http://dx.doi.org/10.5392/IJoC.2011.7.3.006

The letter recognition using BCI system

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ABSTRACT

In this paper, we show how such enhancement of Farwell-Donchin BCI enables a fresh, inexperienced user to achieve quickly an accurate BCI control with a high information transfer rate. This paper presents the results of a BCI experiment where the participant, who had no previous BCI experience, obtained, in about 20 min, a highly reliable and fast control over the BCI spelling device based on the Farwell-Donchin paradigm. Offline analysis showed that the high performance of the BCI was, to a high extent, due to the use of the ERP component N1, in addition to component P300, which has been considered the only ERP component important for the prediction of user's choice in the Farwell-Donchin paradigm in many publications.

Keywords: *BCI system, letter recognition, EEG*

1. INTRODUCTION

Brain-Computer Interface (BCI) is a novel technology enabling direct control of a computer or other external devices from the human brain. It was first invented and currently being developed further primarily in a hope to assist heavily paralyzed patients, especially those of them who are 'locked in' (completely paralyzed). Nowadays, it is also considered a highly prospective new element of computer games and other entertaining technologies. It is based on brain signal acquisition, extracting signal components carrying the user's commands, identifying the commands (in most modern BCIs, this is often done with some pattern recognition technique) and their execution, typically coupled with feedback to the user (Wolpaw et al., 2002)[1]. The brain signal best fitting the practical needs of BCI technology is the electroencephalogram (EEG), i.e. voltage fluctuations recorded from the head skin surface over the brain, originating from the summation of synchronously varying electrical potentials at many neural cells.

EEG recording does not require any procedures which may damage the brain or other human tissues in any way. Modern EEG recording devices are portable and relatively inexpensive. However, all the components of the EEG signal vary considerably amongst subjects, and therefore accurate adjustment of the parameters of signal processing and classification procedures is necessary for stable BCI control. Moreover, since BCI is based not on the usual brain "output" through muscles, which is the only executive brain output in humans and animals, but instead involves more direct type of output never practiced before within the whole era of biological evolution, special training of the BCI users is also needed before the control over the computer is achieved.

Unlike most of the BCI technologies, the one introduced by Farwell and Donchin as early as twenty years ago (Farwell and Donchin, 1988) requires only little training for achieving a reliable control[2]. After being merely neglected for many years, this variant of BCI has become flourish in late 2000th, especially when reinforced by generalizing to multichannel EEG using the electrical signals from many brain areas.

Farwell-Donchin BCI paradigm was originally designed as based on the detection of the positive wave elicited about 300 ms after a rare task-relevant stimulus noted by a subjected. This wave, observed in a wide area of human scalp with maximum at central and parietal areas, is one of the components of the so-called event-related potentials (ERP), stereotyped electrical correlates of the brain reactions which can be extracted from the EEG by averaging signal epochs time locked to a repeatedly presented stimulus.

In Farwell-Donchin paradigm, the user watch a matrix (often of size 6x6) containing cells with letters, numbers, any other symbols or pictures. The rows and columns of the matrix are highlighted (intensified, flashed) for a short time in a random order. The user attends to a given cell and keeps a running mental count of the number of times it flashed. Farwell and Donchin suggested that a P300 wave will be elicited each time a column or row including the attended cell is flashing. Therefore, the averaged EEG epochs related to flashing of these relevant rows and columns will be characterized by more positive amplitude in the typical P300 time latency range and spatial locations (electrode positions) comparing to the observed for non-relevant rows and columns. The attended cell could be identified as the cell at the intersection of the row and column that demonstrate the most positive amplitude in these

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Manuscript received Aug 08, 2011 ; accepted Sep.10, 2011

latency interval. In fact, the P300 was successfully recognized by the computer and the subjects using it communicated up to 2.3 characters per minute [2].

