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CONTROLLING FALSE POSITIVES ON A BCI IMPLANT FOR COMMUNICATION

M. P. Branco[1], Z. V. Freudenburg[1], E. G. M. Pels[1], S. Leinders[1], M. A. van den Boom[1], T. Denison[2], M. J. Vansteensel[1], E. J. Aarnoutse[1] and N. F. Ramsey[1]

[1] Brain Center Rudolf Magnus, University Medical Center Utrecht, Department of Neurology and Neurosurgery, Section Brain Function and Plasticity, Utrecht, The Netherlands
[2] Neuromodulation Core Technology, Medtronic, Minneapolis

E-mail: N.F.Ramsey@umcutrecht.nl

ABSTRACT:

A fully implanted Brain-computer Interface was recently applied in a locked-in patient allowing for a one-dimensional control of a spelling board on a computer. The patient attempts to move her hand in order to generate a 'click', which is used to select letters. The optimal parameters to generate an accurate click were estimated from a cursor control task where the control signal was used to control the y-velocity of a cursor on the screen. However, the set of parameters used for the cursor control task was not accurate enough to be used for clicks. In order improve accuracy, three filters were designed to add features, smooth and z-transform the signal before conversion to a click, in order to provide a more reliable communication channel that has less false positive events.

INTRODUCTION

People with severe paralysis who have lost the ability to communicate have only limited options to regain this ability. Since the 1990's Brain-Computer Interfacing (BCI) has been proposed as an assistant technology to reestablish this lost communication [1]. For optimal usability in daily life at the homes of the target population, such a system should be accurate and intelligent (i.e., it incorporates smart decoding algorithms that dynamically adjust to e.g. slow signal changes), fully implantable (i.e., permanently available and invisible), safe, stable, easy and comfortable to use [2]. However, even though technology advances fast, many of these requirements have not been met so far.

Recently, a fully implantable BCI communication system [3] (Utrecht NeuroProsthesis, UNP, Figure 1) was implemented, which translates neuronal activity elicited upon attempted hand movements into a binary control signal for selection of characters in spelling software running in 'switch-scanning mode', where so-called 'brain-clicks' can be used to select characters, or groups of characters, that are highlighted automatically and sequentially by the computer. The UNP system was implanted in a locked-in patient with late stage Amyotrophic Lateral Sclerosis, with a four-electrode strip covering the hand sensorimotor cortex. The bipolar pair to use for BCI control was chosen based on the highest correlation to a motor localizer task, where the patient alternated between trials of attempted hand movement and rest. The patient gave informed consent to this study, which was approved by the ethics committee at the University Medical Center Utrecht in accordance with the 2013 provisions of the Declaration of Helsinki.

Extraction of good parameters

A standard Cursor Control task (CCT, in BCI2000 [4]) was used to estimate the optimal signal processing parameters for a one-dimensional continuous control signal. In this task the subject controlled the y-velocity of a ball on the screen (Figure 2), while the ball moved at constant speed on the x-direction in attempt to hit one of two targets displayed on the right hand side of the screen. The subject attempted to move her hand to move the ball up and relaxed to move it down.

Across several months the average CCT performance using high-frequency broadband power (80±2.5 Hz) was 90.73±6.42 % (N=70 runs), which is significantly above chance (50%, $p<0.01$). However, the high performance with this continuous signal did not predict performance using the same electrode pair and frequency band for a binary signal (above or below a fixed threshold) to generate brain-clicks. The threshold was initially based on the midpoint between the averaged high-frequency band power during the active and during the inactive states. This resulted in a lower than expected performance during spelling and a need for frequent calibration. Errors were mainly unintended clicks (false positives), although misses also occurred.

Hence, we were interested in investigating how the continuous brain signal could be translated optimally into brain-clicks that were usable for high accuracy spelling, with a low false positive rate and without compromising the sensitivity to intended actions. Two hypotheses based on the acquired signals were defined:

1) Many false positives (FPs) were caused by the noisy and spiky morphology of the signal, hence smoothing of the signals would decrease the FPs;
2) The power signal was not stable over time, hence

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normalization of the signal would improve performance.

UTRECHT NEUROPROSTHESIS

Figure 1: Utrecht NeuroProthesis (UNP) fully implanted brain-computer interface system.

