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A multi-signature brain–computer interface: use of transient and steady-state responses

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Abstract
Objective. The aim of this paper was to increase the information transfer in brain–computer interfaces (BCI). Therefore, a multi-signature BCI was developed and investigated. Stimuli were designed to simultaneously evoke transient somatosensory event-related potentials (ERPs) and steady-state somatosensory potentials (SSSEPs) and the ERPs and SSSEPs in isolation. *Approach.* Twelve subjects participated in two sessions. In the first session, the single and combined stimulation conditions were compared on these somatosensory responses and on the classification performance. In the second session the on-line performance with the combined stimulation was evaluated while subjects received feedback. Furthermore, in both sessions, the performance based on ERP and SSSEP features was compared. *Main results.* No difference was found in the ERPs and SSSEPs between stimulation conditions. The combination of ERP and SSSEP features did not perform better than with ERP features only. In both sessions, the classification performances based on ERP and combined features were higher than the classification based on SSSEP features. *Significance.* Although the multi-signature BCI did not increase performance, it also did not negatively impact it. Therefore, such stimuli could be used and the best performing feature set could then be chosen individually.

S Online supplementary data available from stacks.iop.org/JNE/10/026005/mmedia

(Some figures may appear in colour only in the online journal)

List of Abbreviations

DV	decision value
TransStim	condition with transient stimulation to evoke, and analysed for, ERP responses
FlutterStim	condition with flutter stimulation to evoke, and analysed for, SSSEP responses
CombSSSEP	condition with both transient and flutter stimulation, analysed for SSSEP features
CombERP	condition with both transient and flutter stimulation, analysed for ERP features
CombDV	condition with both transient and flutter stimulation, classified for both SSSEP and ERP features. The decision values of both classifiers are combined.

1. Introduction

A brain–computer interface (BCI) is a direct communication pathway between a brain and an external device. The idea is that signals from the brain can be recorded and translated into a command for controlling the external device. Such a device

could be a cursor on a computer screen, or a spelling device for communication (for a review, see van Gerven *et al* 2009). In rehabilitation, the use of a BCI could be applicable. Patients who have a damaged peripheral nervous system, like a spinal cord lesion, could perhaps use signals from their own brain to restore movement. Furthermore, locked-in patients, who are totally paralysed, could use such a BCI to communicate.

The two most frequently investigated BCI systems are the 'visual speller' BCI, which is based on the paradigm of Farwell and Donchin (1988), and the imagined movement BCI (see, for example, Pfurtscheller *et al* 2006). Recently, however, researchers have been trying to extract more reliable information from the subject's brain signals. One direction in increasing the amount of transferred information is to make the BCI 'hybrid'. Although several different types of BCIs have been called hybrid, we refer to a hybrid BCI when the brain signal is measured in several different ways. Electroencephalography (EEG) could, for example, be combined with Near-InfraRed Spectrospcopy (NIRS) as proposed by Fazli *et al* (2012). Another direction in improving the BCI design is to make use of several modalities at the same time. This is called a multi-modal BCI. An example of this is the extension of the visual speller with an auditory (Belitski *et al* 2011) or tactile component (Thurlings *et al* 2012).

These previously described BCI systems all have some disadvantages. Although the 'visual speller' can be controlled independently of the eye position (Treder and Blankertz 2010), to achieve good performance a patient has to be able to control his gaze. This means it is not suitable for completely locked-in patients. The imagined movement BCI normally requires extensive training of the participant, although researchers are trying to shift this burden of training to the machine utilizing advanced machine learning techniques (Blankertz *et al* 2007). Furthermore, even after training a reasonable number of participants are not able to control an imagined movement-based BCI (Nijholt and Tan 2008). For a hybrid BCI the costs of two types of brain signal measuring systems could be a disadvantage for home-users. And finally a multi-modal BCI could be more difficult to learn to control, and occupies several modalities in patients who are already disabled in one way or another.

In this paper, we will therefore investigate a new type of BCI, namely a multi-signature BCI. In this BCI, users receive stimuli in a single modality, the somatosensory modality. The stimuli are designed to elicit two distinct neurophysiological responses, both of which will be extracted and used as input to the classification procedure. The brain signals that were focused on here are the event-related potentials (ERPs), and the steady-state somatosensory evoked potential (SSSEP). Both these responses are modulated by attention (for the early and late somatosensory ERPs, see Bruyant *et al* (1993), Eimer and Forster (2003) and Iguchi *et al* (2005); for the SSSEP, see Giabbiconi *et al* (2004)). The advantage of the combination of these two responses is that the subject has only one task, namely attending to a particular stimulus, while both responses will be modulated and can be used as information for the classifier. This could improve the classification performance in two ways. First, the two signals could contain different information. Although both signals are modified by attention, the generators of the attentional modulation processes could be different. This could result in extra information in one of the two. Secondly, even if the underlying source of the attentional process is the same, the noise in the different signals could be different. The SSSEP originates from somatosensory areas (Giabbiconi *et al* 2007) whereas attentional effects in ERPs are also seen in central locations (Eimer and Forster 2003). Therefore, the signals could be affected differently by external and internal noise sources. Hence, the information that can be extracted from both signals could be different.

To test if a multi-signature BCI can improve the classification performance, three sub-questions have to be investigated. First, does combining two stimulus types to elicit both transient and steady-state responses affect the strength of the response compared to using a single stimulus type (i.e. transient or steady-state stimuli alone)? We hypothesize that this combination does not affect the strength of the response, because the signals have different sources. Second, does including the second response in the classification procedure give useful additional information such that the BCI performance is improved. We hypothesize that the classification performance of the multi-signature BCI will be higher than the standard BCI using just a single brain response, because of the different information in the signals or noise. The final question is how such a BCI performs in an on-line setting. Furthermore, this design lets us directly compare the performance of a BCI using ERP and SSSEP features. In the auditory domain classification performance with ERP features is higher than with steady-state features (Hill and Schölkopf 2012); therefore, we expect to find similar results in the somatosensory domain.