In the recent years, some of the researchers using Farwell-Donchin paradigm observed an earlier negative ERP component, which was more prominent after attended flashes[3-6]. This component seems to represent the spatial attention or spatial discrimination processes possibly involved in this task; therefore, it may be equivalent to the component N1 (i.e., the one responsible for the first large negative peak in ERP) in the tasks specially designed to activate such processes. We recently demonstrated that more explicit including its amplitude into the set of features for pattern recognition algorithms makes possible recognizing of the relevant rows and columns even given a small number of the averaged EEG epochs. We hypothesized that this opens a way for a dramatic improvement of the overall effectiveness of the BCI procedure, because the time needed for the recognizing each character shortens already at the very early stage of BCI practice, providing the user with the opportunity to highly concentrate his/her attention on the task, to get the feedback from the computer early and to become involved into the interaction with the computer deeper and, therefore, learn most quickly.

In the current paper, we show how such enhancement of Farwell-Donchin BCI enables a fresh, inexperienced user to achieve quickly an accurate BCI control with a high information transfer rate. Alexander Lenhardt present a P300-based online BCI which reaches very competitive performance in terms of information transfer rates[7].

2. THE PROPOSED METHODS

2.1 Data acquisition and experiment design

A female volunteer with normal vision and no previous BCI user experience participated in the experiment. Before attaching the electrodes, she was shown the matrix display and was given preliminary instructions about the use of BCI (see the description of the subject's task below). Additional short instructions were also given at different stages of the experiment.

Seven standard EEG electrodes with Ag/AgCl surface were located at positions C3, C4, P8, PO7, PO8, O1, O2 according to the international 10-10 system[8], referenced to connected electrodes at mastoids, and grounded to P7. The EEG was filtered 1-30 Hz, amplified (30,000x), digitized at 128 Hz and stored. All data collection and processing, stimuli presentation and other operations needed by experimental design were controlled by BCI2000 system[9].

The subject sat in a comfortable armchair in 90 cm from a computer monitor and viewed a matrix display. The 6x6 matrix, typical for Farwell-Donchin task, consisted of 36 alphanumeric characters (Figure 1). During the recording, the matrix rows and columns flashed (i.e., their characters intensified), and the subject's task was to mentally count the number of times the target character intensified, no matter it was part of a row or column intensification. The duration of intensification was 125 ms, and the duration of the interval between intensifications was 62.5 ms. Flashing was organized as a certain number of flashing cycles (this number is denoted below as nfcyc), within each of them each row and column flashed once. The order of flashing rows and columns within each cycle was random and did not depended on the order of flashing in the previous cycles.

In the first and second stages, the target word (here, "BRAIN") is displayed in the first line above the matrix. The current target letter (one of the letters of the target word) is displayed in the parenthesis. At the moment of taking the screenshot, the 3rd (from the top) row is highlighted; at other moments (except pauses), any of the rows or columns could be highlighted. The subject's task is to count silently highlighting ("flashing") of the row and the column which includes the target letter (here, the 1st row and 2nd (from the left) column. In the second and third stages, after flashing each row and column N times, the second line displays the predicted symbol or (if some symbol(s) where already predicted before) sequence of symbols.

Fig. 1. Screenshot of the standard BCI display viewed by the subject.

The first stage of the experiment was "copy-spelling" without feedback. Its aim was collecting the data which were used to train the classifier. At this stage, an English word was shown above the matrix. The target letter was one of its letters. To indicate which particular letter is target for the moment, it was displayed after the word in the parentheses (see example in Figure 1). The switch to the next target letter occurred after nfcyc=10 flashes of each of the 6 rows and 6 columns. Thus, flashes highlighting each target letter had to be counted 20 times, while the other 100 non-target flashes appearing within the same period of time should be not attended. Each time the new target letter appeared in the parentheses, there were no flashes for 5 seconds; a 2.5 second pause (no flashes) appeared also after the set of flashes, i.e. just before switching to another letter or before the end of work with the current word.

After training the classifier (see below), the second stage started, which was also "copy-spelling", but with feedback. A word and one of its letters (the target letter) in the parentheses were displayed in the same way as in the first stage. The subject's task was the same as at the first stage. However, in a line below it the subject now could see the result of classification of his brain signals, i.e. letters "guessed" as the target letters by the computer program on the basis of online EEG analysis. The number of flashing cycles nfcyc was set to either 10 or 5.