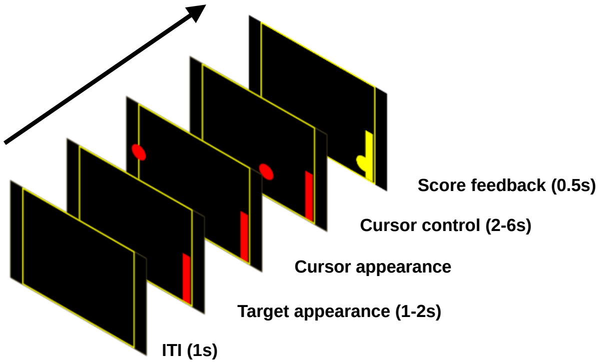

Figure 2: CCT design as implemented in BCI2000. The ball moves towards the target at constant speed while the subject controls the y-velocity of the ball towards the target.

MATERALS AND METHODS

General description of the system

The UNP system (Figure 1) consists of four 4-electrode ECoG strips, from which one strip is placed over the hand region of primary motor cortex. The subcutaneous amplifier and transmitter device, placed subclavicularly, transmits power signals to an antenna attached to the clothing, every 200ms (5 Hz) for one bipolar pair. As a first step to improve the reliable conversion of continuous brain activity into a 'brain-click' control signal, instead of only using the high-frequency band, we used a filter (linear classifier filter) that summed two frequency bands (Low Frequency Band, LFB, 20±2.5Hz, weight -1; and High Frequency Band, HFB, 80±2.5 Hz, weight +1) of the same bipolar pair (F_{HFB} - F_{LFB}). For more details about the motivation behind this filter see [3]. The resulting control signal was then thresholded through a threshold filter and converted into a binary signal, where 1 represents the samples above the threshold and 0 otherwise (Figure 3). Finally, this binary signal was converted into a click signal in the click translator filter, which defined a click when more than 5 samples (1 s) exceeded the threshold (Figure 3). The click was then sent to a spelling program where rows of characters, or individual characters, could be selected with a brain-click (Figure 4). Additionally, in order to address the two hypotheses, we tested and implemented two additional filters.

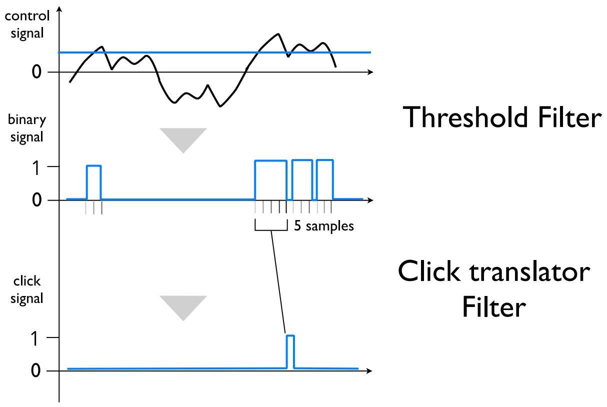

Figure 3: The threshold filter converts the control signal (F_{HFB} - F_{LFB}) into a binary signal, whereas the click translator filter converts the binary signal in a click signal.

Figure 4: Spelling program used during online research runs to spell 5 or 7-letter words. The computer automatically highlights each row or item sequently, looping from top to bottom and left to right, respectively. Each row of characters, or individual characters, can be selected with a brain-click.

Addressing hypothesis 1: The Smoothing filter

To tackle the problem of noisy and spiky signals intrinsic to neuronal recordings, a smoothing filter was designed to smooth each feature signal (F_{LFB} and F_{HFB}) independently (Figure 5). In the design of real-time feedback BCI systems the use of future samples to

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smooth the signal is not possible. Therefore the smoothing function here implemented averages each incoming sample with the previous 5 samples (i.e., 1.2 s smoothing window).

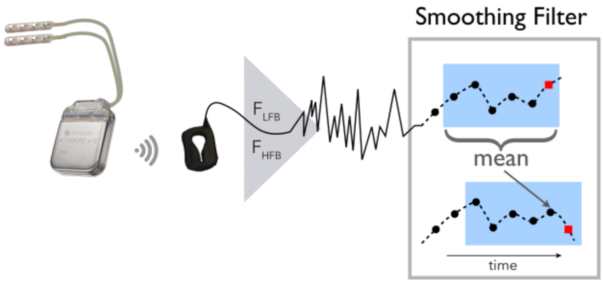

Figure 5: Smoothing filter averages each incoming sample (red square) with the previous 5 samples (black circles). The smoothing filter is applied to each feature signal (F_{LFB} and F_{HFB}) independently.

