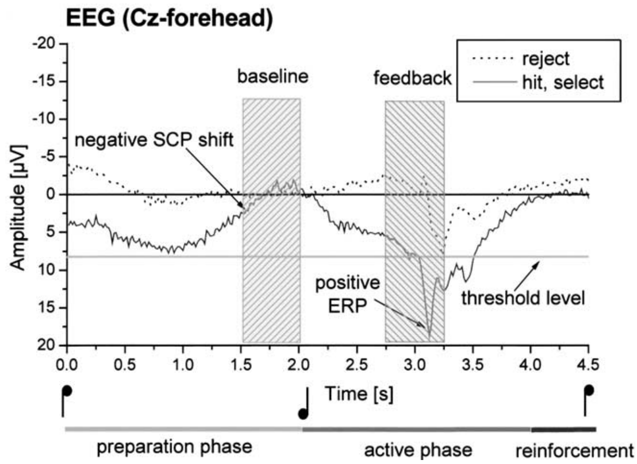

Fig. 1. Trial structure for the communication training using a combination of SCP and ERP-brain signals and the average EEG waveforms during a trial. The trial was subdivided into a 2 s preparation phase followed by a 2 s active phase during which the patient had to apply his response strategy. Reinforcement was presented during the last 0.5 s of the trial. The beginning of the preparation phase and the active phase was indicated by a short high or low auditory signal. The cursor movement itself (feedback) started with a vertical jump of the cursor causing a controllable positive ERP during the cursor movement. The graph depicts the grand average of the unfiltered EEG trace of about 1000 trials separately for each task requirement. The EEG here and the SCP during feedback were referenced to the average potential of the 0.5 s baseline period. The solid line shows the course of the EEG when a selection response was required (cortical positivity), the dotted line when a rejection response was required. The waveforms of the two tasks differ mainly in the negative SCP shift during the preparation phase and the positive ERP-peak during the feedback period. A selection was realized when the threshold level was reached or exceeded during feedback.

window was 500 ms starting 750 ms after the low-pitched tone. The detailed trial structure is depicted in Fig. 1.

2.4. Communication

For communication with the aid of this feedback system, the patient used the LSP (Perelmouter et al., 1999; Birbaumer et al., 1999). This program allowed the patient to select a group of letters or a single letter within one trial leading to a binary choice through the production of an SCP shift. Letters were presented in the bottom rectangle. Selected letters appeared in the top rectangle. To select a presented item (single letter or a set of letters), the patient was required to move the cursor downward by producing cortical positivity and hit the bottom rectangle. To reject the presented item, the patient had to avoid the hit by moving the cursor upward. The spelling procedure and the letter arrangement in the binary decision tree are described in detail in Hinterberger et al. (2001).

Before the patient could communicate with the LSP, he needed to be trained in a stepwise procedure (Kübler et al., 2001). The first stage was the *feedback training* as described previously, by rewarding the patient for producing cortical shifts in a requested direction. The next stage of training, the *copy-spelling* mode, required the patient to copy a text, which was presented in the upper rectangle of the screen. After the patient could copy the text with sufficient accuracy (75% correct responses), he was asked to self-select letters and words (i.e. the *free-spelling* mode).

2.5. The data set

The off-line analysis was performed only on data from the feedback-training and the copy-spelling modes because the task requirements of both these modes were clearly defined, whereas in the free-spelling mode, the task is dictated by the patient and establishing a performance criteria on trial basis is difficult.

Two data sets of 5 consecutive daily sessions were selected at random from more than 1000 runs or about 100 sessions. The criteria for the selection were that the parameters were not changed during those 5 days, the patient should be adapted to the current training mode and that no disturbing events occurred (e.g. the patient was tired). Set 1 consisted of 36 runs (3057 trials) and set 2 of 38 runs (3593 trials). The patient's average correct response rates in the on-line training were 83 and 72% in sets 1 and 2, respectively. Set 1 was conducted in the feedback-training mode with a ratio of required selections N_{pos} to required rejections N_{neg} of about 1:1. After that, the training was changed to the copy-spelling mode. Set 2 was conducted 2 months later when the patient was adapted to use the copy-spelling mode with constant performance. The spelling task required 3.5 times more selections than rejections (a selection/rejection ratio of 3.5:1). This depends on the letter arrangement in the binary decision tree and the correct response rate (CRR). The following classification methods were applied off-line to data sets 1 and 2, and then compared to determine which classification approach yielded the highest accuracy.

