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PASSIVE DETECTION OF FEEDBACK EXPECTATION: TOWARDS FLUENT HYBRID EYE-BRAIN-COMPUTER INTERFACES

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ABSTRACT: We present a general approach to the development of an unobtrusive and fast passive brain-computer interface that could be deeply integrated with gaze based control for fluent translation of intentions into actions, as well as the results of a pilot test of its online version in 9 healthy participants. The new hybrid Eye-Brain-Computer Interface (EBCI) utilizes an electroencephalogram component presumably related to the expectation of feedback from the gaze controlled interface. Online operation of the EBCI was made possible using *Resonance*, a new platform for fast prototyping of BCIs, enabling fast synchronized processing of multimodal signals from varying hardware with scripts written in *R*. In the online mode, EBCI provided the result of 19 channel EEG classification almost immediately when gaze dwell on a screen object (a colored "ball") exceeded 500 ms time threshold. For the first time, non-random online EBCI classifier performance was demonstrated.

INTRODUCTION

Selection with gaze – Selection of an object among several different objects on a screen is one of the most fundamental user's operation in interaction with computers. This operation typically involves a gaze dwell on the same object, so automatic detection of such dwells with the eye tracking technology can be used to predict a user's command. Based on this approach, various systems for assisting paralyzed people with preserved gaze control and for helping healthy users in certain situations have been developed [1]. While these systems are serious competitors of the non-invasive brain-computer interfaces (BCIs), they all suffer from their inherent limitation known as the Midas touch problem [2]: a system that respond to a certain intentional gaze behavior, such as an intentional gaze dwell on a link to a web page, would respond in many cases to unintentional gaze behaviors, i.e. spontaneous gaze dwells used for vision or related to mind wandering. While this problem is not critical in gaze typing, it severely hinders the use of gaze based input in many other application areas. Approaches developed for solving the Midas touch problems (e.g., using long dwell time threshold or additional gaze gestures for command confirmation) requires additional efforts from the user [1, 3].

Selection with gaze plus a passive BCI – A radical solution to the Midas touch problem could be the use of a BCI that would produce "mouse clicks" only when they are required by the user: "point with your eye and click with your mind!", proposed as early as in 1996 [4]. Unfortunately, typical noninvasive BCI technologies, such as mental imagery based BCIs, are rather slow for such a task (e.g., [5]); moreover, they are based on execution of additional mental tasks that require attentional resources. A promising alternative is the use of passive BCI approach [6], here, the use of a BCI that make a click only when the gaze fixation is accompanied by an EEG pattern specific to the intention to act at the fixated location. Early attempts to implement this approach [7, 8] made use of rather long fixations (1-2 s; this is still a relatively inconvenient duration); more importantly, experimental paradigms in these studies involved elements of visual search (see the next paragraph), where strong P300 could arise and enable good classification, while the approach could fail if targets were not assigned in advance.

Communicating intention vs. communicating relevance – The gaze plus passive BCI combination is currently actively explored in the explicit visual search paradigm (e.g., [9, 10, 11]) and its applications for estimation of the implicit information's relevance to the user are also developed [12, 13]. Similarly to these tasks, communicating intention involves informing a computer about what is relevant to the user in the

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context of his or her current task. Both communicating intention and visual search tasks may involve single-trial analysis and immediate triggering of the interface. Both communicating intention and communicating implicit relevance use primarily individual information. Specific to the communicating intention is that the user can form his or her intention freely at any time moment, and typically can also refrain from forming an intention. Communicating intention with a BCI combined with gaze fixations can be done only if sufficient accuracy is achieved already with single-trial analysis of short EEG segments, because immediate response of the interface is needed and because group average (which can be relevant in the visual search tasks) is typically not possible. While communicating a user's intention is the most usual task for human-computer interfaces, including BCIs, specific for gaze plus passive BCI combination (if it would be successfully applied for this task) could be that it would turn intentions into computer actions in the most effortless way.

An EEG marker for the new hybrid Eye-Brain-Computer Interface (EBCI) – In our previous study [14] we recorded and compared the electroencephalogram (EEG) during gaze dwells intentionally used for control and during similar spontaneous gaze dwells (all 500 ms duration or longer). In the gaze dwells used for control, but not in the spontaneous ones, a slowly progressing negative wave was found in the occipitotemporal area, likely related to the expectation of the interface feedback. Feature extraction was oriented on using this wave as their main source. It was possible to classify the "controlling" vs. spontaneous dwells using features from 13 EEG channels and only 300 ms length epochs [14].