Finally, the subject and one of the experimenters decided, secretly from the experimenter operating the BCI system, which word should be spelled at the third stage. At this third stage, the subject "entered" this word, again letter by letter, into the computer, by counting mentally how many times the letter flashed. The number of flashing cycles nfcyc was 5. The result was displayed to the subject, as in the previous stage.

At all the stages of the experiment, the subject was encouraged to maintain physically relaxed but attentive state, to refrain from blinking or producing movement-related artifacts during flashing, and feel free to blink or make small movements in the pauses between the periods of repetitive flashing.

2.2 Feature extraction and machine learning

Data from the first stage of the experiment contained markers for target rows and columns (i.e., those which included the character which should be attended by the subject) and nontarget rows and columns (those which contained only the characters which should not be attended). As shown by Farwell and Donchin (1988) and many their followers, the task conditions are beneficial for eliciting a relatively large positive wave (with the amplitude of several microvolts) with a maximum approximately at 350-450 ms after the onset of the target stimulus, i.e. P300. From the research made within several recent years (Sellers et al., 2006, 2007; Krusienski et al., 2008; Hoffmann et al., 2008; Shishkin et al., submitted) one may also expect to observe an earlier negative wave N1 with a peak approximately at 200-250 ms. The feature vector for the classifier, therefore, may consist of the amplitude estimates in spatial and temporal areas where these two components are expected to be most pronounced.

Due to high intersubject variability and the low signal-to-noise ratio (considering the strong non-time-locked components of the EEG, produced by various brain processes, as the "noise"), the a priori knowledge about the one it is necessary to tune the classifier to the difference between the individual shape of the target and non-target potentials as precisely as possible. On the other hand, the subject should not be required to perform a long execution of the task without any feedback (which could cause fatigue and the decrease of the level of attention), solely for supplying the classifier with sufficient data; the training sample size, therefore, should be strongly limited, and the due measures should be undertaken to avoid overfitting a classifier. Thus, feature set should not be large, feature selection should be based on the existing knowledge obtained in previous studies as much as possible, and the classifier should be able to select the relevant features, but in a non-exhaustive manner.

Stepwise Linear Discriminant Analysis (SWLDA), a well-known discriminant analysis algorithm, meets these criteria (Sellers et al., 2006; Krusienski et al., 2008). It was applied to a limited feature set designed based on our and other groups' research (e.g., Sellers et al., 2006; Krusienski et al., 2008; Shishkin et al., submitted). Epochs starting at 100 ms and finishing at 600 ms after the onset of each intensification (flashing) were extracted from the raw EEG signals in each of 7 channels. Each epoch was further divided into small consecutive windows whose length corresponded to 50 ms, and amplitudes were averaged separately within each of them; thus, 10 features were obtained for each of the channels. The maximum number of features to be kept in the SWLDA model was set to 20. The classifier was trained on the EEG recorded during mental counting of flashing of each letter of four 6-letter words, i.e., on 6x4=24 pairs of target and non-target averaged epochs.

2.3 Online signal processing and classification

SWLDA coefficients (weights) obtained offline were entered to BCI2000 online system to be used at the 2nd and 3rd stages of the experiment. Now, the online processing included: (1) averaging signal amplitudes separately in epochs time-locked to each column and row flashing, over all of their flashing during "entering" one character; (2) multiplying them by corresponding weights of the classifier; (3) summation of this product over all time points and EEG channels; (4) defining the predicted column as the one with the highest result of summation among columns, and the predicted row as the one with the highest result of summation among rows; (5) identifying the predicted cell (character) as the intersection of the predicted column and row.

3. THE SIMULATION RESULTS

At the first stage of the experiment four recordings of 2.5 min length each were made, with short (0.5-1.5 min) breaks between them. The first one of them was considered as a practice, the other three were used for training the classifier. During computing the classifier, additional recording in the same mode was made, but it was used only for offline testing (see below). The total time of the subject's practice and obtaining the data for training the classifier was about 16 min, including the pauses between recordings; together with the time for giving the instructions to the subject, it was about 20 min.

