A Passive Brain-Computer Interface for Supporting Gaze-Based Human-Machine Interaction

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Abstract. Tracking eye movements to control technical systems is becoming increasingly popular; the use of eye movements to direct a cursor in human-computer interaction (HCI) is particularly convenient and caters for both healthy and disabled users alike. However, it is often difficult to find an appropriate substitute for the click operation, especially within the context of hands-free interaction. The most common approach is the use of dwell-times, but this can lead to the so-called “Midas-Touch” problem. This problem is defined by the fact that the system incorrectly interprets fixations due to long processing times or spontaneous dwellings as a user command. The current study explores the event-related potentials (ERPs) that might indicate a user's intention to select. Therefore, Electroencephalography (EEG) data was recorded from 10 participants during an interaction with a dwell-time system within a selection process. The aim was to identify EEG potentials related to the intention to interact (i.e. the selection of targets on a screen) and to classify these against EEG potentials unrelated to interaction during random fixations on the screen. As a result, we found a clear negativity over parietal electrodes for the intention of item selection. This negativity did not occur when participant fixated an object without intention to select (no specific intention). We robustly could classify the underlying brain activity in most of our participants with an average accuracy of 81%. The presented study provides evidence that the intention to interact evokes EEG activity that can clearly be detected by passive BCI technology. This leads to a new type of implicit interaction that holds the potential to improve human-machine interaction by increasing efficiency and making it more intuitive.

Keywords: EEG, passive BCI, implicit interaction, gaze-based interaction.

1 Introduction

Imagine a surgeon operating on a patient: both her hands are occupied, but, at the same time, she may want to be able to control a computer in order to retrieve

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information about the patient's physiological state. In such a situation, a hands-free mechanism for computer control, i.e., cursor movement and object selection (similar to a mouse click), is desirable. In the early 1990s, Jacob ([1], [2]) has proposed to use the human gaze as input channel for human-machine interaction (HMI) in order to provide a natural and hands-free way of interaction (see also [3]). With recent technical developments that make eye tracking systems more exact and affordable, this form of interaction has become popular and first systems have arrived on the consumer market.

An advantage of gaze-based human-machine systems (HMSs) is the fact that it is very natural to use the eye for cursor movements. Usually, humans direct their attention towards an object by looking at it before pointing at it. Therefore, it is convenient to have the cursor position at the user's gaze location. However, it becomes tricky to determine an appropriate substitute for the selection operation as the eye does not provide a natural mechanism for this. Blinking and dwell time, i.e., a gaze fixation on an object for a particular duration, provide just limited solutions. The former has the disadvantage of involuntary blinks leading to a large amount of unintended selections. When using the latter, one faces the problems that fixations unrelated to the intention to select are interpreted as commands. Unintended selections can therefore occur due to spontaneous dwellings at random objects [4]. Moreover, it is hard to find an optimal dwell time for all stimulus complexities. The stimulus processing time might exceed the dwell time leading to an involuntary selection. This problem of unintended selections has been termed Midas-Touch-Problem because the user tends to feel comparable to the ancient King Midas who had the gift that everything he touched, even his food, turned into gold and because of this he almost starved to death ([1], [2]). Prolonging the dwell time may be one solution; however, in that case experienced users might become annoyed because the speed of the system is too slow leading to a speed-accuracy-trade-off.

Therefore, it may be worthwhile to make use of other hands-free input channels to find a more natural way of substituting the selection process. In the last years, brain-computer interfaces (BCIs) have been proven to be useful as a new communication channel independent from standard human output channels ([5], [6]). These systems transfer activity of the human brain linked to certain cognitive states as measured with electroencephalography (EEG) into commands for the computer. In the context of HMI, especially active and passive BCIs seem to bear good prospects to improve natural interaction ([7], [8]). For active BCIs, the user has to generate a certain brain state or EEG potential (e.g., by imaging an action like moving hands), whereas passive BCIs utilize information about the ongoing user state (e.g., situational awareness, user intentions, affective state) for an automated adaptation of the system [8]. Passive BCIs establish a secondary interaction cycle, next to that of the primary interaction the user is involved in. This additional interaction is implicit [23], meaning that users do not consciously send commands through the BCI. They might not even be aware that they are providing input through the passive BCI. Implicit interaction through a Passive BCI opens up BCI-based applications for users without disabilities [24] by decoupling them from the transferred information bit rate [24]. Additionally, nowadays dry and portable EEG electrode systems became available [9–11], so that HMI based on brain activity is more than mere utopia.