The problem of fast prototyping of multimodal interfaces – The new interface, the EBCI, should be able to classify the EEG synchronized with gaze events in online mode and provide a response as soon as possible when the dwell time threshold is exceeded. Creating such an interface from scratch would require a vast amount of programming work, because many computational and user interface configurations may need to be tested before finding optimal ones, while each of these configurations should be adapted for sufficiently synchronized operation together with quite different sources of data streams, the interface and the experiment control tools. A platform specifically oriented on developing multimodal interfaces could be a solution, especially if it could support high-level programming languages for more flexible, fast and inexpensive designing of highly varying configurations needed at the early stage of the development of the new types of human-machine interfaces. A number of open source software platforms for BCI prototyping have been developed ([15, 16, 17, 18, 19]; see also [20, 21] for reviews); however, as follows from the publications, online fusion of signals from different sources was either not planned by their developers or was not their primary concern.

The Resonance platform – The *Resonance* platform is developed (by Y.O.N.) specifically for supporting the development of the interfaces that need to process online data streams from different sources. The platform takes care of data and event transmissions, synchronization and recording, and running classification algorithms. An *R* package (also named *Resonance*; freely available at https://github.com/tz-lom/Resonance-Rproj ; [22]) allows not only to process data in online mode but also to apply efficiently the same *R* code offline to the recorded data for a precise reconstruction of the online processing to debug and verify the algorithms. For programming the visual part of the interface, its "behavior" in response to detected user's intentions and organization of an experiment, integration with *QML* is provided. This platform (in its earlier version) was used to create a gaze controlled game *EyeLines* for capturing EEG synchronized with gaze interaction events in [14]. Recently, it was used for the online EBCI tests using the same game [23].

The problem of the access to a ground truth in relation to EBCIs – In our first attempt to test the EBCI online [23] we found it especially difficult to obtain the ground truth when the user is given freedom in defining the ways to solve a task. Similar problems may appear in free operation using any kind of interface, yet their severity can be specific to EBCIs because both the gaze and brain components may contribute to it: gaze dwell may occur out of conscious control at a location that is already studied unconsciously as a candidate for making a click on it, and similar patterns can be expected from brain's activity that accompany preparation to the action. Indeed, our participants told us that EBCI false alarms (the events they were not going to elicit) often looked as meaningful "hints", and that in such cases it was tempting to them not to report these events as false alarms. In addition, in this preliminary study we asked to press a key for reporting a false alarm, and this instruction also could lead to the refrain from reporting because of the need to switch to a manual task from a fully non-manual one (this problem can be also observed in pure BCI and gaze control studies). Therefore, we could not evaluate the online performance of the EBCI reliably.

The aim of the current study was to test several changes in our previously developed protocol for EBCI performance evaluation: modified instruction (focus on the identity of the interface response with intention instead of its "correctness") and reporting tool (use of the EBCI instead of the keyboard for reporting deviations from intentions) in the free operation test; two new tests with fixed tasks for separate estimation of sensitivity and specificity (see details below). We also planned to get the preliminary EBCI performance estimations if the changes would turn to be successful.

METHODS

Participants – Nine healthy volunteers (four female; age 18 to 50, median 24) took part in the study after signing an informed consent.

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Apparatus and software were generally the same as in our previous work [23]. *Resonance* platform (see above) and specific modules controlled all aspects of the experiment. The game module (written in *QML*) implemented game logic and presented the game visual interface on a computer screen. It communicated with *EyeLink 1000* eye tracker (SR Research, Canada) to control its settings and acquire gaze data. Eye tracking data (at 500 Hz rate) were converted to dwell events with a spatial (dispersion-based) criterion: the events were generated when gaze stayed in a 2° × 2° square region for 500 ms (the dwell time threshold), and medians of X and Y coordinates during the dwell were taken as its position. When the game module received such event, it sent a message to the *Resonance* data processing module which ran an *R* script that performed synchronization of the EEG and gaze dwell events, feature extraction and classification. If classification result was positive, a "click" event was sent back to the game, typically in tens of milliseconds after exceeding the dwell time threshold. The EEG data (also at 500 Hz sampling rate) were captured by *actiCHamp* EEG amplifier with *actiCAP* active electrodes (Brain Products, Germany). Its synchronization with the eye tracking data was based on synchronization pulses sent from the eye tracker to the EEG amplifier trigger port at the beginning of each trial.