To illustrate the difference between the brain responses to target and non-target stimuli, Figure 2 presents averages of the same data epochs which were used to make the classifier. For simplicity, only two channels are shown: the first one was selected due to the highest difference of the positive peak and the second one due to the highest difference at the negative peak. To provide a measure of statistical difference between the target and non-target responses, r2 values are also shown. The non-targets were associated with a periodical activity, typical for such stimulation conditions and possibly resulted from the overlapped responses to consecutive non-target stimuli. In both plotted channels (similarly to what was observed in the rest of the EEG channels), a clear difference between targets and non-targets is found in the approximately 350-550 ms range, i.e., in the typical range of P300 ERP component. The average response to targets was more positive than the average response to non-targets in the same range. In the interval of approximately 150-350 ms, i.e. the range where N1 component can be found, the average response to targets was more negative than the response to non-targets.

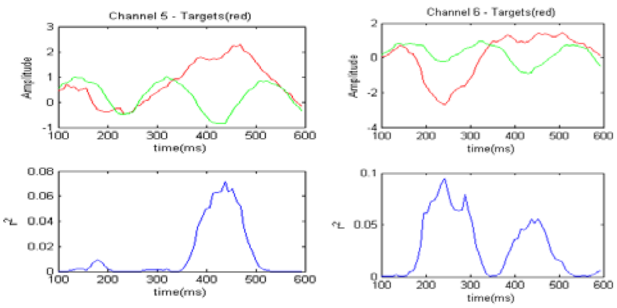

Fig. 2 Averaged amplitude and r2 values for two channels of the data used to make the classifier.

Channel 5 had the highest difference of the positive peak, channel 6 had the highest difference at the negative peak. Mean amplitudes in epochs related to non-target flashes are shown in green, and those related to target epochs are shown in red. Zero time corresponds to the beginning of a flash (intensification).

The classifier weights were first applied to the same data on which it was computed (three recordings), but for different number of flashing cycles. These results are shown in Table 1, cell 1A. High correspondence between the target and predicted symbols was evident, thus this classifier was considered ready for the use in the feedback mode (second stage of the experiment).

Interestingly, applying the classifier in the offline mode to the recording made during the time when it was computed yielded results which were even better than those obtained by applying the classifier to the data on which it was constructed (Table 1, cell 2A): the first 2 flashing cycles were enough to obtain the 100% accuracy.

Table 1, cells 3A and 4A shows the symbols predicted offline using the same classifier as in the online mode, but, again, for different number of flashing cycles (in the online mode only one number of flashing cycles can be used). The highest number of flashing cycles was the same as the number used for feedback in the experiment.

The first 5-letter word was spelled without any mistake. Due to this, we set the number of flashing cycles for the second 6-letter word two times lower (i.e., 5), to reduce the time spent for “entering” each letter. The last letter in this second word was incorrectly spelled as a letter neighboring to the target one (same for different number of flashing cycles), though the first 5 letters were spelled correctly starting already from 1 flashing cycle.

At the final stage of the experiment we again used 5 flashing cycles per letter. All letters of the “secret” 3-letter word (FLY) were correctly recognized.

We hypothesized that the high accuracy obtained after very short time spent for both human subject and machine training was due to the intended use of the N1 component in addition to P300. According to our previous study, combining features from both P300 and N1 can highly improve the efficiency of the “P300” BCI in the most of the subjects, comparing to the use of P300 alone.

In the current study, we applied SLWDA separately to (1) interval 100..300 ms after stimulus onset, containing N1 but not P300, (2) interval 350..550 ms after stimulus onset, containing P300 but not N1. Interval (1) was slightly shifted back to earlier time to avoid intersection with the P300 range; it included most of the range of N1 and no P300. Interval (2) included the whole P300 range of the given subject and no N1.