Addressing hypothesis 2: The Z-Transform filter
Another property of the signal that is crucial for accurate performance is the stability of the signal over long periods of time, i.e., the minimization of slow amplitude trends of the signal. A constant signal amplitude allows for the use of constant parameters, such as the threshold, across sessions. For that, normalization to a z-score can be used to diminish signal variability. Furthermore, when adding two different feature signals, their separate z-transformation allows for a straightforward combination for the signals (weights -1 for LFB and +1 for HFB, see [3] for more details). Hence, a z-transform filter (Figure 6) was implemented, by subtracting each incoming sample (of each feature signal F_{LFB} and F_{HFB}) with the mean of a 30 s calibration window and dividing it by the standard deviation of the same window.

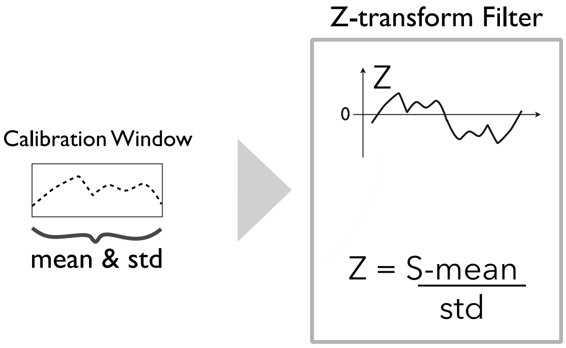

Figure 6: The z-transform filter subtracts from each incoming sample (S) the mean of a 30s calibration window and divides the resulting value by the standard deviation (std) of the calibration window.

Hypotheses testing
Click-performance during online copy-spelling runs (see Figure 4 for an explanation of the speller application) was compared before and after the filter implementation, which also includes the addition of the LFB feature. An overview of the implemented filters can be found in Figure 7.
Performance was assessed by means of false positive (FP) rate and true positive (TP) rate of the online runs. The patient performed a total of 35 copy-spelling runs before (words with 7 letters) and 69 after filter implementation (words with 5 letters). The number of FP, TP, true negatives and false negatives were determined automatically from the data recorded during online runs and visually inspected by two independent observers. Please note that no offline (post-hoc) processing was applied to the recorded data.

RESULTS

For comparison of click-performance before and after the filter implementation the FP rate and true positive (TP) rate during online runs (where the patient was asked to spell dictated words) were computed. Notably, we observed that many events classified as FPs were in fact intended clicks that were slightly too early or too late in time. For this reason a FP-rate-corrected was calculated, which did not include these timing mistakes. Timing mistakes were identified and marked by visual inspection of all runs performed by two independent observers.

Performance before filter implementation
There were on average 2.06 FP/min (N=35 7-letter words), yielding a FP rate of approximately 9%, a FP rate-corrected of 6% and a true positive (TP) rate of 84% (Figure 8).

Performance after filter implementation
Regarding the smoothing filter, the optimal smoothing window (number of samples used to average each incoming sample) was optimized together with the threshold via a heat map (see supplementary material in [3] for more details), where the highest performance region was mapped in a two-dimensional matrix. For that the offline classification accuracy of recorded runs replayed with different smoothing window and threshold was computed. Within the hotspot, multiple sets of parameters were chosen and tested by the patient (compromise between effort and accuracy of the system) and the optimal ones (1.2s smoothing window and 0.85 threshold) were used for spelling [3]. This resulted in a score of 1.02 FP/min (N=69, 5-letter words), and a significant decrease in FP-rate and FP rate-corrected to 7% and 2%, respectively ($p<0.001$). True positive rate (TPR) also decreased significantly ($p<0.05$) to 76% (Figure 8), mainly due to an increase of False Negatives (FNs, i.e. a miss to click), which the user prefers over FPs because they do not require spelling correction (back-space).