The gaze controlled game – As in our previous work [23] *EyeLines*, the gaze controlled version of the computer game Lines (also known as Color Lines), was used both for the EBCI classifier training and its online testing. In *EyeLines*, each move consists of at least two gaze "clicks": the participant had to select one of the colored balls presented in the game board with a gaze dwell on it (the selected ball was indicated by a frame around it), and then make another dwell to indicate the location where it should be moved. The game board subtended 18 × 18° on the monitor screen (Fig. 1). When 4 balls of the same color formed a line, it disappeared, and the player get a score. After each move, three new balls of randomly selected colors appeared on the board at random positions (see [14] for details).

Figure 1. *EyeLines* game board.

Classifier training – EEG data for classifier training were collected, for each participant, in four games that were played with 500 ms (or longer) gaze dwells (each game lasted 5 min). An additional element (shown left to the 7 × 7 square board in Fig. 1) was used in the game interface at this stage of experiment, as in [14, 23]: participants had to switch on the gaze based control prior to each move by fixating a special "switch-on button" (a location outside the game board). Dwells not preceded by switching control on made no effect in the game and were considered as spontaneous. 271 to 369 EEG epochs related to controlling gaze fixations (on balls and on new locations for them) were collected. In [14, 23], the "switch-on button" disappeared from time to time, to provoke more spontaneous gaze dwells. In the current study, we used EEG related to spontaneous dwells only to adjust the classifier threshold and to test the classifier. Thus, less such data were needed, and the "switch-on button" was made available to a participant during all the game. It was found in our previous study [14] that averaged EEG related to spontaneous fixations has very low amplitude. Therefore, we now decided to use EEG epochs sampled from random time instances to imitate "spontaneous" data for classifier training. The number of such epochs was equal to the number of control-related epochs for each participant.

To obtain 152 features, EEG amplitudes from 19 channels (Fz, F3, F4, Cz, C3, C4, Pz, P1, P2, P3, P4, POz, PO3, PO4, PO7, PO8, Oz, O1, O2) were averaged in 50 ms windows started at 8 time instances (+300, +320, ... +440 ms relative to dwell start), separately per channel and window. +200..+300 ms interval was used for baseline correction. No high-pass filter was used. It was shown earlier that such a procedure ensures that the features are not affected by EOG contamination [14]. Shrinkage LDA from Fieldtrip toolbox [24] (http://www.ru.nl/neuroimaging/fieldtrip) was used to train the classifier. Threshold was adjusted to obtain specificity of about 0.90 on a validation subset.

Game playing with online EBCI – After classifier training, participants played another four *EyeLines* games, now with a hybrid EBCI. Now, control was always switched on, and 500 ms gaze dwells made effects if confirmed by the EEG classifier. To compensate for the EEG classifier's misses, additional threshold was used (following a suggestion from [8]): if gaze dwell time exceeded this threshold (1000 ms), "click" was made in any case, without applying the classifier to the EEG. In the first game using the online EBCI, the rate of its positive responses was computed and used in two of the remaining three games for a "random classifier" that provided responses with this rate irrespective the current EEG data.

The participants' task in the games was almost the same in the classifier training stage and in the online EBCI stage of the experiment: they were asked just to play the game with gaze dwells only. They were told that their EEG will help to recognize their intention to click in the online EBCI stage, so there will be no "switch-on button", but sometimes their intentions will

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be not recognized correctly. They were also told that it is important to report each case when they notice that the selected ball is not exactly that one that they decided to select, and even cases when a "good" ball was selected when they were about to make a decision to "click" on it, but before they actually made a clear decision. Unlike in our previous study [23], the participants did not need to switch to manual tools for reporting such cases: instead, they had to deselect the ball by continuing looking on it. However, they were not aware of the difference between the real and random classifier conditions.