2.6. EEG response curves

Fig. 1 shows the average EEG response curve during a trial. Therefore, 1000 trials collected in one session were averaged. Two curves are depicted: the solid line shows the response of the required 'select' condition where the patient had to hit the rectangle at the bottom of the computer screen by producing cortical positivity. The dotted line shows the response for the 'reject' condition, where a negative or a positive potential shift of less than 7.7 μV was allowed to avoid the hit of the bottom rectangle. To produce cortical positivity, a preceding negative SCP shift can be seen during the preparation phase. This negative preparatory potential helped to establish a more negative baseline level at the end of the preparation phase. In other words, by producing a negative SCP shift during baseline the patient can promote his ability to produce a positive SCP shift in the active phase.

During the active phase, the patient received immediate feedback from the cursor movement on the screen. The onset of the cursor movement itself caused an event-related potential (ERP) superpositioned on the SCP. This ERP was smoothed by the slow-wave filter which minimized any ERP contribution. However, as it can be seen in Fig. 1, the patient produced both SCP shifts and a positive ERP peak (P300 type component) with a latency of about 340 ms following the onset of the cursor movement. Thus, to perform a selection, he produced a large negative SCP shift during the preparation phase, followed by a positive SCP shift and an additional ERP during the feedback interval. The ERP was sharper, with a larger amplitude and appeared with shorter latency, compared to the rejection response curve.

2.7. Mixed filtering (MF)

Perception of the feedback signal, i.e. the cursor movement, produced a positive ERP, which in turn appeared to facilitate the patient's ability to enhance an SCP shift with identical positive polarity. For the feedback of both components (SCP and ERP), the mixed filtering method (MF) was introduced, which used two low-pass filter settings alternately for calculating the feedback signal; to allow feedback of the SCP only, a low-pass filter realized by a 500 ms moving average (cut-off at 1 Hz) was applied during the entire feedback period except for a small time window (62.5 ms duration) during which the ERP was expected with a latency of 340 ms after the onset of cursor movement. During this time window (312.5–375 ms after feedback onset) the average of the last 62.5 ms defined the feedback signal (i.e. a cut-off of 8 Hz) to facilitate the production and feedback of the ERP. To elicit an ERP, onset of cursor movement had to be clearly visible. Thus, cursor movement started with a vertical jump 750 ms after the low-pitched tone. This additional stimulus element stabilized and intensified the ERP, leading to the response curve as shown in Fig. 1. All the data described subsequently were recorded using this on-line MF feedback method.

2.8. The CRR as performance index

The CRR is defined as the percentage of trials in which correct responses were performed. The CRR was calculated for each of the two response conditions (positivity/negativity resp. selection/rejection) separately (CRR_{pos} and CRR_{neg}). This was done with the TTD software on-line during the training as well as in off-line simulations for evaluating the following classification methods also using the TTD. The total CRR is defined as the ratio between the number of correct responses including both tasks and the total number of trials. The CRR is determined by the classification method.

2.9. Response classification

For BCIs the precision of on-line discrimination between SCP positivity and SCP negativity is crucial. Three classification methods, the threshold method, the linear discriminant analysis (LDA), and a z-scale based discriminant analysis (ZDA) are described below:

1. The threshold method consisted of a simple decision strategy to determine whether a threshold amplitude was met. A trial was classified as successful if the patient generated an SCP amplitude sufficiently large to move the cursor into the rectangle at the bottom of the screen. This method was used for the on-line training condition with a threshold set at 7.7 μV. The first aim of this study was to improve the CRR by sequentially optimizing the threshold. Therefore, the effect of the threshold on the CRR was studied off-line by varying the threshold amplitude and simulating the feedback process with the two data sets using the TTD software in replay mode.
2. LDA is a statistical approach to separate two response curves. Here, Fisher's discriminant analysis method (Fisher, 1936) was applied to the time series of the current EEG $\vec{x}$ (with a 4 s interval in each trial the vector $\vec{x}$ comprises 64 elements), taking into account the mean time series ($\vec{G}_{pos}, \vec{G}_{neg}$) and the covariance matrix $\hat{S}_W$ of the means of many trials estimated from previous runs. These prior data served as reference data and should be representative for the current EEG time series. The LDA assumes equal variances in the distribution of both response curves. Those assumptions are used to define a weighting vector $\vec{w}$ (off-line)