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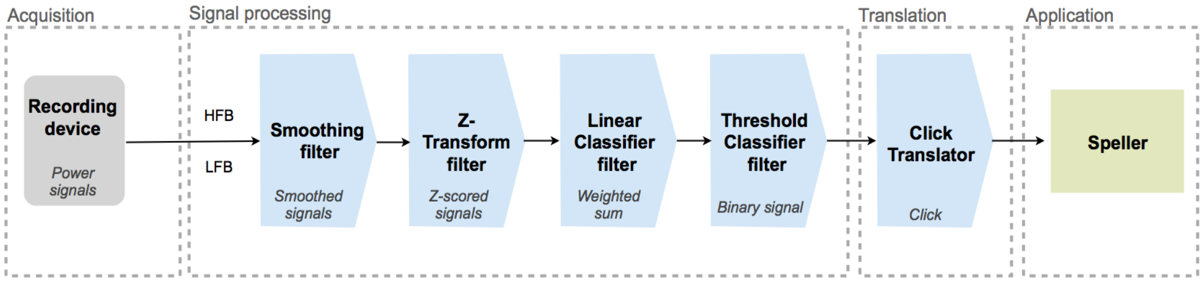

Figure 7: Filter pipeline implemented on the BCI2000 platform. The recording unit (gray block) streams power signals every 200 ms. Two frequency bands, LFB and HFB, are recorded, smoothed, z-transformed and summed (linear threshold classifier) with -1 and 1 weights, respectively. The resulting control signal is then thresholded and converted into a click. The latter was used to select rows or itens on a spelling program. Figure adapted from [3].

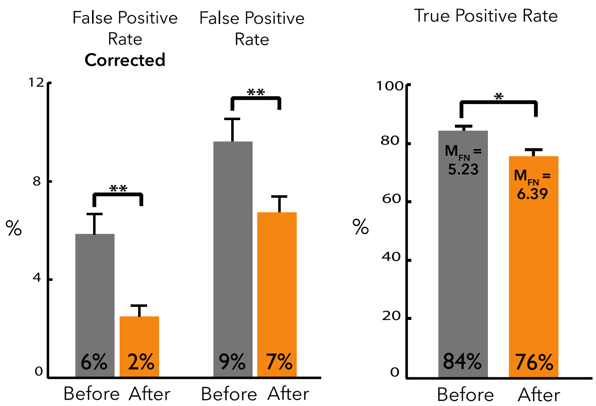

Figure 8: FP rate and FP rate-corrected before and after the filter implementation. True positive rate before and after filter implementation, where mean FN is indicated as M_{FN}. **p<0.001; *p<0.05.

DISCUSSION AND CONCLUSION

In our previous article [3], we demonstrated for the first time that a fully implanted BCI (UNP system) could be used to control a spelling program on a computer by converting brain activity into a one-dimensional 'click'.
Here we address in more detail than in our previous publication, the filter pipeline implemented to convert the continuous brain signal to binary brain-clicks, for control of a spelling program on a computer. As a first approach the settings used to produce a click were derived from the optimal settings of a standard Cursor Control task. However, this set of parameters was sub-optimal for a reliable click production. Besides implementing a filter that combines two feature signals with a certain weight (F_{HFB} - F_{LFB}), the motivation for which can be found in [3], we implemented two filters to overcome the unstable characteristics of the signal: a smoothing filter and a z-transform filter. Combined, these three filters allowed for a more stable signal and a significant improvement of the performance of the system. The FP rate and FP rate-corrected for timing mistakes were significantly reduced after filter implementation. At the same time, the TP rate also reduced, mainly because of the increase in FN, which the patient preferred over FPs, because they do not require spelling correction.
Finally, one note for the calibration window used for the z-transform filter. After actual implementation, this calibration window was recorded for multiple runs and the mean and standard deviation across runs showed to be consistent. These values were then used for z-transformation, without need for repeated calibration and without a continuous adaption. Due to the normalization of the signal, the combination of feature signals with different amplitude ranges (i.e., F_{LFB} and F_{HFB}) was possible, and allowed for the setting of a constant threshold (to convert the control signal into a click) for over 9 months. During this period, user satisfaction of the UNP system was high or very high on all items of a modified QUEST2.0 user satisfaction questionnaire and the user used the system at home for communication without any technical staff present.

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