The results shown in the Table 1 demonstrate that when only P300 features were used for constructing the classifier (cells 1C-4C in Table 1), the performance was much lower comparing not only the combined use of N1 and P300 features (cells 1A-4A in Table 1), but also N1 features alone (cells 1B-4B in Table 1). Moreover, adding P300 features to the N1 features have not substantially increased the performance.

These data were computed offline using the same classifier which was used online (A), the classifiers computed in the same way on the reduced time intervals to test the effectiveness of using alone the traditionally used component P300, related to stimulus relevance and probability (B), and the component N1, related to spatial attention (C).

n_{fcyc} , the number of flashing cycles (from the beginning of flashing) whose data epochs were used to predict the symbol. Each flashing cycle consisted of flashing once each of all 6 rows and 6 columns.

% Correct, the percentage of symbols predicted (recognized) correctly (the classification accuracy rate, here expressed in % for better readability).

Predicted symbols, the symbols which were predicted (recognized) offline applying the same classifier as in the experiment to the averages of first n_{fcyc} flashing cycles for each symbol. The predicted symbol was the symbol on the crossing of the column and row which had the highest classifier's output among all columns and rows, respectively.

The time t_s (in seconds) spent for entering one symbol can be computed as

$$t_s = n_{fcyc} \cdot n_{flash} \cdot t_{SOA} \ ,$$

where n_{fcyc} is the number of flashing cycles, n_{flash} is the number of flashes in one cycle (which was always equal to 12 in this experiment), and t_{SOA} is the stimulus Onset Asynchrony, i.e. the time between the onsets of the two consecutive flashes (equal to 187.5 ms).

According to [1] the information transferred while entering one symbol can be calculates as

$$B_s = \log_2 n_s + P\log_2 P + (1 - P)\log_2((1 - P)/(n_s - 1)),$$

where B_s is the amount of information per symbol in bits/symbol, n_s is the number of symbols (the total number of possible predictions, equal to 36 in our experiment) and P is the classification accuracy rate.

The “theoretical” information transfer rate B_{theor}, in bits per minute (bits/min), can be calculated as