To investigate the first question, three different stimulation types were used: a transient stimulation in which the transient ERP was elicited, a flutter stimulation in which the SSSEP was elicited, and finally a combination of the previous two stimulation types which elicited both responses. To investigate the second question, the EEG data of the combined stimulation condition will be analysed and classified for ERP and SSSEP features separately, and the outcome of the classifications will be combined. This will be tested off-line with the data of the first session. The best stimulation condition will be used in a second session to test the on-line performance.

2. Methods

The experiment consisted of two sessions: the first session was an off-line comparison between the three stimulation conditions and the feature sets for the classifier, and the second session tested the on-line performance of the multi-signature BCI while subjects received feedback.

2.1. Participants

Thirteen healthy volunteers (mean age 24 year, SD 10 year, 5 males, 8 females) participated in this experiment. One subject did not show up for the second session and hence was removed from the data analysis. All subjects were healthy and none of

Figure 1. Braille stimulators are placed inside five stacked discs. The discs of the cylinder could be rotated individually to adjust optimal placement of the Braille stimulators on the fingers of the subject, when he grasped the cylinder. Reprinted from Severens (2010). Copyright (2010), with permission from Elsevier.

the subjects has ever been diagnosed with any neurological disorder. They all gave written informed consent before the start of the experiment. The experiment was approved by the ethical committee of the faculty of social sciences at the Radboud University Nijmegen.

2.2. Materials

Piezo-electrical Braille stimulators were used to mechanically stimulate the fingertips. Two Braille cylinders were used, one for each hand, which the subjects could grasp (see figure 1). Each Braille stimulator had two rows with four pins each. The pins could be pushed out by about 0.7 mm. The stimulation pattern and frequency varied per block (see section 2.3.2). The index finger, middle finger and ring finger were stimulated simultaneously per hand. Subjects had to attend stimuli on either the left or the right hand. The Braille stimulators were placed inside sound-proof boxes to minimize any auditory responses evoked by the sound of the stimulators.

2.3. Session 1

2.3.1. Stimuli. Three stimulation conditions were used in the first session to test if combining two stimulus types affects the strength of the response compared to using a single stimulus type. The transient stimuli were designed to evoke transient ERP responses, among which is the P300. The flutter[4] stimuli were designed to evoke SSSEP responses. The combined stimuli were designed to evoke both transient ERP and SSSEP responses. In each condition there were a number of 'targets', which the subject had to count. All stimulus types lasted 16.5 s per trial.

[4] Flutter here refers to mechanical vibrating stimulation with frequencies up to 50 Hz. It should not be confused with Wow and flutter measurements like it is used in the area of analogue tape recording.

Transient stimuli. In the transient stimulation condition, two pins of the Braille stimulators moved out for 50 ms, with an inter stimulus interval (ISI) of 444 ms on the left hand, and 667 ms on the right hand, lasting 16 s in total. Stimulation on the left and right hand was precisely timed to avoid overlapping of the transient taps. The pins moved in a regular three-beat pattern (see figure 2(a)) to make paying attention to stimuli on one of the two hands easier. The first two taps in this three-beat pattern involved movement of the two most distal pins (non-accented tap). The third tap was accented and consisted of pushing out the two most proximal pins. These accented taps were randomly omitted and exchanged with a standard non-accented tap (except for the first two three-beat patterns in a trial), which was called a target. This happened 0, 1 or 2 times on the left and right hand separately in each trial.

Flutter stimuli. In the flutter stimuli, the four central pins moved with a constant frequency: the pins on the left and right hand moved with 18 and 21 Hz, respectively, in a square wave with a duty-cycle of 50%. The target was a short omission (1 tap) in the flutter stimuli, which randomly occurred 0, 1 or 2 times during each trial (see figure 2(b)). For the choice of the various parameters, we relied on existing literature on stimulus intensity (Tobimatsu *et al* 1999, Müller *et al* 2001), the shape of the stimulus (tap versus sinusoidal Müller-Putz 2004) and frequency (Tobimatsu *et al* 1999).

Combined stimuli. In the combined stimuli, the transient stimulation was presented on top of the flutter stimulation. On the time points of the transient stimuli, the flutter stimulation was omitted (see figure 2(c)). The target was the same as in the transient condition: it was an accented tap that was exchanged by a non-accented tap. No omissions in the flutter part of the combined stimuli were used, to keep the stimuli simple and comprehensible.

2.3.2. Procedure. After electrode placement, subjects were seated in an electrically shielded room in front of a computer screen. Subjects were instructed to look at a fixation cross during the recordings and to avoid eye movements as much as possible. In the first session, the three stimulation conditions (transient, flutter and combined) were tested in three blocks.

A trial started with the appearance of an arrow on the computer screen, which indicated to which hand the subject had to pay attention. Subjects were instructed to count the targets on the attended hand. After 1.5 s a fixation cross appeared, and 0.5 s later the tactile stimulation started. After the end of the tactile stimulation (about 16 s later) a question was presented on the screen in the off-line blocks (session 1 and training block of session 2), asking how many targets were present in the stimulation of the attended hand. Subjects could choose between four answer possibilities and respond with a button press controlled by the feet.

Before the start of the experiment, a practice block was executed in which the different stimulations were explained step by step. The experiment continued when the subject correctly detected the targets in three trials for all three stimulation conditions. The order of the three blocks,