Online tests for sensitivity and specificity were run in the end of the experiment to obtain online classification data with well known ground truth. For these tests, a 5 × 5 board was used instead of the 7 × 7 used in the games. First, balls with random colors appeared one by one at random locations, and the participants had to set them into four lines from left to right, top to bottom (Fig. 2). This test was used to estimate online EBCI sensitivity. Then, the participant was asked to remember the locations of the balls with three colors most frequently presented at the moment. The remembering task lasted for two minutes, and then the participant had to indicate the ball locations on a paper sheet. The EBCI was on but not used intentionally, and participants were told to ignore ball selections that sometimes happened. This test was used to estimate online EBCI specificity. Two pairs of the tests, one with real and one for random classifier (in random order), were used for four participants, and a double number of them was used for another five.

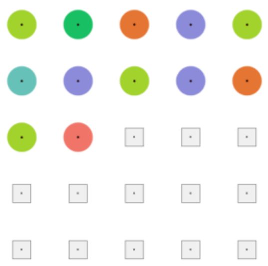

Figure 2. The board being filled with balls during a test for estimating online EBCI sensitivity.

EBCI classifier performance was estimated for ball selection in the first four games where no online EEG classification was used (Offline Performance in Games), for next four games played with online EBCI (separately for real and random classifiers, Online Performance in Games), and for the final tests (also separately for real and random classifiers, Online Performance in Tests).

Offline Performance in Games was estimated using five-fold cross-validation (the test subset did not overlap with the validation subset for threshold estimation). We computed ROC AUC, sensitivity, specificity and Youden's J index (J = sensitivity + specificity – 1; similarly to ROC AUC, it can be helpful when specificity gets higher on expense of sensitivity, and vice versa. While it is less reliable estimate than ROC AUC, its advantage is that it could be computed both for offline and online classifier performance.)

Online Performance in Games was quantified as sensitivity, specificity and J values, assuming the following meanings of the observed events: *true positives* for the gaze "clicks" with the short (500 ms) dwell time threshold (i.e., confirmed by the EEG classifier) not followed by de-selection; *true negatives* for dwells with duration between 500 ms and 1000 ms not confirmed by the EEG classifier; *false positives* for gaze "clicks" with the short (500 ms) dwell time threshold (i.e., confirmed by the EEG classifier) followed by de-selection; *false negatives* for gaze "clicks" with the long (1000 ms) dwell time threshold (spontaneous dwells of this duration are rare in playing *EyeLines* [14]).

Online Performance in Tests was also quantified as sensitivity, specificity and J values, but sensitivity and specificity were computed separately for the two tests (see above their description).

RESULTS

EBCI offline performance appeared to improve compared to our previous results: ROC AUC was 0.74 ± 0.04 ($M \pm SD$) for classification of dwells on balls (Tab. 1, second column), while, for example, in [14] it was 0.69 ± 0.09 for dwells on "switch-on button", where more prominent EEG potentials were observed comparing to dwells on balls. Among the changes in methodology that account for this improvement could be, as our additional pilot analysis suggested, the use of randomly sampled EEG epochs instead of spontaneous fixation-related data as the non-target class in classifier training.

Estimation of the EBCI online performance in games yielded, unfortunately, inconsistent results (not presented in Tab. 1): the random classifier demonstrated apparently non-random behavior. It seemed that the participants often did not reported the false positives for at least two reasons: because of not noticing the selection (especially if it appeared just before a saccade to a different location) or because of difficulty to differentiate a clearly formed decision from a decision that was yet being prepared during the dwell.

EBCI online performance in tests appeared more sensible (see Real and Rand columns in Tab. 1). Youden's J index for the random classifier did not differ from zero significantly ($p = 0.15$, according to Wilcoxon signed rank test), while for the real classifier it differed from zero ($p = 0.016$) and from random classifier J values ($Z = 2.52$, $p = 0.012$). Specificity was also significantly higher for the real classifier comparing to the random one ($Z = 2.10$, $p = 0.036$). Difference between real and random classifier for sensitivity was not significant ($Z = 1.52$, $p = 0.13$), but it was also in favor for the real classifier. Thus, although tests used to measure sensitivity and specificity were performed under different conditions, it appeared to be

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very likely that the significant difference in Youden's J represented non-random online performance of the EBCI. Nevertheless, online performance in tests was lower than offline performance (compare Offline and Real columns in Tab. 1). Significant decrease in online mode was observed, comparing to offline results, for Youden's J (Z = 2.55, p = 0.01) and for sensitivity (Z = 2.55, p = 0.01), while for specificity it decreased nonsignificantly (Z = 0.18, p = 0.86).

