A passive BCI for monitoring the intentionality of the gaze-based moving object selection

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Abstract. An investigation of whether the E-wave can be useful in the context of selecting moving objects through smooth eye movements. To conduct the study, 18 participants selected moving objects by gazing at them. Their gaze was recorded using low-cost eye-tracker that was placed on the computer screen. Participants also took part in tasks unrelated to voluntary selection during another experience. The results show a component similar to the e-wave in voluntary selection. Using linear discriminant analysis with shrinkage regularization, conscious and spontaneous eye movements with smooth eye movements could be classified significantly well using 300 ms EEG segments in a single trial in eight participants.

Keywords: brain computer interface, gaze interaction, E-wave, contingent negative variation, stimulus preceding negativity, smooth pursuit eye movement, selection

1 Introduction and state of art

Dr. Grey Walter contributed great improvement to the technologies of brain waves by discovering the expectancy wave (E-wave) in the electroencephalogram (EEG) with his colleagues in 1966. He also suggested the use of this component for the direct cerebral control of machines. (G, 1966)
Some decades later, in 1991, Thorsten et al (K, 1991) proposed using the E-wave to tackle the so-called Midas touch problem. Namely the struggle of machine interfaces to differentiate, voluntary eye behaviors from spontaneous ones.
This issue was tackled in different ways. Many of them were not efficient enough since they required extra effort from the user like long time gazing(dwell). (VELICHKOVSKY; SPRENGER; UNEMA, 1997) (MAJARANTA; BULLING, 2014) The most efficient way is of course, when the BCI works in a way that the user shall not put extra focus on how long shall she or he keep gazing. The last mentioned interface is rather called eye brain computer interface (EBCI). (ZANDER et al., 2011)
Zander's group's objective with this is to actively communicate the user's intent rather than automatically informing what is relevant to them.
It has been shown that EEG recorded in both visual search tasks and in those where participants look at items of different relevance to them, can be helpful in identifying the target or measuring significance, namely through the P300 wave, since this wave is associated with stimulus relevance. This led to the development of a specific type of passive hybrid BCI.
In the studies that led to the previous-mentioned conclusion, participants did not know the location of the relevant objects in advance, which seemingly made it possible for the P300 wave to be triggered when they found the objects.
Because it is important for the BCI to be able to differentiate between voluntary and spontaneous gaze, it is preferable that this task not be dependent on the P300

wave; consequently, many studies have focused on this task. For example, Shishkin et al recorded the EEG of participants who typically knew the position of an object before they began looking at it to select it, so the occurrence of the P300 wave was unlikely. The threshold for the dwell time was set at 500 ms, which made the interaction sufficiently comfortable and did not prevent immersion in the game. (L NUZHDIN Y O; M, 2016)
Relatively recently, the selection of moving objects with smooth pursuit eye movement (dynamical fixation) was found to be highly effective, in addition to the long-used gaze fixations (dwells) (Vidal et al (M; H, 2013), (M; H, 2015).
Thus, fluid tracking eye movements can enable interaction without the need for calibration (Pfeuffer et al (K VIDAL M; H, 2013)). The eye movement correlations to the trajectories of moving objects are calculated and the highest correlated object is assumed to be the one the user is looking at. Given that smooth tracking is quite accurate, it is a particularly attractive approach as a solution for small displays, such as smartwatches, where eye-sensitive objects cannot be separated at distances large enough to reliably differentiate between the gazes on them (Esteves et al (A VELLOSO E; H, 2015)).
During this study, Zhao et al optimize their preliminary studies ((G ISACHENKO A V; L, 2018a) (G ISACHENKO A V; L, 2018b)), in which they observed an E-wave-like EEG component prior to the selection of a moving object with a gaze. The issue is that a similar wave also accompanied the smooth pursuit eye movement in control conditions, where the intention to select an object could not appear. they concluded that some form of expectation or at least estimation of time to perform certain operations (a related cognitive activity) readily appears under various conditions when the pursuit is used intentionally to follow instruction. This paper shows how they designed a control condition free of the mentioned defect and correction of some other details. collecting data from a larger group of participants allowed them to analyze the difference between the EEG accompanying spontaneous smooth pursuit and intentional selection of moving objects with gaze, and also to model their classification in an EBCI using a convolutional neural network. To analyse their research they used linear discriminant analysis with shrinkage regularization (sLDA).

2 Methodology

2.1 Data collection and Task

The details of how the data for the experiment were gathered are briefly described in the table 1.