Recently, a system combining gaze input for cursor movement and an active BCI for the selection process was presented ([12], [13]). There, the users had to look at an object on the screen and simultaneously imagine a hand movement in order to select it. Over different stimulus complexities participants were as successful in using the BCI-based selection as in solely gaze-based interaction triggered by dwell times optimally chosen for the given stimulus complexity. As the selection based on active BCI is independent from stimulus complexities, it outperforms the common dwell time selection. Additionally, participants favored this system as they could work in their own pace, not disturbed by false selections when resting their eyes. To our knowledge this was the first study enhancing gaze-based HMI with the help of BCI input that was demonstrated in an online system. As a downside, the imagination process loaded some extra workload on the users, so that it may be promising to utilize a passive BCI to elicit the selection.

Based on a pre-study presented in [14]1 we investigate the passive BCI in based gaze interaction. Participants were asked to find a target in a set of distractors. In trials where the target was present they were asked to select it by dwell time (class 1), in trials where no target was among the stimuli they were asked to return their gaze to the fixation cross and wait for the experiment to continue (class 2). Participants were not informed that the experiment would only continue if they rest their eyes on the cross for the same dwell time as during target selection. Hence, participants must show a very similar behavior during both classes, but clearly have a different state of mind. Our hypothesis is (based on the results from [14]), that we can discriminate the difference between these two states of mind (intention to interact / waiting) by a passive BCI. Such a passive BCI could then be used as a selection command in a very intuitive gaze based interaction. Items you intend to select are selected automatically, without the need of sending any additional command, while items you are just studying or looking at, will not be selected.

Here we will validate this hypothesis by an offline analysis of EEG data collected in the above-mentioned experimental paradigm.

2 Methods

2.1 Experimental Set-Up

Data sets from 14 participants (6 male; average age of 27 years) were included in the analysis. All of them were right-handed and reported being free of neurological

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[1] The experimental setup of [14] was refined in this study as it included an unintended confounder between the two classes. The post-selection behavior was different between both classes. As subjects were asked to move their eyes to the center of the screen in Class 1, they might prepare for a saccade might have induced a readiness potential. As they would not have such an eye movement in Class 2 it is unclear what the basis of the signal investigated in [14] was. The experimental setup used in this study is corrected for this flaw.

disorders. EEG and electrooculogram (EOG) were recorded using 135 impedance-optimized electrodes (actiChamp, BrainProducts, Gilching, Germany). Eye movements were tracked with an IG-30 remote eye-tracker (IntelliGazeTM System, alea technologies, Teltow, Germany) module, which was also used for gaze-based interaction.

All participants were given verbal and written instructions and had to calibrate the eye tracker and to train how to interact gaze based. Each trial started with the presentation of a fixation cross for one second. Then a set of two or four different geometric objects containing either no or one target (a triangle or a hexagon) was added to the scene, at different locations on the screen (figure 1). In case a target was presented (class 1, intent to interact), participants had to selected the target out of either one or three distractors by means of dwelling at it for 1s. After successful selection of the target, it was replaced by a cross hair starting the next trial and with a new set of geometric objects. The cross hair did always appear at the location were the fixation of the last trial ended. In trials where no target was present on the screen participants were asked to look at the fixation cross until the new trial starts (class 2, no specific intention). Participants did not know that a new trial only would start after a successful fixation of the cross hair for 1 s. The experimental design ensured participants showing the same gaze-based behavior in both classes even though they had a different intent.

2.2 Data Analysis

Event Related Potentials (ERPs). For the analysis of event-related potentials (ERPs), we compared the averaged EEG signal at central electrodes relative to the dwell time selection in both classes. Scalp topographies were inspected for spatial location of the ERP. All scalp-electrodes were considered for the topographies.

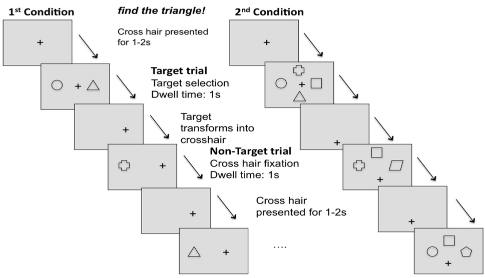

Fig. 1. Trial procedure: target and task combinations

The experiment consisted of twelve blocks, each containing 20 trials (10 for each class). While in six of the blocks 2 items were displayed per trial (condition 1), the other blocks contained 4 items each trial (condition 2). All participants completed three blocks of each target and task combination in randomized target and block order. Thus, a total of sixty target and sixty non-target trials for each condition was recorded.

Classification. For defining our BCI approach, we used the open-source toolbox BCILAB [15]. Features were extracted by the Windowed Means approach [16] and classification was done with a Linear Discriminant Analysis (LDA, [17]) regularized by Shrinkage [16]. The defined approach is a subsampling of the data catching the trend of the signal and resulting in normally distributed features. Hence, a LDA is a very well chosen classifier for this decision problem, as it provides an optimized decision plane and suffices a very low Vapnik–Chervonenkis (VC) dimension [18].