$$\vec{w} \propto \hat{S}_W^{-1}(\vec{G}_{pos} - \vec{G}_{neg}) \tag{1}$$

which is then used on-line for the calculation of the classification outcome K according to

$$K = \vec{w}^{T}(\vec{x} - \vec{G}_{pos+neg}) > 0 \text{ or}$$

$$K = \vec{w}^{T}(\vec{x} - \vec{G}_{pos+neg}) < 0. \tag{2}$$

$\vec{G}_{pos+neg}$ is the mean amplitude of both tasks and $\vec{w}^T$ is the transposed weighting vector. The LDA can be used as an on-line method for providing feedback. Each single EEG amplitude x_i is classified according to Eq. (2) to a preliminary decision value $K_i = w_i(x_i - G_{i,pos+neg})$ during feedback. This value determines the current position of the cursor. At the end of each trial, all decision values K_i are combined to the outcome K according to Eq. (2). The sign of this outcome leads to the binary response, indicating whether the current trial fits more to the mean curve of the required positivity or negativity.
3. Another method uses a fast discriminant analysis algorithm based on z-scores (ZDA). This approach is derived from signal detection theory (Baird and Noma, 1978). Here, the standard deviations of the mean of each task requirement are regarded separately. The weighting

factors w_i are defined as

$$w_i = \frac{G_{\mathrm{pos},i} - G_{\mathrm{neg},i}}{S_i}, \qquad \text{with } S_i = \sqrt{S^2_{\mathrm{neg},i} + S^2_{\mathrm{pos},i}} \tag{3}$$

where i is the index of time in-between a trial and S_i is the standard deviation of the EEG signal amplitude x_i. The weight w_i at each time point denotes the ability to discriminate the current signal. The weights w_i were exclusively obtained from prior reference runs. Similar to the LDA, the outcome K is defined as the sum of the preliminary decision values of the individual time points as

$$K = \sum_i K_i w_i \tag{4}$$

To account for the different variances, each single EEG amplitude was transformed to two z-scores, one for the negativity condition $z_{\mathrm{neg},i}$ and one for the positivity condition $z_{\mathrm{pos},i}$. The sum K_i of the z-scores denoted the polarity of the classified EEG:

$$K_i = z_{\mathrm{neg},i} + z_{\mathrm{pos},i} = \frac{x_i - G_{\mathrm{neg},i}}{S_{\mathrm{neg},i}} + \frac{x_i - G_{\mathrm{pos},i}}{S_{\mathrm{pos},i}} \tag{5}$$

A positive K_i classified a value x_i as a selection response, where positivity had to be produced (if $G_{i,\mathrm{pos}} > G_{i,\mathrm{neg}}$) and a negative K_i indicated a higher probability of the rejection response curve. In case of $K_i = 0$, no decision was possible as the two z-scores in Eq. (5) were equal with opposite signs.

2.10. Wavelet transform (WT)

The presence of various time-locked waveforms such as the SCP shifts and the ERP, which appeared roughly at the same point in time in each trial, provided an opportunity to transform the EEG time series into wavelets. Wavelet transformation transforms time-locked waveforms into a few meaningful coefficients that can be classified with higher precision. The same classification algorithms of LDA and ZDA that were used for time-series classification were applied to the wavelet transformed data. In order to function as an on-line algorithm for single trial classification, the wavelet transformation was implemented as a fast pyramidal algorithm using Daubechies wavelets. The basic wavelet Ψ has to constitute a suitable time-series function which means it should be similar to the detected wave shapes (here the ERP-waveform and the SCP-waveform). Daubechies wavelets were chosen because of their physiologically shaped basic wavelet (Dickhaus and Heinrich, 1996). The various wavelet coefficients w_{ab} are obtained by the convolution of the time-series EEG $x(t)$ with a function Ψ_{ab}

$$w_{a,b} = \frac{1}{\sqrt{|a|}} \int_t x(t)\Psi_{a,b}(t)\, dt \tag{6}$$

The function Ψ_{ab} is obtained by a dilatation of the wavelet Ψ and a delay in time. The dilatation factor a produces the different frequencies, whereas the variable b delays the function in time to obtain the location in time of the wavelet Ψ:

$$\Psi_{a,b}(t) = \Psi\left(\frac{t-b}{a}\right) \qquad \text{with } a \neq 0 \tag{7}$$

Instead of this continuous WT, a fast discrete WT using the pyramidal algorithm is available (Daubechies, 1988). Therefore, a and b can be chosen in steps of 2^m and $2^m k$ ($m,k \in Z$). The discrete Daubechies D4 wavelets were used because they consist of only one wave cycle and thus are non-oscillating (Press et al. 1988–1992). Fig. 2 illustrates the process of the fast Daubechies algorithm with the example of an average EEG response of the patient. The Daubechies discrete WT resulted in the same number of wavelet coefficients w_i as there were time points. The discrete variables a and b were arranged into the wavelet coefficients i as illustrated on the right side of Fig. 2.