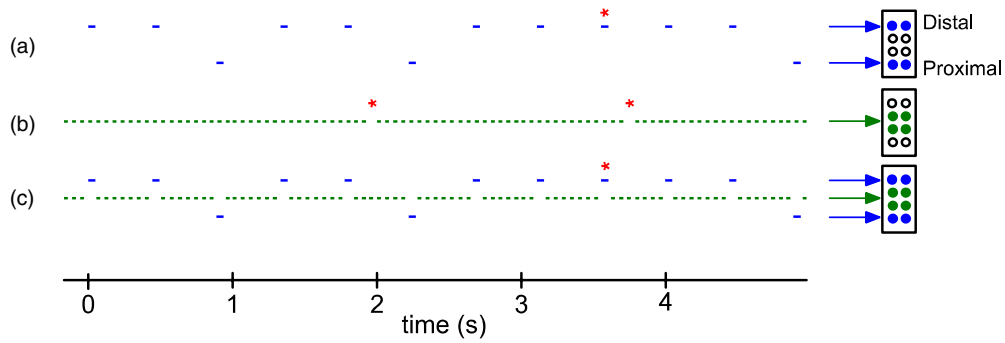

Figure 2. The tactile stimuli characteristics for the left hand. Coloured circles indicate pins that are pushed out, whereas light circles indicate withdrawn pins. Red asterisks indicate targets. (a) For the transient stimuli, the four outer pins moved in a regular three-beat pattern (like the tic-tic-toc pattern as used in the auditory domain): two non-accented 'tics' were followed by one accented 'toc' tap. The target was the replacement of the accented tap with a non-accented stimulus. (b) The flutter stimuli consisted of constant frequency vibration of the four central pins. An omission of one tap in this constant stimulation was the target. (c) The combined stimuli were based on the flutter stimuli (four central pins). With the same interval as in the transient stimuli the flutter stimuli were replaced by transient taps, which occurred in the three-beat pattern and hence are non-accented, accented or target (outer pins). Stimuli on the right hand were the same, with the only difference being other ISIs between transient and flutter taps. Note that this schematic shows only a part of the whole 16.5 s trial.

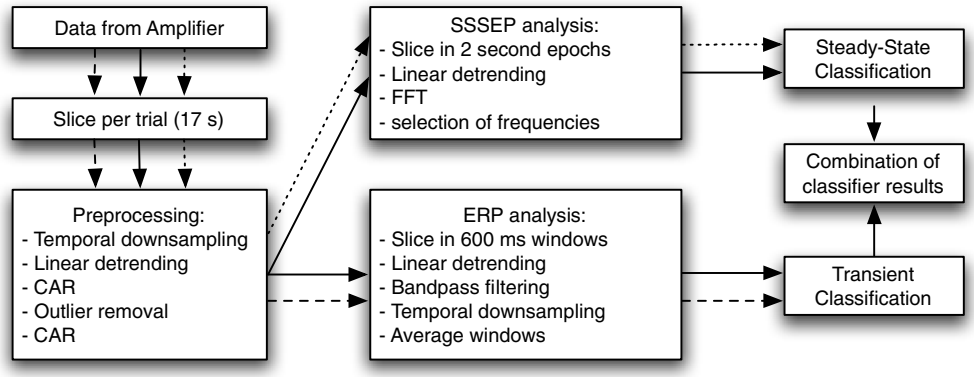

Figure 3. Schematical overview of the off-line analysis steps. Dotted arrows indicate the processing pipeline for the FlutterStim and CombSSSEP conditions, dashed arrows for the TransStim and CombERP conditions and the solid arrow for the combDV condition. For the on-line analysis, outlier removal was left out. Because the *window feedback* block required a classifier outcome every 2 s, the preprocessing steps in this block were not performed on the 17 s trial, but on each 2 s window instead.

and hence stimulation conditions, was counterbalanced over subjects.

2.3.3. Electrophysiological recordings. EEG was recorded with 64 sintered Ag/AgCl active electrodes referenced to the mean of all electrodes. The EEG signals were amplified using a Biosemi ActiveTwo AD-box and digitized at a sampling rate of 2048 Hz. To ensure good recordings, values for offset amplitude and jitter in offset were kept below 25 and 0.2 mV, respectively.

Off-line data were preprocessed to remove artifacts using the following steps. First the data were cut into epochs of 17 s (a trial), which corresponds to 0.5 s before until 0.5 s after the tactile stimulation. Then, the data were temporally downsampled from 2048 to 256 Hz, linear trends were removed and a common average reference was subtracted from the data. Subsequently, outliers in first trials and then electrodes were removed, if the variance was separated more than three standard deviations from the median variance. To allow for interactions between the two types of removal, this step of outlier removal was repeated twice. On average 5.5 (SD 3.8) trials and 6.9 (SD 3.8) electrodes were identified as outliers and removed from further analysis. Finally, a common average reference was subtracted from the data again, to remove the influence of the removed electrodes.

To control for the possibility that subjects grasped the attended stimulators stronger than the unattended stimulators, the electromyographical (EMG) activity of muscles involved in grasping was recorded with the same Biosemi Active2 amplifier. A reference electrode was placed on the elbow (the lateral epicondyle of the humerus) and one electrode was placed on the belly of the m.flexor digitorum superficialis on both arms.

2.3.4. Data analysis. The data were analysed for two feature sets: the SSSEP and ERP features. Figure 3 shows a schematical overview of the analysis steps.

For the analysis of SSSEP responses, the data were cut into 2 s epochs. This allowed us to estimate the classification performance either in only 2 s, or in multiple time windows when applying sequence classification. On these smaller time windows, linear trends were removed. Subsequently, the

absolute frequency spectrum was calculated with a fast Fourier transform (FFT).

For the analysis of the ERP responses, the data were cut into windows of 600 ms after each transient tap for the two ISIs separately. These smaller epochs were linearly detrended. Next, they were filtered between 0.1 and 15 Hz and temporally down-sampled to 64 Hz. The epochs within a time window of 2 s (four or five epochs) were averaged for the two ISIs speeds separately. This means that one average was calculated for responses to unaccented, accented and target taps on the attended hand, and one for responses to all taps on the unattended hand. Such an approach has been used before in the auditory domain (Hill and Schölkopf 2012).

To separate the classes (attended versus unattended stimuli), a classification analysis was performed. For the SSSEP features the frequency bins of the stimulation frequency, the subharmonic and two higher harmonics were selected for both hands, resulting in a feature set containing a set of amplitudes for each electrode and epoch at the following frequencies: 9, 10.5, 18, 21, 36, 42, 54 and 63 Hz. For the ERP features, the averaged responses for the two ISI speeds were concatenated. On the feature set resulting from either the SSSEP or ERP analysis, a linear classifier was trained using a L_2 regularized regression algorithm (Bishop 2006) and was used to separate attention on left versus right hand. Leave-one-sequence-out cross validation was used to set the regularization strength. The sequence classification (performance over time) was calculated by combining the outcome of the classification, i.e. by adding the decision values (DV), of the individual 2 s windows within a trial. In a Bayesian sense, this is equal to making the assumption that the windows are independent (Vlek *et al* 2011). Furthermore, this means that all windows are weighted evenly in the final outcome of the sequence classification.