The Windowed Means approach was parameterized with a series of non-overlapping windows of 50 ms length starting at 1050ms and ending 400 ms before the item (geometrical or cross) was selected resulting in a 13 (windows) x 128 (EEG channels) = 1664 dimensional feature space. Due to volume conduction, features in each temporal time slice (each 50 ms window) are spatially correlated [19]. Hence, the number of independent features is unknown but should be lower. Nevertheless, the ratio between independent dimensionality and the number of trials (240) is very bad.

We defined a classification model along this approach for each subject individually, calibrated on the data of both of the sessions (with 1 and with 3 distractors). An estimate of the online reliability of the defined model was derived by a [5,5]-times nested cross-validation [17] with margins of 5 (default by BCILAB, [15]). The inner runs of the nested cross-validation were 5-folded and served for the selection of the regularization parameter of the Shrinkage. The outcomes of the 5-folded outer runs, regularized by the one Shrinkage parameter derived in the appropriate inner runs) gave the estimates for the reliability of each runs model. The overall reliability was then given by the average of each single runs' reliability. The validity of this estimate is supported by the low probability of over-fitting of classifiers with low VC dimension [18], by the fact that the bad ratio between feature dimensionality and number of trials can be counterbalanced by a well-chosen Shrinkage regularization [16] and that we properly applied a nested cross-validation.

3 Results

Here, we present results from a selection of 10 of the 14 investigated subjects. Data from four subjects was skipped as we encountered technical problems with our eye tracker (mainly with the calibration) during their sessions. Estimates of classification accuracies and the average can be found in Table 1. Average accuracy of the skipped subjects was about 51.5%.

Table 1. Classification accuracies resulting from offline cross validation in 10 selected subjects

Subject ID	Accuracy	Subject ID	Accuracy
1	0.65	6	0.81
2	0.81	7	0.75
3	0.82	8	0.75
4	0.91	9	0.85
5	0.91	10	0.82
Average:		**0.81**	

Figure 2 shows event-related potentials (ERPs), averages of multiple instances of preprocessed EEG signals related to a specific event, in fronto-, central- and parieto-central electrodes. They show a negativity, starting 1100 ms before the final selection. This Negativity is strongest on parietal sites and attenuating while moving to frontal sites, as it can be seen in the related topographic plots. Figure 3 shows ERPs for channels reflecting eye movements. Here we see clear differences between classes from 1200 to 1050ms before selection.

4 Discussion

The aim of this study was to identify EEG potentials that occur during gaze-based HMI and can be utilized as possible input in a passive BCI system to select target objects on the screen. Especially it should show that it is possible to classify eye gaze fixations that are related to the intention to interact with objects on the screen against spontaneous, selection-unrelated fixations in a relatively natural HMI environment.

Classification results strongly support our hypothesis. The fact that features evoked from eye movements are clearly separable in time from those taken for classification, and the fact that the investigated negativity can be found clearly localized at parietal sites contribute as well. Taken ?together with the fact of a different topography in Class 1, showing only a 5^{th} of the activity present in Class 1, supports a validation that the presented passive BCI indeed is based on cortical processes and not on artifact activity like eye-movements or muscular activity. This is important as the presented passive BCI is intended to work in gaze-based systems in very different environmental contexts. We assume that behavior changes easily with such contexts, which would lead to changes in eye and muscular activity. This would reduce the reliability and robustness of the classification of the passive BCI. As it is very likely that this is not be the case for cortical activity related to cognitive processes, we are confident that the approach presented here will be stable in different application scenarios.