	Description
Candiates	20 volunteers: 11 Male + 9 Female 13 had prior experience with gaze-based control of a computer. 14 had normal vision, while the rest had corrected to normal vision.
Material	**Consumer-grade eye tracker:** Name: Tobii 4 C, Frame rate: 90Hz **LCD monitor:** 1440 x 900, refresh rate: 75Hz
Recordings EEG/EOG	EEG was recorded from 19 locations, most of them from the posterior area. (F3, Fz, F4, C3, Cz, C4, P1, P3, Pz, P2, P4, PO7, PO3, POz, PO4, PO8, O1, Oz, O2) Bandpass: 0 - 200Hz, SR: 500Hz EOG was also recorded near the outer canthi for recording the eye movement. The ground electrode was positioned at the Fpz position.
Experiment layout	15 balls on the screen with the diameter 80 px, numbered from 1 to 15. The numbers are encounterd by 5-8 dots. Figure 1 shows a screenshot of the an experimental setting. **2 kinds of tasks:** static: balls don't move, dynamic: moving balls that change direction when they hit each other. 10 sets of 15 ball images are generated. Each set consisted of 15 images. On 3 of them, the balls had 5 dots. 4 had 6,7,8 dots.

Table 1: Methodology explained.

The experiment consisted of 4 different blocks:

1. **Selecting moving balls (SMB):** select the 15 moving balls one by one according to their number in ascending order, then (only for participants 7-14) in descending order.

2. **Select Static Balls (SSB):** select 15 balls one at a time as in the SMB condition, but in this case the balls are fixed in their initial position.

3. **Find accelerated ball (FA):** find the randomly selected ball that has accelerated once suddenly after 15-20s.

4. **Counting task (CT):** participants had to find a ball with the number of points specified by the experimenter five times in a row (this number could be from 5 to 8, chosen randomly each time). After finding an appropriate ball, they had to add its label number with the number(s) of the previous ball(s).

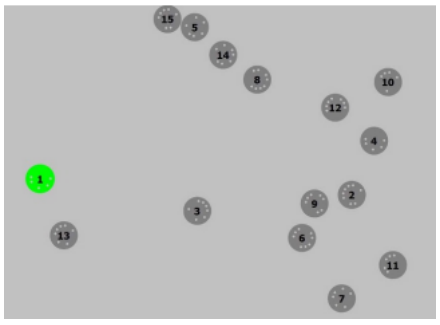


Figure 1: A screenshot of a typical experimental layout.

By each block of experiment a set of images was randomly chosen and numbers from 1 to 15 were randomly assigned.
The SMB and SSB tasks modeled voluntary gaze selection. By contrast, the FA and CT tasks modeled a situation in which smooth eye movements devoid of the intention to make a selection, can occur, but the visual representation remains the same in all tasks.

2.2 Selection Procedure

For the different tasks, the online algorithm was the same. Though, under the SMB and SSB conditions, the selected ball that was looked at for a certain amount of time changes to the color green. (See 1) If another ball is selected, the previous one turns gray again. This color change was not part of the FA and CT conditions. Technically speaking, the ball that has the smallest average distance to the line of sight is selected.
The selection algorithm was implemented in C++ and QML. The time at which the selection was triggered was recorded along with the EEG, using a photosensor placed at the lower left edge of the screen, where a circle not visible to the participant changed its brightness when the algorithm was triggered. In the SMB and SSB conditions, this change occurred in the same video frame where the visual feedback began (a selected ball changed color). The number of the ball selected by the algorithm was recorded whether it was visually highlighted or not.
As shown in Figure 2, the experiment was composed

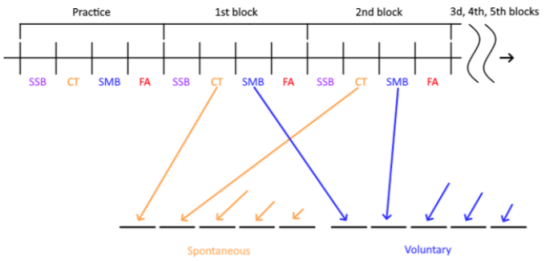


Figure 2: Experiment timeline.

of six blocks. Each block contained all four conditions arranged in the same order. This order was counterbalanced among the different participants. Each condition in a block comprised a run of ca. minutes duration. The first block was considered an exercise, and participants were allowed to ask questions during the runs. Data from the subsequent five blocks were used for analysis.