For the classification of wavelet transformed data using the LDA and ZDA algorithms, the time series $\vec{x}$ needed to be replaced by the wavelet coefficients $\vec{w}$. In addition, the means, the covariance matrix and the standard deviations of Eqs. (1)–(5) had to be substituted by the means and variances of the wavelet transformed data. $G_{\mathrm{neg},i}$, $G_{\mathrm{pos},i}$, $S_{\mathrm{neg},i}$, $S_{\mathrm{pos},i}$ and $\hat{S}_W$ were then containing wavelet coefficients.

For all classification methods, an important question is the choice of the reference data. These reference data are used to estimate the means and variances $G_{\mathrm{neg},i}$, $G_{\mathrm{pos},i}$, $S_{\mathrm{neg},i}$, $S_{\mathrm{pos},i}$ and $\hat{S}_W$. The first run of a session served as reference for the current training day. Reference runs themselves were not classified. When the first run did not lead to a representative result, the last run of the previous session was included.

2.11. Summary of the different classifications

For the classification of time-series data as well as for the wavelet transformed data, the first 4 s of each trial were classified. Thus, both the preparation and the active phases were included. The last 500 ms at the end of the trial were reserved for the positive reinforcement (smiling face) and were not included. As the position of the feedback cursor was updated 16 times a second, the discriminant analysis resulted in 64 coefficients. Similar to the classification of the EEG as a time series, the wavelet classification was applied to the data sets 1 and 2. The EEG was filtered to exclude frequencies above 8 Hz and then transformed into 64 wavelet coefficients. Classification was realized using all the 64 coefficients.

To summarize, the following methods were compared:

- threshold method using unmodified SCP ($f < 1$ Hz);
- threshold method using MF (on-line training situation);
- LDA-based classification using time-series EEG ($f < 8$ Hz);