The EEG data of the transient (TransStim) and of the flutter (FlutterStim) stimulation conditions were analysed with the corresponding procedure described above and then classified. The data of the combined stimulation condition were analysed and classified for the SSSEP (CombSSSEP) and ERP (CombERP) features separately. In addition, the outcome of these two classification procedures on the separate SSSEP and ERP feature sets was combined by adding the individual classifiers decision values to simultaneously use both feature sets (CombDV).

2.3.5. EMG analysis. EMG data were first down-sampled to 512 Hz and filtered with a band-pass filter of 18–250 Hz. The signal was then rectified and low-pass filtered with a cut-off frequency of 15 Hz (Winter 2005). The average ipsi- and contralateral EMG amplitude (EMG activity in the attended side and unattended side respectively) was calculated per trial. To assess a difference between these two amplitudes, a paired samples *t*-test was used.

In addition, the influence of EMG activity on the classification of EEG data was investigated to test if performance was better when subjects grasped the attended stimulators harder. A relative EMG amplitude in the ipsilateral arm was calculated by subtracting the contralateral EMG from the ipsilateral EMG. Using a median split, both left and right attended trials were divided into a set with relative low EMG amplitude and a set with a relative high EMG amplitude in the ipsilateral arm. EEG data of the high EMG set and low EMG set were classified separately, using the same classification algorithm as described above. The classification accuracies of the two sets were compared using a paired samples *t*-test.

2.4. Session 2

Unless mentioned otherwise, the methods used in session 1 were also applied in session 2.

2.4.1. Procedure. Based on the results of the classification performance in the first session (see section 3.2), the combined stimulation condition was chosen and used in another three blocks (a *training*, *sequence feedback* and a *window feedback* block). The first block was a *training* block and was the same as the blocks in the first session. Subjects were also instructed to count and report the number of targets. After the *training* block, a classifier was trained on the data of this *training* block with the same method as used for the classification of the blocks in session 1. This classifier was then applied on-line in two subsequent feedback blocks (*sequence feedback* and *window feedback* block) in which the subject received feedback about the performance of the classifier. In these feedback blocks, the subjects were still instructed to count the number of targets, but they were not asked to report it, because the feedback was now based on the classification outcome. In the *sequence feedback* block, the feedback was presented at the end of a trial (after about 18 s) replacing the behavioural feedback on reporting the number of targets. The subjects saw the words 'correct' or 'wrong' indicating a correct or wrong classification of the previous trial. The other feedback block was the *window feedback* block, in which the subjects received new feedback every 2 s. This was added because it was hypothesized that giving feedback earlier and more often could improve learning within this block. In this block a green ball was presented on the screen. Every 2 s, this ball changed colour according to the calculated probability of the classes. The higher the probability for the left class, the more blue the ball was coloured, and the higher the probability for the right class, the more red the ball coloured. A colour bar above the ball explained this mapping to the subject. The order of the feedback blocks was counterbalanced.

2.4.2. Stimuli. Because the left and right hand are stimulated at the same time, with different ISIs, the response to the left hand stimulation will always contain some response to right hand stimulation and vice versa. If the ISIs from the left and right hand have a large greatest common divider, the response to the other hand stimulation will occur at varying time points within the response of the current hand. By averaging, the response to the other hand will therefore be averaged out. In session 1, the ISIs were not completely averaging out the response for the other hand. Therefore, the ISIs were slightly adjusted for session 2. The ISI for the left and right hand transient stimulation was now 611 and 476 ms, respectively. The other tactile stimulus characteristics were not changed.

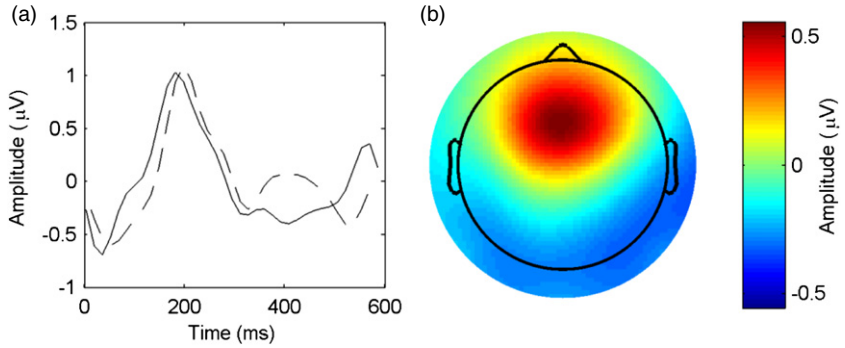

Figure 4. The grand average difference (attended minus unattended) ERP response time locked to the transient taps. (a) The response in electrode FCz is depicted for the transient (solid line) and combined stimuli (dashed line). (b) The topography of the ERP component (150–300 ms) is shown. Data are averaged over left- and right-hand attention condition and non-accented, accented and target taps.

2.4.3. Analyses. Analyses on the training block were the same as for the blocks in the first session (see figure 3). On average 4.3 (SD 2.2) trials and 3.1 (SD 2.2) electrodes were identified as outliers and removed from further analysis. From the classification results for the three feature sets of the *training* block, the best performing classifier was chosen for the on-line blocks based on the following criteria. For good performing subjects (CR $\geqslant$ 70%) the CombDV feature was advantaged to test the on-line performance of the multi-signature BCI. When the performance was highest for the CombDV, or when this was similar to another condition (difference $<$ 5%), the combined features were chosen. When the CombERP performance was clearly higher, ERP features were used. For poorly performing subjects (CR $<$ 70%) the best feature was chosen to be able to give the most reliable feedback possible.

Before application of the classifier with the on-line data of the two feedback blocks, the data were preprocessed in a similar way as for the off-line analysis. Data were detrended, electrodes that were removed in the train block were also removed from the subsequent blocks and a common average reference was applied. In the *sequence feedback* block, these preprocessing steps were performed on the data of a whole trial (17 s); in the *window feedback* block, they were performed on each 2 s window. Further analysis for the ERP and SSSEP. Features were the same as in session 1. Finally the classifier from the *training* block was applied, resulting in a decision value per window in both the *sequence* and *window feedback* block. The classification results for the feature sets and classifiers that were not selected for on-line evaluation were calculated off-line.