$$B_{theor} = B_s \cdot (\ 60 / t_s\ )$$

Table 1. Classification results

	A. 100..600 ms after stimulus onset (N1&P300)			B. 100..300 ms after stimulus onset (N1)		C. 350..550 ms after stimulus onset (P300)	
1. Classifier applied to the same data on which it was trained (offline) Target words: NATURE BRAIN SIGNAL	1A			1B		1C	
	N_{fcyc}	% Correct	Predicted Symbols	% Correct	Predicted Symbols	% Correct	Predicted Symbols
	1	65%	NA?URD BFAIH SIGTAJ	59%	NA?URD BKAIG XIGTAJ	41%	NMZSRL BJAQB SIJ?AF
	2	88%	NANURE BFAIN SIGNAL	88%	NANURE BRAIH SIGNAL	41%	NA?UOF TCAYB Y1JNAL
	3	100%	NATURE BRAIN SIGNAL	94%	NAHURE BRAIN SIGNAL	65%	NA?UOA TRAHB SIGNAL
	4	94%	NATUPE BRAIN SIGNAL	88%	NANUQE BRAIN SIGNAL	65%	NA?UOE TRAHB SIGNAG
	5	94%	NATUPE BRAIN SIGNAL	94%	NATUME BRAIN SIGNAL	59%	NA?UOE TPAHB SIGNBL
	6	100%	NATURE BRAIN SIGNAL	94%	NATURE BRAHN SIGNAL	65%	N.TUOE TRAIB SIGNBK
	7	100%	NATURE BRAIN SIGNAL	100%	NATURE BRAIN SIGNAL	76%	NATUOE TRAIB SIGNAK
	8	100%	NATURE BRAIN SIGNAL	100%	NATURE BRAIN SIGNAL	76%	NATUOE TRAIB SIGNAG
	9	100%	NATURE BRAIN SIGNAL	100%	NATURE BRAIN SIGNAL	82%	NATUOE NRAIN SIGNAK
	10	100%	NATURE BRAIN SIGNAL	100%	NATURE BRAIN SIGNAL	88%	NATURE NRAIN SIGNAK
2. Classifier applied to new data (offline) Target word: MATRIX	2A			2B		2C	
	N_{fcyc}	% Correct	Predicted Symbols	% Correct	Predicted Symbols	% Correct	Predicted Symbols
	1	83%	MATRCX	83%	MAWRIX	17%	AEURE,
	2	100%	MATRIX	100%	MATRIX	50%	MALRC,
	3	100%	MATRIX	83%	MATLIX	67%	?ATRAX
	4	100%	MATRIX	83%	MATLIX	50%	HCTRGX
	5	100%	MATRIX	100%	MATRIX	67%	GATRIF
	6	100%	MATRIX	100%	MATRIX	83%	GATRIX
	7	100%	MATRIX	100%	MATRIX	100%	MATRIX
	8	100%	MATRIX	100%	MATRIX	100%	MATRIX
	9	100%	MATRIX	100%	MATRIX	100%	MATRIX
	10	100%	MATRIX	100%	MATRIX	100%	MATRIX
3. Classifier applied to new data (online) Target word: FIRST	3A			3B		3C	
	N_{fcyc}	% Correct	Predicted Symbols	% Correct	Predicted Symbols	% Correct	Predicted Symbols
	1	60%	FIROH	40%	FGROH	20%	FOP?G
	2	100%	FIRST	100%	FIRST	20%	FH2NN
	3	100%	FIRST	100%	FIRST	20%	FHPVN
	4	100%	FIRST	100%	FIRST	40%	FINVN
	5	100%	FIRST	100%	FIRST	20%	F1NPN
	6	100%	FIRST	100%	FIRST	40%	F1RPN
	7	100%	FIRST	100%	FIRST	80%	FZRST
	8	100%	FIRST	100%	FIRST	60%	FHRMT
	9	100%	FIRST	100%	FIRST	40%	FHQMT
	10	100%	FIRST	100%	FIRST	60%	FHRMT
4. Classifier applied to new data (online) Target word: ONLINE	4A			4B		4C	
	N_{fcyc}	% Correct	Predicted Symbols	% Correct	Predicted Symbols	% Correct	Predicted Symbols
	1	83%	ONLIND	83%	ONLIN-	33%	UNRIMB
	2	83%	ONLIND	83%	ONLIND	67%	ONXINA
	3	83%	ONLIND	83%	ONLIND	83%	ONLIRE
	4	83%	ONLIND	83%	ONLIND	67%	ONXIME
	5	83%	ONLIND	100%	ONLINE	100%	ONLINE

This index (often used in the BCI literature) shows how much information could be transferred in the case that there where no pauses between entering each symbol. The pauses are of especial importance when the user (operator) has not enough experience of work with BCI yet, and they can be substantially reduced, especially in the free spelling mode, as he/she gains experience.

In the experiment described in the paper, the operator never had any BCI experience, thus we used long pauses. "Experimental" information transfer rate B_{exp} (i.e., information transfer rate observed or could be observed taking into account the pauses) can be obtained with a small modification of the formula given above, i.e., as:

$$B_{exp} = B_s \cdot [\, 60 / (t_s + t_{pause}) \,] ,$$

where tpause is the sum of length of the pre-trial and post-trial time intervals (in our experiment, 5+2.5 = 7.5 s).

The values in the parentheses in the two formula are, in fact, another useful indexes, the number of symbols transferred per minute, the highest one possible theoretically and the one observed (or could be observed) in the real experimental conditions:

$$S_{theor} = 60 / t_s ,$$
$$S_{exp} = 60 / (t_s + t_{pause})$$

The number of symbols per minute and information transfer rate, both in the theoretical and experimental forms, for the actually observed data and for the best offline results are shown in the Table 2.

Predicted symbols, the symbols which were predicted (recognized) offline applying the same classifier as in the experiment to the averages of first n_{fcyc} flashing cycles for each symbol. The predicted symbol was the symbol on the crossing of the column and row which had the highest classifier's output among all columns and rows, respectively. 100% accuracies are printed in bold for better readability.