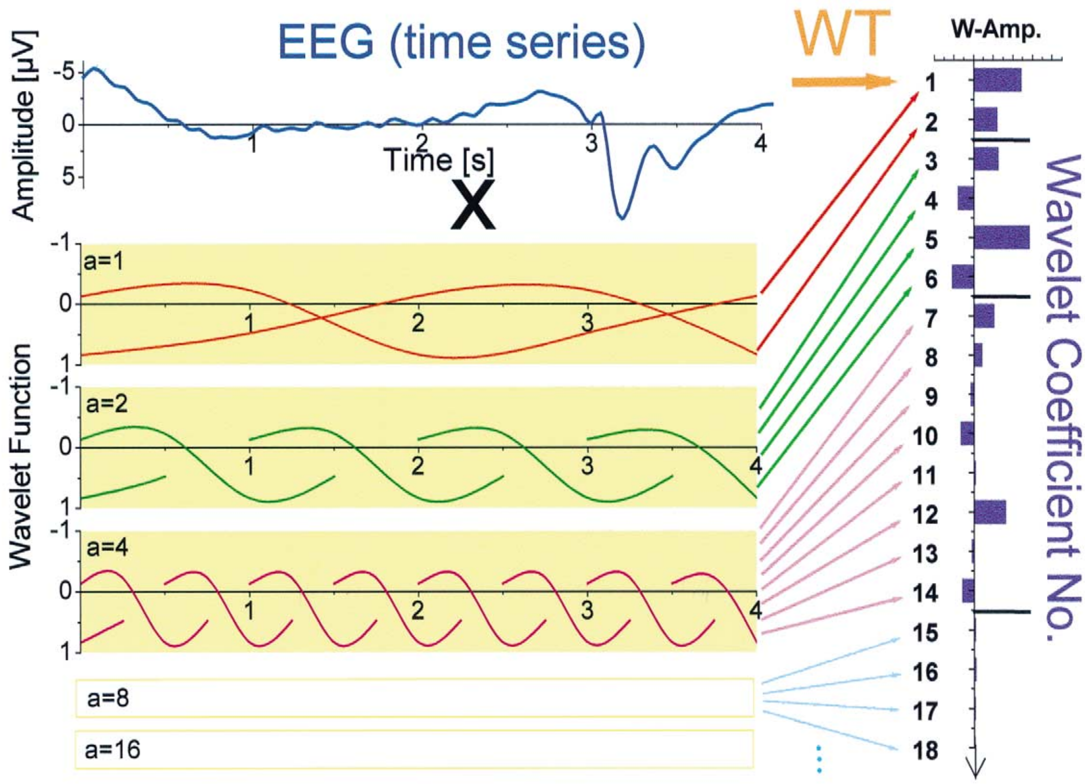

Fig. 2. Wavelet transformation. The EEG time series (here a grand average EEG trace is depicted as an example) is transformed into wavelet coefficients by convoluting it with different wavelet functions displayed in the yellow graphs. They are arranged in the order as shown by the arrays. The wavelet functions are obtained by a dilatation of the basic wavelet and a time delay. The dilatation factor is decreased by the index a, which is doubled each step. The number of delayed wavelets is also doubled each step leading to higher time resolution in higher wavelet coefficients. The index a is increased until the number of wavelet coefficients meets the number of samples in the time trace e.g. the ERP at 3.2 s is represented by wavelet coefficient numbers 5 and 12.

– ZDA-based classification using time-series EEG ($f < 8$ Hz);
– LDA-based classification using wavelet-transformed data; and
– ZDA-based classification using wavelet-transformed data.

3. Results

3.1. The threshold method

The average CRR was calculated off-line for various threshold values (from 1 to 9 µV) for both data sets, feedback training and copy spelling. As Fig. 3 illustrates, the CRRs are strongly dependent on the threshold. Because the ratio R between the required selections and rejections constitutes the main difference between the two data sets, it is important to consider the CRR_{pos}, CRR_{neg} and the total CRR separately. Depending on the ratio R, the total CRR reached its maximum at a different threshold value despite similar CRR_{pos} and CRR_{neg} (Fig. 3). The analysis was performed using the original unmodified SCP feedback mode as well as the MF feedback mode, where both SCP and ERP were fed back in an off-line simulation.

3.1.1. The MF method

The training was carried out using the MF feedback method at a fixed threshold voltage level of 7.7 µV. This threshold value was optimal for the feedback training with an equal number of selections and rejections (data set 1) and led to the highest accuracy of 83% CRR (Fig. 3b). The threshold level was kept constant after switching to the copy-spelling mode (data set 2, Fig. 3d), and the total CRR dropped to 72%.

Two facts are responsible for this. First, the spelling task required two cognitive operations (selecting the letter and producing the SCP), as opposed to the single task (producing the SCP only) of the feedback training. Second, as the copy-spelling procedure requires a higher selection/-rejection ratio, the total CRR curve changed and its maximum moved to a lower threshold value of about 3.0 µV. Under this condition, an 80% CRR could have been achieved on-line. All CRR values were highly significant above chance level ($P < 0.001$, Wilcoxon test).

3.1.2. MF method versus unmodified SCP

With data set 1 (feedback-training mode), the CRR obtained with the MF method on-line was 83% (at 7.7 µV), which was higher than the CRR obtained with unmodified SCP off-line for all threshold values. For this data set, the