2.5. Statistical analysis

Differences in P300 and SSSEP amplitude between the single and combined stimulation conditions were analysed using paired samples *t*-tests. The chance level of the classification was 50% with a 95% confidence interval between 36.66% and 63.34% (Müller-Putz *et al* 2008). Classification performances between the conditions were compared with a repeated measures ANOVA for each session. In session 1, the factors were condition (stimulation condition and feature set) and time. In the second session the factors were feedback, feature set and time. If appropriate, *post hoc* analysis on significant main and interaction effects were performed with Tukey's test.

3. Results

3.1. Session 1

3.1.1. ERP. A clear positive deflection was visible between 150 and 300 ms in the difference between attended and unattended responses for both the transient and the combined stimuli (see figure 4). This ERP was strongest in fronto-central electrodes. No difference between single and combined stimulation was found in the mean amplitude for this ERP in FCz, $t(11) = -0.9676$.

3.1.2. SSSEP. In the spectral plots, clear peaks at both stimulation frequencies (18 and 21 Hz) are visible; hence, a SSSEP was found for both stimulation frequencies. However, a clear difference between attended and unattended trials could not be detected in the grand average for both the flutter and combined stimulation conditions. In individual subjects, this difference was visible (see figure 5 for a subject with a clear attentional effect). This can be also seen in the topographies for the same subject in figure 6. In all four topographies a strong SSSEP can be seen in fronto-central and parietal electrodes, which is representative for most subjects. Furthermore, in this subject the SSSEP was stronger for the attended stimuli compared to the unattended stimuli. In other words, the SSSEP at 18 Hz was stronger when attention was directed to the right hand (stimulated with 18 Hz, see figure 6(a)) compared to when attention was directed to the left hand (stimulated with 21 Hz, see figure 6(b)). Similar effects were found for the SSSEP at 21 Hz (see figures 6(c), (d)). This attentional effect was only visible in about 8 out of 12 subjects, and was not always consistent over the two stimulation frequencies and the two stimulation conditions.

3.1.3. Behavioural results. Subjects counted the number of targets in the stimulus stream for each trial. For the transient stimulation, the mean percentage correct reported trials were 77%. For the flutter stimulation condition and the combined stimulation condition this was 79% and 75%, respectively.

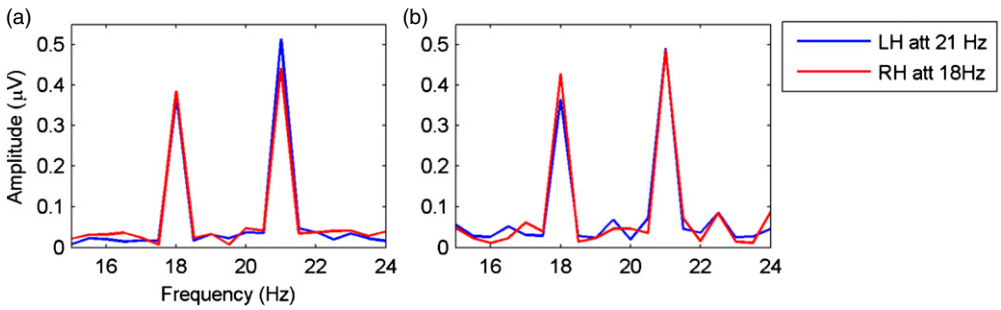

Figure 5. Spectral amplitude on FCz of a subject with a strong attentional modulation (s1) for the (a) flutter stimulation and (b) combined stimulation. Data are separated for attention to stimulation on the left hand (21 Hz, blue line) and right hand (18 Hz, red line).

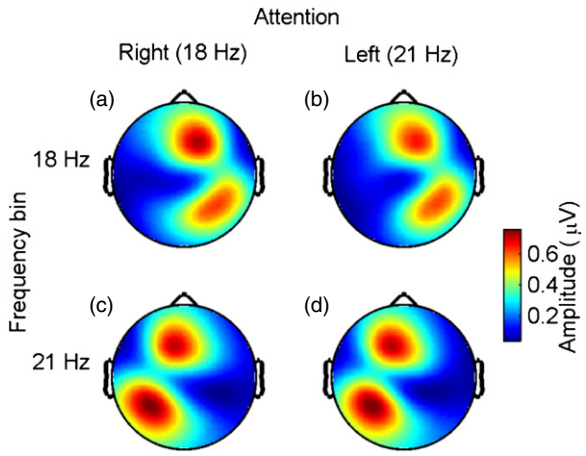

Figure 6. Attentional effects on SSSEP topographies from subject (s1) for the combination stimulation are shown. The topographies are separated for frequency bin in the rows, and side of attention (right versus left) in the columns. In (a) and (d), attention was directed to the stimulated hand with the frequency that is shown in the topography: attention was directed to 18 Hz in (a), and to 21 Hz in (d). Increased amplitude in these plots, compared to when attention was directed to the other hand, in (b) and (c), shows the attentional modulation.

These differences were not statistically significant $F(2,33) = 0.19$.

3.1.4. Off-line classification. On the feature sets described above, a classifier was trained off-line (see figure 7). After the first 2 s time window, the average performance was lowest for the combined stimuli using SSSEP features (CombSSSEP, 58%) and highest for the transient stimuli (TransStim, 74%). With ongoing stimuli and inclusion of the features of all previous windows, the performance increased for all stimulation condition and feature sets. After eight time windows (16 s) the lowest performing condition was the flutter stimulation (FlutterStim, 68%), whereas the transient stimuli performed best (TransStim, 93%).

These effects were confirmed with statistical analysis: a main effect of time ($F(7,440) = 16.68$, $p < 0.01$) and condition ($F(4,440) = 112.21$, $p < 0.01$) was found, with no significant interaction effect, $F(28,440) = 0.42$. The main effect of time showed that the performance was higher in the third to eighth window compared to the first window. The average performance with ERP features was above chance level (63.34%) for all windows. For conditions with only SSSEP features, the performance in the first (FlutterStim and CombSSSEP) and second (CombSSSEP) window was below chance level. With more time and data, the average performance increased above chance level. The main effect of condition showed that the performance was lower in the two conditions in which only the SSSEP features were used (FlutterStim and CombSSSEP) compared to the conditions in which ERP features were used (TransStim, CombERP and CombDV). Although the subject with best SSSEP performance reached 96% correct in the CombSSSEP condition (see figure 7(b)), some subjects did not perform above chance level at all with these features (FlutterStim, see figure 7(c)).