Table 1: Performance of the classifier: offline results for games and online results for tests

	AUC	**Sensitivity**			**Specificity**			**Youden's J**		
Sbj	**Offline**	**Offline**	**Real**	**Rand**	**Offline**	**Real**	**Rand**	**Offline**	**Real**	**Rand**
29	0.80	0.50	0.10	0.10	0.86	1.00	0.90	0.36	0.10	0.00
30	0.74	0.39	0.25	0.09	0.88	0.87	0.90	0.27	0.12	-0.01
32	0.74	0.42	0.15	0.08	0.88	0.85	0.86	0.30	0.00	-0.06
33	0.67	0.22	0.11	0.00	0.90	0.94	0.84	0.12	0.05	-0.16
34	0.79	0.37	0.05	0.05	0.91	0.92	0.92	0.28	-0.03	-0.03
35	0.74	0.29	0.21	0.25	0.89	1.00	0.78	0.18	0.21	0.03
36	0.75	0.36	0.30	0.23	0.87	0.80	0.73	0.23	0.10	-0.04
37	0.69	0.29	0.17	0.14	0.89	0.88	0.84	0.18	0.06	-0.02
38	0.70	0.22	0.24	0.29	0.96	0.87	0.74	0.18	0.11	0.02
M	**0.74**	**0.34**	**0.18**	**0.14**	**0.89**	**0.90**	**0.83**	**0.23**	**0.08**	**-0.03**
SD	**0.04**	**0.09**	**0.08**	**0.10**	**0.03**	**0.07**	**0.07**	**0.08**	**0.07**	**0.06**

DISCUSSION

This pilot study, for the first time, provided substantial evidence indicating that the Eye-Brain-Computer Interface based on the user's expectation of gaze controlled interface feedback may function in online mode. However, there were several issues in this study that should be resolved in future work:

(1) Online performance in this study was lower than in offline modeling. This could be related to unfavorable testing conditions. In the previous study [14] we found that the EEG marker for the gaze dwell used to send a command degrades along controlling gaze dwells that closely followed each other. Although it was not fully clear whether this was indeed a result of close positioning of the controlling dwells in time, the same effect, if it exists, could affect the marker in many gaze dwells intentionally used for control in the *EyeLines* game, because moves are often made rather automatically, without much thinking. In the sensitivity test, the required actions could be also too automatic for developing a strong expectation-related activity in the EEG.

(2) Sensitivity and specificity were calculated from data obtained under different conditions. This could bias Youden's J metric if these conditions affected classifier sensitivity and specificity differently.

(3) The EEG components that are related to the completion of a visual search task rather than to freely formed intention/expectation could contaminate the online test results. The participants had to locate each new ball in the test for sensitivity and to locate the balls related to the same color in the task of specificity, so the components related to finding a target, such as the P300 wave, could arise each time the fixation on these balls started. If the classifier was sensitive to these components, the results of these tests would be biased toward higher sensitivity and lower specificity compared to what should be observed under the use of intention-related components only; if the effect on sensitivity prevailed, Youden's J would be inflated. The time courses for the intentional dwells in *EyeLines* on which the classifier was trained (both them and topographies were similar to what was observed with our earlier studies with *EyeLines*, see Fig. 4 and Fig. 7 in [14]) were different from what is specific to the P300, however, this could not guarantee that classifier was completely insensitive to the P300 in tests.

All these issues imply that better methodology must be designed for EBCI testing. Issue (3) is especially important to resolve to finally prove if the expectation based EBCI is selectively sensitive to the user's intention. For assessing prospects for practical application, other challenging factors should be included into tests, such as saliency of relevant and irrelevant objects [25]. It is also evident that EBCI performance improvement is strongly needed. As suggested by our preliminary results, this may become possible with finding more adequate feature sets [26] and classifiers [14] for the EBCI.

If its further development will be successful, the expectation based EBCI could practically implement the idea of Grey Walter who proposed, as early as in 1960s, to use the expectation-related activity in the EEG for "the direct cerebral control of machines", "by-passing the operant effector system" [27].

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