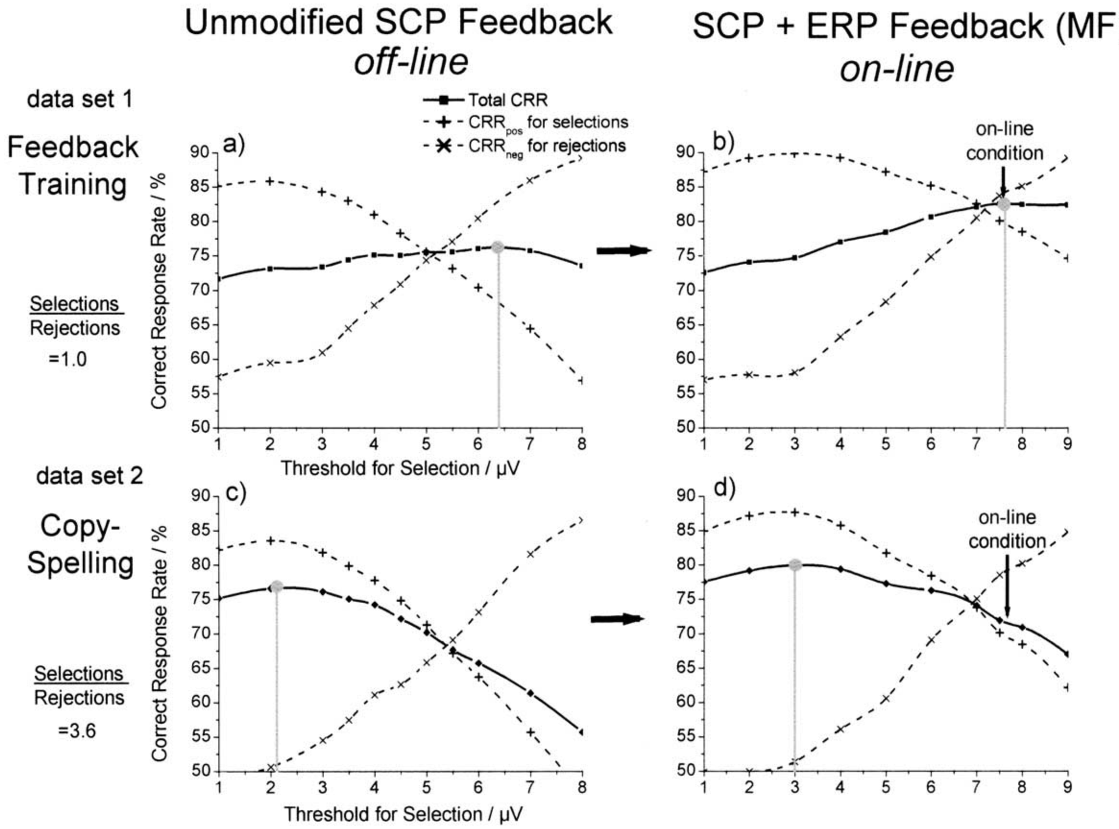

Fig. 3. Classification results with the threshold method. The diagrams show the CRR for trials with required positivity (selections) CRR_{pos}, the CRR_{neg} for required rejections and the total CRR for various threshold voltages for both data sets. The first data set was acquired in the feedback-training mode with a ratio of required selections/rejections of about 1.0. The second data set represent the copy-spelling mode with a selection/rejection ratio of 3.6. For the latter, the threshold voltage for the maximum CRR moved to lower values. Comparing the CRR for an unmodified SCP feedback with the MF feedback, both data sets lead to higher success rates with the MF feedback.

maximum CRR for unmodified SCP was 76% (at 6.4 μV), which is significantly worse than the MF result ($t = -4.6$, $P < 0.001$).

For copy spelling (data set 2), the CRR for unmodified SCP was 77% (with optimal threshold of 2.1 μV), which is significantly better than the on-line result ($t = 2.87$, $P = 0.002$). The maximum CRR with MF reached 80% at 3.0 μV, which is significantly better than the on-line result at 7.7 μV ($t = 5.36$, $P < 0.001$).

3.2. Discriminant analyses classification

The time-series classification using the LDA improved the CRR of data set 1 significantly from 83 to 87% ($t = 2.7$, $P = 0.004$) (Fig. 4). For the copy-spelling data set 2, however, the LDA (74%) did not significantly improve the on-line CRR (72%) ($t = 1.0$, $P = 0.16$) and did not reach the maximum CRR of the MF method (80%).

The use of time-series classification with ZDA produced CRRs of 76 and 72% for feedback training and copy spelling, respectively, both of which did not improve the on-line performance ($t = -4.0$, $P < 0.001$, $t = 0.1$, $P = 0.46$).

3.3. Wavelet classification

A single trial classification of wavelet transformed EEG data was applied to the data sets. The LDA led to a CRR of 86% for data set 1 (feedback training) and a 75% CRR for data set 2. Only for the feedback-training data set, the LDA was significantly better than the on-line training results ($t = 2.57$, $P = 0.005$). The ZDA combined with the WT resulted in a 85.4% CRR for feedback training and 82.4% CRR for copy spelling. Both results were significantly better compared to the on-line condition ($t = 1.89$, $P < 0.05$ for data set 1; $t = 6.56$, $P < 0.001$ for data set 2; see Fig. 4).