3.2. Session 2

Based on the best results after the whole trial, and the fact that still all feature sets can be evaluated with the combined stimulation, this combined stimulation was chosen for the on-line evaluation. After the *training* block of each subject, the classification performance was calculated. The performance in the *training* block was comparable to the results of the first session (see figure 8): a main effect of condition $F(2,264) = 92.35$, $p < 0.01$, and time, $F(7,264) = 6.23$, $p < 0.01$, was found with no interaction effect, $F(14,264) = 0.61$. Again, the ERP and combination features performed better than with the SSSEP features. The feature set was chosen for the on-line blocks, based on the results per subject and the criteria mentioned in section 2.4.3. This resulted in the use of ERP features in five subjects and combined features in seven subjects (see table 1 showing the chosen feature set with the on-line classification performance).

To be able to compare the classification performance between the different feature sets, the results were calculated off-line with the classifiers that were trained on-line for all feature sets (see figure 9). No differences were found between the *sequence* and *window feedback* block, $F(1,528) = 0$. Hence, these results were averaged for the statistical analysis. Again a main effect of features was found, $F(2,264) = 50.01$, $p < 0.01$: the classification with ERP features performed better than the classification with the SSSEP features. However, the difference in classification rate between combined and ERP features is not significant. *Post hoc* analysis on the main effect of time $F(7,264) = 7.65$, $p < 0.01$, showed that the performance was higher in windows five to eight (after 10–16 s) compared to the first window (after 2 s).

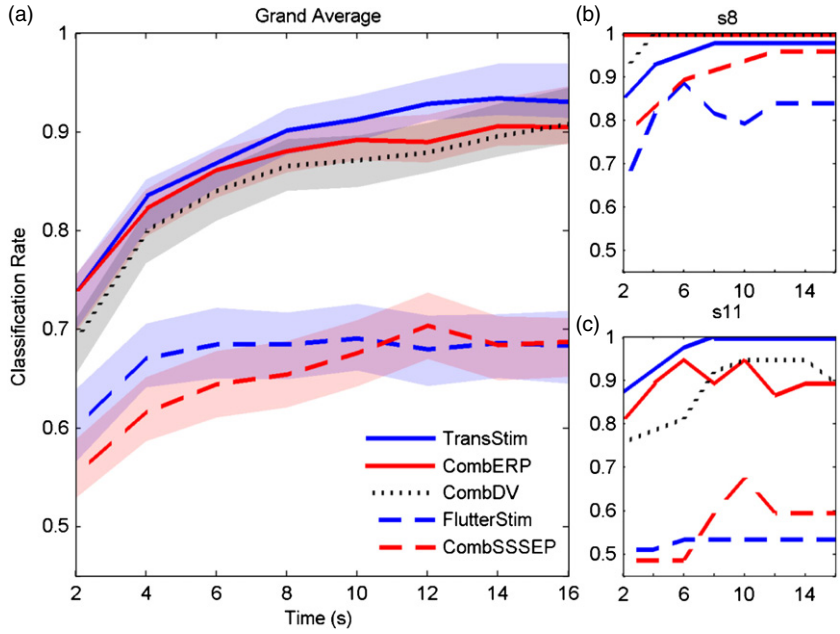

Figure 7. Classification performance for the (a) grand average, (b) an example subjects with high SSSEP performance and (c) an example subject with low SSSEP performance. Light bars around the average performance indicate the standard error over subjects.

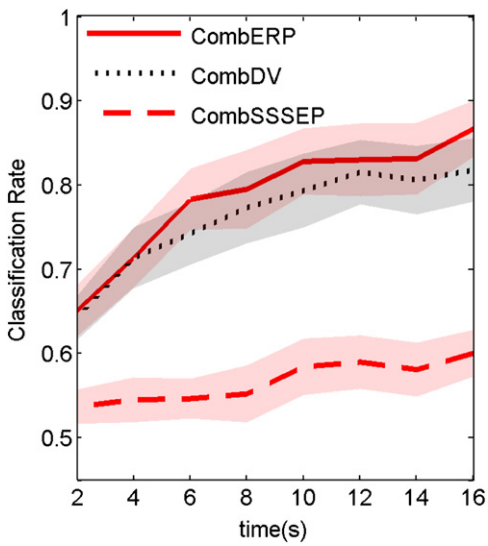

Figure 8. Classification performance of the *training* block of the second session. The performance with increasing time intervals is shown for the SSSEP features (red dashed), the ERP features (red solid) and the combination of the decision values of the last two classification procedures (black dotted). Light bars around the average performance indicate the standard error over subjects.

Table 1. Feature sets chosen for on-line classification. The on-line results at the end of the trial (after 16 seconds) are depicted for the *sequence* and *window feedback* block in classification rate (CR) and information transfer rate (ITR). The number between brackets indicates the order of the feedback blocks.

		Sequence		Window	
Subject No.	Feature set	CR	ITR (bits min^{-1})	CR	ITR (bits min^{-1})
1	ERP	92% (1)	2.2	90% (2)	2.0
2	Comb	82% (1)	1.2	86% (2)	1.6
3	Comb	60% (1)	0.1	84% (2)	1.4
4	Comb	76% (2)	0.8	74% (1)	0.6
5	Comb	86% (1)	1.6	82% (2)	1.2
6	ERP	68% (2)	0.4	64% (1)	0.2
7	Comb	50% (2)	0.0	80% (1)	1.0
8	ERP	48% (2)	0.0	48% (1)	0.0
9	Comb	92% (1)	2.2	72% (2)	0.5
10	ERP	100% (2)	3.8	86% (1)	1.6
11	ERP	88% (2)	1.8	94% (1)	2.5
12	Comb	76% (1)	0.8	66% (2)	0.3
Average		77%	1.2	77%	1.1

3.3. Information transfer rates

The information transfer rate, or bit rate, was calculated for the off-line and on-line blocks using Wolpaw's definition (1998). Averaged over subjects, the maximum bit rates over the eight analysis windows were highest for the TransStim (5.3 bits min^{-1}) and the CombERP (5.1 bits min^{-1}) conditions, for session 1 (see figure S1a available at stacks.iop.org/JNE/10/026005/mmedia). The on-line information transfer rate after the end of the trial was on average 1.2 bits min^{-1} (see table 1). The maximum information transfer rate, averaged over subjects, for the feedback blocks was 1.5 bits min^{-1} for the CombDV condition in the *sequence feedback* block, and 1.2 bits min^{-1} for CombDV condition in the *window feedback* block (see figures S1b and c available at stacks.iop.org/JNE/10/026005/mmedia).