To avoid errors, participants were advised to take their time during the selection process. However, if an error occurred, participants were instructed to continue trying to choose the ball with the closest number to the previous correct choice. For capturing spontaneous choices, participants were not aware of the online detection of their smooth pursuit eye movement in the FA and CT conditions.
The FA task was previously employed in our preliminary studies (Zhao et al (G ISACHENKO A V; L, 2018a), (G ISACHENKO A V; L, 2018b)) , where some negative E-wave-like deviation was observed in the trigger-related EEG time courses averaged for this task. We hypothesized that this negative deviation was related to waiting for the moment when a ball that a participant was looking at as a target approached another ball, for the purpose of comparing their speeds.
In the current study, the CT task was added to the study design as a primary condition to elicit spontaneous smooth pursuit.

2.2.1 Data Analysis

EEG Preprocessing: The EEG analysis was made offline. The data was filtered with zero-phase lowpass

4th order Butterworth filter with a cutoff frequency of 30Hz.
EEG segmentation was based on the triggering of the algorithm. A trigger was considered to constitute a trial, regardless of the nature of the smooth pursuit or gaze dwell that might cause it. EEG/EOG epochs-1200...+1200 ms relative to the trigger were extracted.
An alternative segmentation from the same raw EEG related to the onset of pursuit was performed.

As its direct estimation is a complicated task, as a reference time the moment when the gaze lands before the pursuit (or the static pause, in the SSB condition) was used. Since the license of the used eye tracker does not allow the collection of gaze coordinates and their analysis offline, this time was found by using the gaze velocity extrapolated from the EOG before the online trigger.
Artifact removal and rejection: Components associated with eye movements were removed from the EEG signal by independent component analysis (ICA) using the runica algorithm with default EEGLAB software settings. (Runica algorithm and EEGLAB are toolbox implemented to help perform ICA). (A; S, 2004)
Feature Extraction The SMB (voluntary prosecution), SSB (voluntary arrest), and CT (spontaneous prosecution) conditions were used for classification. Within one analysis, SMB vs CT was classified, and within another, SSB vs CT.
For each participant, the number of epochs per class was balanced separately in the pairs of classes, SMB vs CT and SSB vs CT, towards a class with fewer epochs. For this purpose, some epochs were randomly removed from a class with larger number of epochs such that the number of epochs in the two classes matched each other before classification.
As features, the average amplitudes of adjacent 20 ms long time windows in the interval from -300 to 0 ms relative to the selection trigger were used (15 windows per channel). The choice of this time interval is intended to avoid the lambda wave, which is highly sensitive to factors irrelevant to selection. Figure 3 shows that in our data, the lambda wave latency was about -500. The need to simulate the online application of BCI justifies the choice of the right boundary of the interval.
A baseline interval of -100ms was used. This will make the amplitude characteristics sensitive to the slope of the E wave.
Features from all EEG channels were concatenated, forming a vector of 19 × 15 = 135 features for a single epoch. a single epoch.

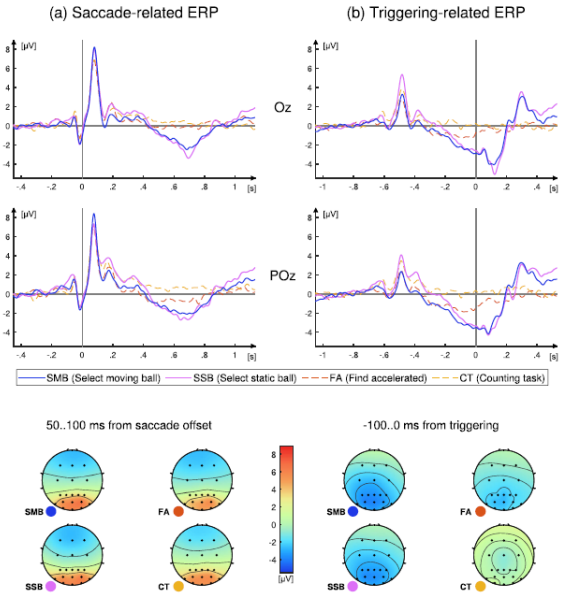


Figure 3: Time course at POz and Oz electrodes and topographical maps of the grand average ERP (N=18) time locked to the end of the last saccade before the dwell(a), and to gaze based selection algorithm triggering(b).