4. Discussion

4.1. The threshold method

The patient was originally trained with the SCP threshold method, but reached a higher accuracy level with the MF modification. The results show that the CRR is highly dependent on the threshold parameter, which should be cautiously adjusted. The total CRR is also highly dependent

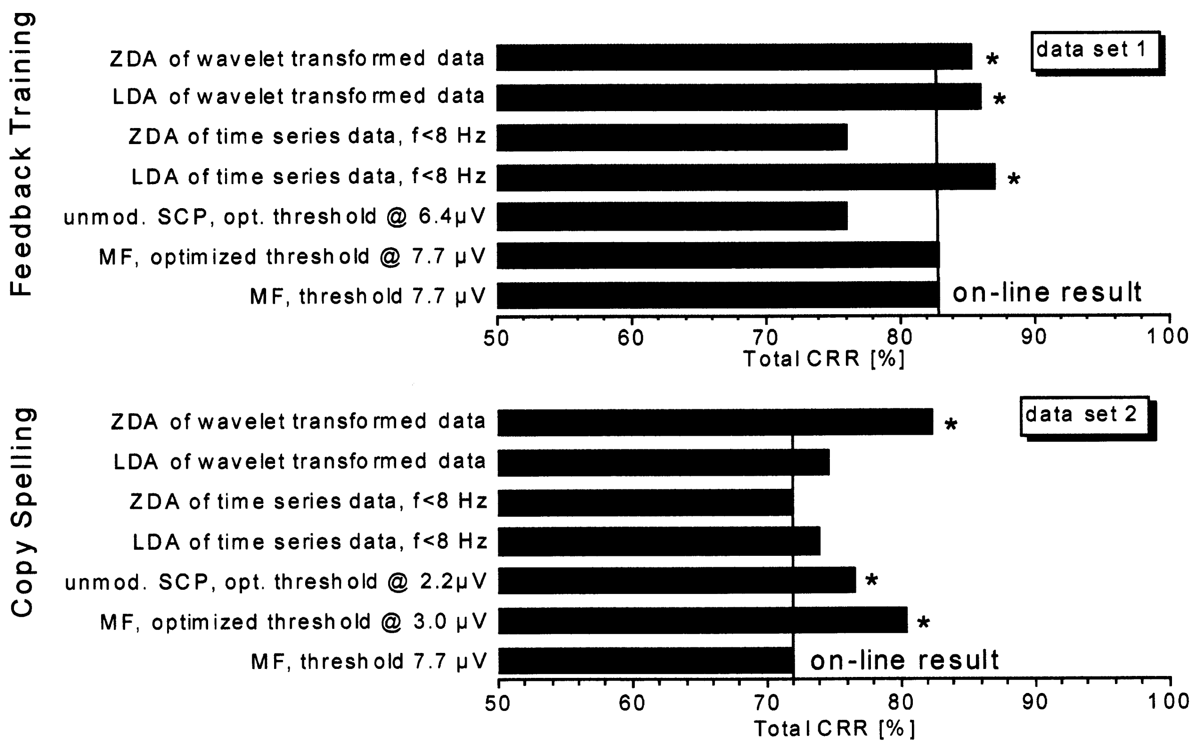

Fig. 4. The correct response rates for the various methods are compared with the on-line MF threshold classification method separately for both data sets, feedback training and copy spelling. The vertical line indicates the on-line result, obtained by the MF threshold method. This was compared with two other threshold methods and four discriminant analysis classification methods, including time series and wavelet classification. The asterisks indicate a significant improvement ($P < 0.05$) in the correct response rates of a particular method compared to the on-line result.

on the ratio R between selections and rejections. Thus, in tasks with an unequal number of required selections and rejections it is suggested to optimize the total CRR with respect to the ratio R by choosing an appropriate threshold voltage.

However, it is not trivial to assume that the optimization of the total CRR by taking into account a priori probabilities will inevitably lead to a higher speed for communication as the speed in the spelling procedure may depend in a different way on false alarms and on missed hits. Also, R is not a constant but rather a function of the CRR. With a different CRR, the user has to navigate in a different way through the decision tree leading to a change in the ratio R (Perelmouter et al., 1999). As it is not clear, how the CRR is influenced by the on-line use of a different classification method which we tested off-line here, the a priori probabilities were taken into account only in the on-line threshold methods, where the choice of the main parameter (i.e. the threshold) is directly connected to the CRR. Thus, the optimization of the other classification methods by taking into account the ratio R would go beyond the scope of this study.