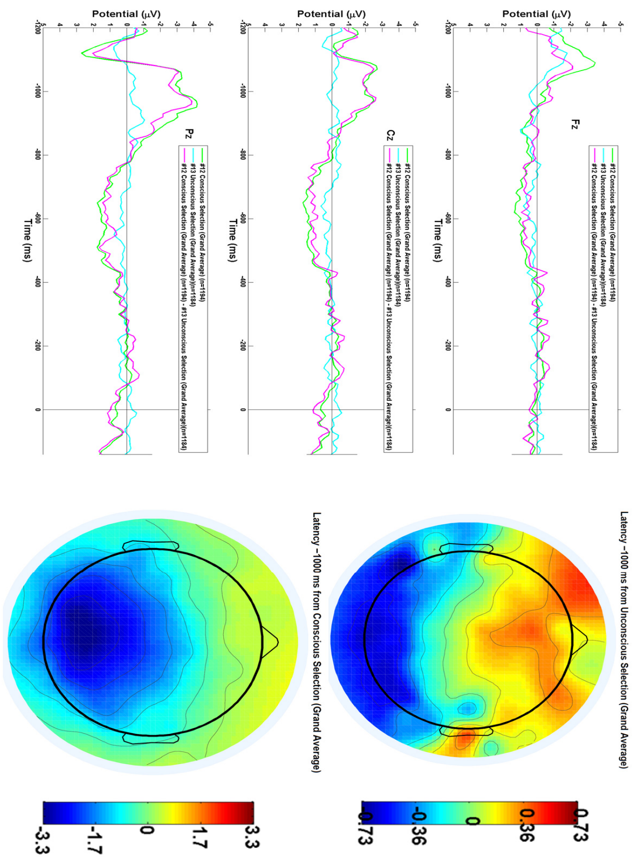

Fig. 2. Top: 3 ERP plots from frontal, central and parietal electrodes. Green curves for Class 1, blue curves for Class 2, purple curves: Difference Plot. Y-Axis in microvolt, X-Axis in milliseconds, 0 is item selection. Bottom: Topographic Plots, left: class 1, intent to interact, right: class 2, no specific intention. We see a clear negativity between -1100 and -850 ms in Class 1, which is not present in Class 2. Class 2 shows no relevant deviations from the baseline.

Looking at the conventional EEG analysis reveals a negativity over parietal electrodes. It clearly is related to the intended selection of an object of the screen (intention to interact) and does not occur in case participants were fixating the cross hair without intention to select (no specific intention). It nicely shows that brain activity in the beginning of a fixation for a selection is different from EEG activity during fixations unrelated to selection and thus may reflect the psychological difference. Future studies need to examine the revealed potential in more depth in order to determine its neuropsychological background. Therefore, source localization of EEG components should be accomplished using independent component analysis (ICA) [20]. By this, cortical generators of the potential can be identified leading to its better neuropsychological understanding. In addition, it is worthwhile to verify the occurrence of this potential in other experiments and real world applications to ensure its robustness, which is necessary for building reliable BCI systems.

Moreover, we performed an offline BCI analysis of the potential in order to provide an estimate for the classification accuracy in a potential online passive BCI system. We were able to robustly classify the revealed brain activation in most of our participants with an accuracy up to 91% using standardized BCI algorithms (e.g., see [21]). This value is well above chance level according to the work of Müller-Putz et al. [22]. Such high classification accuracy suggests that using this potential in a passive BCI system is well possible. Moreover, it seems likely that more complex analysis involving classification on components derived by ICA analysis could even improve performance. Additionally, it would assure even more that classification is based on neuropsychological reasonable EEG activity and not on eye movement or muscle artefacts.

We had technical problems with the eye-tracker in four participants resulting in very low classification accuracies for these participants. This can be explained by the fact that poor eye tracking calibration might lead to a delay in the actual selection of the target object in certain trials. Variability in the length of the fixation could kind of "wash out" the event-related potential as its start may be shifted by up to several hundred milliseconds. This in turn affects the features extracted and may thus deteriorate BCI classification accuracy. All in all, although improving classification accuracy is necessary, it seems that offline BCI classification worked fairly well for the revealed potentials.

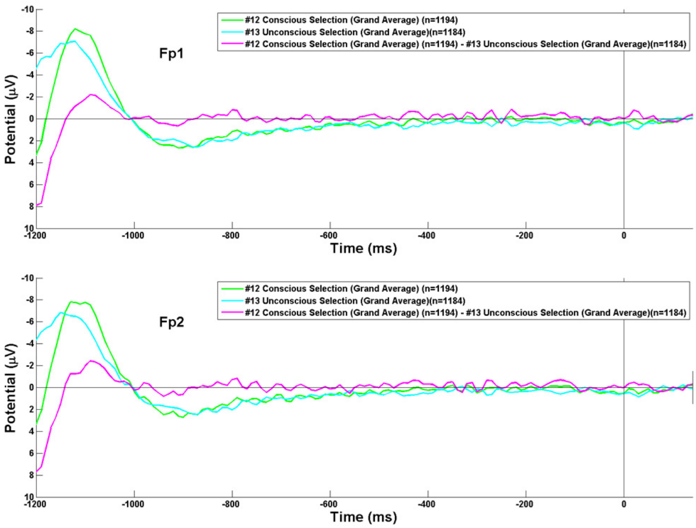

Fig. 3. ERPs reflecting eye movements. Green curves for Class 1, blue curves for Class 2, purple curves: Difference Plot, 0 is item selection. Here, we see a difference in timing between classes while the peak amplitude is stable.

The presented passive BCI could be applied in gaze-based interaction. In a first scenario it could replace dwell times as selection command. The benefit of this approach would be that users could interact very intuitively. Only those items would be selected which they plan to interact with. A drawback would be the lack of a selection command that can be triggered voluntarily. Users might experience this as a kind of loss-of-control [25], which could reduce the usability of systems. A second scenario would be using this passive BCI in addition to a dwell-time triggered selection command. The BCI could be used as a "second guess" improving the reliability by eliminating false positive selections.

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