3.4. EMG results

In five out of six blocks, no significant difference was found in the EMG amplitude between contralateral versus ipsilateral arm. Only for the *training* block of the second session a significant difference was found, $t(11) = 2.301$, $p = 0.042$, with stronger amplitudes for the ipsilateral arm. For this block, separate classifications were performed on sets with high and

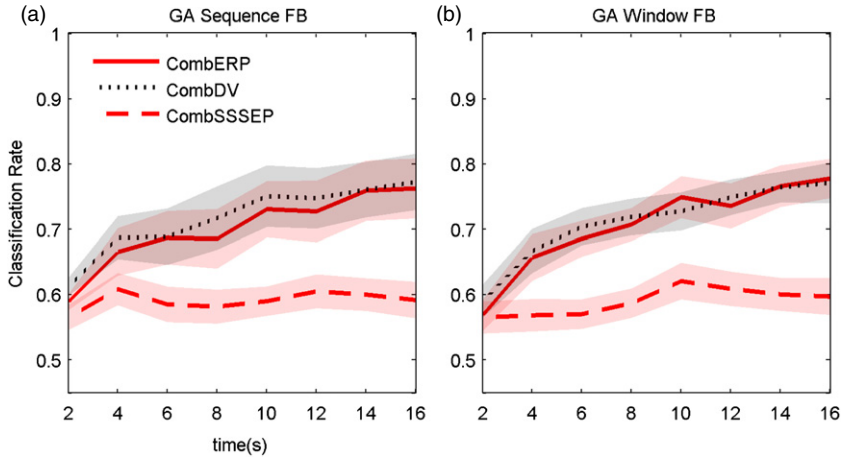

Figure 9. Grand average classification performance of the (a) *sequence feedback* block and (b) *window feedback* block of session 2. The performance over time is shown for the SSSEP features (red dashed line), the ERP features (red solid line) and the combination of the decision values of these two classification procedures (black dotted line). Light bars around the average performance indicate the standard error over subjects.

low differences between ipsilateral and contralateral EMG amplitude. The classification performance of the sequence classification for this high EMG set was 80% (SD 13%), 64% (SD 12%) and 78% (SD 14%) for the P300, SSSEP and combined features, respectively. For the low ipsilateral EMG set, these performances were 78% (SD 16%), 64% (SD 13%) and 80% (SD 9%), respectively. For all feature sets, this difference is not significant.

4. Discussion

In this paper, the performance of an on-line multi-signature BCI is evaluated by investigating the effect of the combined stimuli on the classification performance when using a single feature set, and by investigating the effect of the combination of two feature sets. The amplitude of the somatosensory signals (ERP and SSSEP) did not differ between the single and combined stimulation conditions. This also translated to the classification results: no differences were found between the single and combined stimulation conditions using a single feature. In contradiction to what we expected, the combination of the two feature sets did not increase the classification performance. However, a difference was found between the classification performances when using different feature sets: in general, the performance with transient ERP and combined features was better than the performance with SSSEP features, given the stimulus parameters chosen in this study. This is the first study to directly compare the performance of a tactile BCI using transient and steady-state responses.

Most BCI studies using transient ERPs and a paradigm comparable to the current one report a positive deflection at around 300 ms above central parietal areas, which most often has been defined as the P300 (Farwell and Donchin 1988). In contrast, the positive deflection that we found had a shorter latency and was more frontal than the standard P300 response. Therefore, we cannot conclusively state that the ERP we found was indeed a P300. These differences in latency and topography could be caused by the different paradigm that was used. In the current study, not a standard oddball paradigm was used, but the stimuli were rhythmical and the investigated responses were not just the responses to targets versus non-targets, but responses to all attended versus all unattended stimuli. Such a paradigm has been used in the auditory domain before, and resulted in a somewhat more frontal P300 response (Hill and Schölkopf 2012). However, this does not explain the shorter latency.

One goal of this study was to investigate the influence of the more complex combined stimuli on electrophysiological responses and the classification performance with respect to the single stimulation conditions. Firstly, on a behavioural level, the combined stimuli could be somewhat harder to understand. On the one hand, this could have negatively affected the responses because of the increased task difficulty. On the other hand, the more complex stimuli could have increased attention and thereby increase the ERP amplitude. We found no differences in amplitude between the single and combined stimulation conditions. This indicates that, if present at all, the influence of task difficulty and attention levels compensated each other and hence the combined stimuli elicited similar transient and steady-state responses as the single stimulations. Secondly, the superposition of both somatosensory signals on each other could have caused attenuation of one or both signals. In the analysis of the SSSEP, the selection of the frequency bins filters out most of the ERP responses. Whereas in the analysis of the ERPs, only the SSSEP fundamental frequencies and higher harmonics are filtered out with the band pass filter. However, in the visual domain it has been shown that sometimes subharmonics can be seen in steady-state potentials as well (Herrmann 2001). Therefore, a small SSSEP effect could still be present from the subharmonic. This apparently did not cause differences neither in the P300 amplitude nor in the classification rates between single and combined stimulation. Therefore, we can conclude that the complex stimuli did not hinder the classification performance.

On the other hand, the combination also did not seem to boost performance. On average, the classification results

did not differ between ERP and combined features. This could indicate that the classification automatically chose the ERP features as important, whereas the SSSEP features were less important and no extra information could be extracted from these signals. This suggests that the SSSEP features did not include extra information with respect to the transient responses. The question arises why this was the case? In the visual domain, it has been shown that the steady-state responses can be explained as a superposition of early transient responses (Capilla *et al* 2011). Furthermore, it has become clear that not only the P300, but also these early ERP responses are important for the classification performance using ERP features (Brunner *et al* 2010, Bianchi *et al* 2010). The transient epochs that we use contain both late and early responses to the transient stimuli. Thus, information that the SSSEP contains is already partly included in the transient epochs, because of the early responses. Moreover, in the combined stimulation, some information from the early responses to the flutter stimulation could still be present in the transient epoch, because the subharmonic is not filtered out. The presence of both these SSSEP responses and the early responses to the transient stimuli in the transient epochs could partly explain why the combination of ERP and SSSEP features has no overall benefit over the ERP features alone.