4.2. Discriminant analysis classification

The best off-line CRR for the feedback-training mode (equal task distribution, $R = 1$) was achieved by using the LDA approach. Contrary to copy spelling (unequal task distribution, $R = 3.5$), the LDA did not significantly exceed the CRR of the on-line condition and did also not reach the maximum CRR of the MF method at the optimal threshold of 3.0 μV. This can be explained by the fact that the discrimination function is determined by the means of the time series, which is centered between the positive and negative means. Thus, the classification result is not biased toward any decision and is thus optimal for an equal task distribution of required selections and rejections. This explains the fact that LDA did not increase the CRR in copy-spelling mode, but did so in the feedback training. For copy spelling, the decision of the LDA could be biased by taking into account the a priori probability for a certain result, which is a function of the task distribution (R). An analysis of the effect of a bias on the total CRR has not been accomplished yet and can be considered when using the LDA as a classification method for spelling on-line in a future study.

Using ZDA was not successful with time-series data. ZDA only functions under the assumption of statistically independent coefficients, but in case of response classification of a time trace the coefficients were highly dependent on each other (Fig. 1). In contrast, the LDA worked well with dependent coefficients, as the covariance is taken into account.

4.3. Wavelet classification

In order to reduce the highly dependent coefficients of the time trace to only a few meaningful coefficients, an off-line wavelet classification was considered. Comparing the LDA classification of time-series data with the LDA of wavelet transformed data, the results were similar. However, the ZDA as an empirical classification algorithm can even be preferred for classification of wavelet transformed data as it improved and resulted in similar high CRR values as the LDA with data set 1. As the ZDA with WT exceeded the LDA in the data set 2 with $R = 3.5$ and achieved comparable high scores to the optimized MF method, this method seems to be more robust than the LDA in terms of having an unequal task distribution. The best results with copy-spelling data were achieved with the ZDA classification of wavelet transformed data. This can be explained by the fact that the coefficients of wavelet transformed EEG are more independent than the time series. Also, the ZDA could take advantage of taking into account a priori probabilities of expected results leading to a further increase of performance in spelling tasks.

Although the discriminant analysis of wavelet transformed data performed more reliably than the time-series classification or the threshold method in the off-line analysis, it was not yet tested in an on-line training. In order to implement this method on-line, one problem has to be solved. The patient has to be aware of the importance of hitting the rectangle on the screen to elicit the high positive ERP. Thus, in case of the discriminant analysis methods, a threshold should be shown to the patient which has to be exceeded. This can be easily realized with time-series classification as the classified values are a linear function of the EEG amplitudes, which can be instantaneously fed back. However, the common WT is carried out once at the end of each trial because it needs the information of the whole wave shape. Thus, wavelet classified data do not allow continuous graphical feedback and there is no immediate confirmation of a hit. The result of the classification can only appear on the screen at a fixed time point at the end of a trial, and thus, the feedback no longer will be contingent upon the ERP. One solution would be to present the MF data as a feedback signal to the patient and initiate the wavelet classification immediately after the ERP. But still the result is not contingent upon the feedback which might be irritating to the patient. Another solution would be the use of a stepwise WT by calculating continuously those wavelet coefficients which contain the already sampled time coefficients.

Wavelet classification may be useful only when the patient uses both SCP shifts and ERPs for communication, because the ERPs are detected in another spectral range and are time-locked. Most of our patients communicate with SCP shifts only (see Kübler et al., 1999). Thus, their SCP can be classified sufficiently using a simple time-series ZDA or LDA and do not require the WT as no complex waveforms are generated. This has been shown by Hinterberger (1999).

5. Conclusion

For on-line classification of time-series EEG data, the threshold method (in the present data sets with the MF modification) is an easy and often sufficient method. When improving the results with discriminant analysis methods the feedback cursor movement should be determined by the classification result (Eq. 2) and not by the current SCP shift. The result is then standing in an obvious connection to the feedback. However, when a communication paradigm is used such as in the BCI of Farwell and Donchin (1988), where no continuous feedback is necessary (this is the case when the required response (e.g. a P300) is elicited by the target stimuli themselves), then the application of wavelet classification methods as described should be considered.

To conclude, discriminant analysis classification has been applied successfully to separate negative and positive SCP amplitude shifts superpositioned with task-specific ERP. The classification methods were implemented in the final training program to apply the different EEG classifications on-line in future training sessions. This constitutes an important step in the improvement of the CRR to increase the communication speed of SCP-based BCIs.

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