Table 2. Performance indexes for the actually observed data and for the best offline results, using the same classifier as in the experiment

	n_{fave}	P	T_s, s	S_{theor}, symb./min	S_{exp}, symb./min	B_{theor}, bits/min	B_{exp}, bits/min
Online performance of "copy spelling" the word FIRST	10	1	22.5	2.7	2.0	14	10
Online performance of spelling the "secret" word FLY	5	1	11.3	5.3	3.2	28	17
Online performance of "copy spelling" the word ONLINE	5	0.83	11.3	5.3	3.2	19	12
Best offline performance of "copy spelling" the words: MATRIX, FIRST, ONLINE	2	1	4.5	13.3	5.0	69	26
Best offline performance of "copy spelling" the word MATRIX	1	0.83	2.3	26.7	6.2	97	22

4. CONCLUSION AND DISCUSSION

This paper presents the results of a BCI experiment where the participant, who had no previous BCI experience, obtained, in about 20 min, a highly reliable and fast control over the BCI spelling device based on the Farwell-Donchin paradigm. Offline analysis showed that the high performance of the BCI was, to a high extent, due to the use of the ERP component N1, in addition to component P300, which has been considered the only ERP component important for the prediction of user's choice in the Farwell-Donchin paradigm in many publications.

One should not overestimate the value of the experimental performance indexes obtained online in a relatively small number of trials, and especially of the offline values of "theoretical" indexes showing, only to some extent, a perspective for the improvement of the performance during further learning of the user. It also should be mentioned that, in our experience, not all fresh users demonstrate such high performance, possibly due to the variations in the degree of the concentration on the task. Nevertheless, the performance in general was quite competitive comparing to the top international level of BCI technology.

The high efficiency of the BCI classifier using the features from both P300 and N1 provides the subject operating the device a feedback already on the early stages of the use of BCI. As we suggested in the previous paper (Shishkin et al., submitted), obtaining the control over BCI may provide the user with a feeling of obtaining not just a new skill in controlling a computer, but a completely new kind of ability; moreover, the user may, to some extent, anticipate, with high interest, obtaining such ability. If the training takes too much time, the interest may decrease or even disappear.

Allocation of the attentional resources to the task is critical in BCI, and probably especially critical in Farwell-Donchin paradigm, where attention is, presumably, exactly that type of mental activity what modulates the brain activity "decoded" by the BCI. Therefore, it is important that the user obtains the signs of the control early, when his/her interest is still high, when he/she has not yet become tired or bored. On the other hand, it may be beneficial for maintaining the attention that the feedback is provided soon after starting an operation; and that the attention should be highly concentrated within relatively short time intervals. All this can be achieved if the brain responses can be discriminated after averaging only a small number of trials, so that little time is required to "enter" each symbol. Moreover, short time for "entering" a symbol is also important to give the user an opportunity to completely refrain from blinks and movements, which produce artifacts in the EEG recordings and strongly complicate the recognition of the response. From all the mentioned, it is evident how important could be the intentional use the features of the N1 component for brain response classification.

There still exist a large variety of ways to improve the performance of the BCI system. For example, the spelling error in the word ONLINE was the replacement of the last letter in the word with the letter D, which was its neighbor in the row. Such errors are very common and natural for the Farwell-Donchin matrix type BCI. An "intelligent" BCI system could, for example, easily correct such errors by taking into account both the spelling variants from a dictionary and the classifier values for symbols neighboring to one which is misspelling according to the dictionary. The extraction of features related to N1 and P300 components could be possibly improved, if the components where more carefully extracted, e.g., applying modern factorization algorithms (Independent Component Analysis, etc.), or matched filters in time domain, and so on. Application of more advanced classifiers possibly also may be beneficial. Such approaches can be explored in the future work.

ACKNOWLEDGMENTS

"This work was supported by a Korea Research Foundation Grant funded by the Korean Government (MOEHRD)" (The

Regional Research Universities Program/Chungbuk BIT Research-Oriented University Consortium)

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