A limitation of the current stimulus presentation design is that, to reduce complexity, in the combined stimulation targets were only present in the transient part. Therefore, it could in principle be possible that subjects only attended the transient stimuli, while ignoring the flutter stimuli. However, the classification results show that when using SSSEP features there is no difference between performance with combined stimulation and flutter stimulation only. Hence, there is no indication that this influenced our results. Nevertheless, it would be beneficial for further research to design combined stimuli that include targets in the flutter part of the stimulus as well, to rule out a possible influence.

It is possible that a different way of combining the feature sets could maybe improve the performance of the multi-signature BCI. In the current analysis, an evenly weighing of the output of the classification of SSSEP and ERP features was used. However, it is also possible to optimize the weights based on the training set performance. Unfortunately, when testing this method, it seemed very sensitive to changes in the transition from the training to test blocks and therefore it yielded increased performance in some subjects, but decreased performance in others, leaving an average of no effect. Moreover, a combination of other brain signals could maybe lead to better results. The difference in performance between classification with ERP and SSSEP features was large. Using a combination of two brain signals that have more similar performance levels could perhaps increase the performance of the multi-signature BCI with respect to the single signature ones.

Weaker results were observed for the on-line blocks compared to the off-line and training blocks. An explanation for this result could be the outlier removal. For the off-line blocks, before feeding the data into the classification procedures, the data were checked for outlying channels and trials. Therefore, the results of the off-line blocks were somewhat inflated because the outlier detection removed the difficult cases for the classifier. In the on-line blocks, no outlier removal was performed; hence, results are reported for all trials.

Previous studies describing BCIs using somatosensory signals are rare. Brouwer and van Erp (2010) investigated the use of transient somatosensory signals in a BCI. They showed in an on-line study that, with tactors on the trunk, performances were on average 58% for a six-class problem and up to 73% for a two-class problem. We previously showed that subjects could successfully control a speller with transient somatosensory signals with classification rates up to 80% (van der Waal *et al* 2012). When taking into account the time period of stimulation that was used in the different studies, our results regarding the performance with the ERP features are in line with these previous investigations. The classification performance both with ERP and combined features were well above the chance level and outside the confidence interval. This is also visible in the bitrates. For steady-state somatosensory signals in BCIs some data are available as well. Müller-Putz *et al* (2006) showed that two out of four subjects could successfully control the two-class BCI with performances between 72% and 83%. Our average on-line results for the SSSEP were not above chance level. However, the best performing subject reached 76% correct. This comes close to the performance level that Müller-Putz *et al* described. What had not been investigated so far in the somatosensory domain is the difference in classification performance between the SSSEP and ERP features. Our results clearly show that classification with ERP features performed better than with SSSEP features. However, one has to keep in mind that stimulation parameters can influence these results. Although most parameters for transient and flutter stimulation were adjusted to produce strong responses, we did not use subject-specific stimulation frequencies for the flutter stimulation. These subject-specific stimulation frequencies could increase the SSSEP amplitudes (Breitwieser *et al* 2012) and hence could maybe also increase an attentional effect on this SSSEP. Our results for the BCI based on SSSEP features could therefore be an underestimation of the maximum performance possible with flutter stimulation. However, the absence of a difference in the behavioural responses suggests that the flutter and transient task were similar in difficulty level. Furthermore, in agreement with the current findings, increased classification performance with ERP features compared to SSSEP features has been reported in the auditory domain (Hill and Schölkopf 2012). Taken together, these results concerning both ERP and SSSEP responses are promising for BCIs using tactile stimulation.

A BCI using tactile stimulation has several advantages. First of all, it is not dependent on eye gaze. This eye-gaze dependence could be a problem for locked-in patients. Although we used visual stimuli for instruction and feedback, this could also be replaced by auditory stimuli, or even by stimulation with the same tactile stimulators. Furthermore, for less severely disabled patients, the stimulation could be relatively private compared to, for example, flickering visual stimuli that are used in the standard visual speller. Finally,

with a tactile BCI, the users could still rely on intact visual and auditory modalities to look and listen to whom they are communicating with. This last characteristic of tactile stimulation could be advantageous for healthy users as well, for example, for navigation purposes (Brouwer and van Erp 2010). An application for patients should contain stimulators that can be attached to the body without the need for active holding or grabbing. Furthermore, such stimulators should be light-weighted and small, so they could for example fit in a glove. Finally, they should be relatively inexpensive. To the best of our knowledge, no commercial systems are available right now that match these criteria.

Analysis of the EMG of the arm muscles indicated that subjects grasped the stimulators slightly harder on the side that was attended. However, different EMG patterns did not seem to influence the classification results. This is in agreement with previous reports (van der Waal *et al* 2012). Therefore, we expect similar performance of a tactile BCI in patients who are not able to use the muscles in their arms.

Changes to the stimulation design could still increase the classification performance. For example, the distance between stimulation sites could be increased, because interaction in SSSEP and ERP signals occur when stimulation is close together in time and space (Severens *et al* 2010). Such interaction effects were also found in ERP responses with bilateral stimulation (Shimojo *et al* 1996). Furthermore, hand posture modulates such interaction effects (Hamada and Suzuki 2003) and the positioning of individual fingers influences the ease of discriminating tactile stimuli (Riemer *et al* 2010). Therefore, it could be advantageous in a BCI setting to choose the classes of stimulation sites as far apart as possible, maybe even by using different body parts.

In conclusion, it is evident that, in general, ERP features outperform SSSEP features in a BCI with somatosensory stimulation. With respect to the multi-signature BCI, the combined stimulation and combination of decision values on average does not improve the classification performance. However, it also does not negatively influence the classification performance and in individual subjects can increase performance slightly. Therefore, it would be advisable to use this combined stimulation for selected patients in future experiments.

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