Classification

For classification discriminant analysis with shrinkage (sLDA) was implemented.
The sLDA was trained and tested on SSB trials versus CT trials, to represent voluntary and spontaneous smooth pursuit data, respectively. In addition, as a more distinct data point, SSB trials (voluntary dwells) were also classified against CT. Five-fold cross-validation was used for estimating classifier performance. Folds were trained in the blocks. Specifically, the dataset, separated for voluntary and spontaneous data, was divided into five subsets.
To present the results, we used the ROC AUC measurement, which is not related to the choice of classifier threshold. The ROC AUC measure was computed from the classifier output (for the test subsets) clustered on the folds.
As a check on whether the classification results were significantly better than chance (random guessing), a threshold permutation test [1] was applied. The class

[1] "Permutation tests (also called randomization tests) are non-parametric procedures for determining statistical significance based on rearrangements of the labels of a dataset"(KNIJNENBURG T. A., 2009)

labels were randomly permuted 1000 times, and each time the ROC AUC was calculated. The p-value was calculated as the share of AUC ROC values above the observed value for the unpermuted data. Lastly, the signed quadratic correlation coefficient, r^2 was calculated for each participant to assess the potential influence of eye movement artifacts between two time series. Namely the EEG features used for classification and similarly preprocessed EOG amplitudes and the class probability provided at the sLDA output for each trial when it was a part of the test subset within the cross-validation loop.

3 Results and discussion

3.1 Overview of the ERP

The data of two participants were excluded from the analysis and classification of the EEG due to problems during the experiment.

From Figure 3(a), the time course of the EEG was fairly similar in all conditions in about 300 ms after the end of the pre-pursuit/dwell saccade(a rapid movement of the eye between fixation points.). About 100 ms after the saccade, the lambda wave is observed as a high amplitude positive peak. It can also be seen in the trigger-related (Figure 3(b)), but in this case the amplitude was smaller and more condition-dependent, likely due to the variable time required for triggering across trials and participants.

A slow negative wave, most likely the E-wave, may be observed in the SMB and SSB conditions in the latter part of the tracking/dwell time interval. It grows steadily until the gaze-based online selection algorithm is triggered and heads in the opposite direction not long after, which is obviously in response to the visual feedback. A negative wave with a similar time course in its initial part can also be found in the FA condition (especially in POz, Figure 3(b)), but its growth ends early. In the CT condition, this phenomenon was not observed.

Looking at the average of each participant's waveforms, it appears that the E-wave was evident during both intentional selection conditions, SMB and SSB, in all participants, similar to previous studies of static object selection with gaze. (L NUZHDIN Y O; M, 2016) (O SHISHKIN S L; M, 2017)

Saccade- and trigger-related averages (Figure 3(a) and (b)) further showed additional waves following the lambda wave. EEG amplitude topographic maps were computed for time intervals when the lambda and E waves were most prominent (Figure 3, bottom). They show a typical pattern for the lambda wave in all conditions and a similar pattern to that reported previously for the E-wave (SPN) in intentional selection of static objects with gaze ((L NUZHDIN Y O; M, 2016)) in the SMB and SSB conditions. However, the map for the FA condition reveals a weaker E-wave-like pattern than in the two volunteer conditions, while nothing similar is observed in the CT conditions.

3.2 ERP Analysis

To assess the significance of ERP differences between conditions, the mean EEG amplitude in the surroundings of the component peaks, at Oz for the lambda wave and at POz for the E wave were compared using the one-way Anova [2].

For the lambda wave, there was not much difference between the conditions according to the one-way ANOVA. Whereas, the mean EEG amplitude around the E-wave showed a significant difference between SMB and SSB conditions when compared to CT.

3.3 Classification: sLDA

For classification, sLDA was applied to both adjusted and unadjusted data with ICA.

In both cases, the results obtained were quite similar: for non-ICA-adjusted data, the median ± MAD was 0.57 ± 0.04 and 0.62 ± 0.07 for SMB vs CT and SSB vs CT, respectively. For ICA-adjusted data, the values were 0.58 ± 0.06 and 0.58 ± 0.06 for SMB vs. CT and SSB vs. CT, respectively.

The permutation test showed that SMB vs. CT was classified better than chance ($p < 0.05$) in 8 of 18 participants, and SSB vs. CT, in 11 of 18 participants. (See table 2)

3.4 Classification optimization

Some techniques were used to optimize the classification. For example, extending the left boundary used for feature extraction to -400 ms improved performance in classifying SSB vs. CT, but not SMB vs. CT. As is common with the P300 in BCI, averaging was also attempted. Averaging of classifier output values in a sliding window covering a fixed number of consecutive trials of the same condition. The ROC AUC was calculated by varying the window length from 2 to 10 trials.

[2] One-Way ANOVA compares the means of two or more independent groups in order to determine whether there is statistical evidence that the associated population means are significantly different.

ID	SMB	SSB	CT	SMB vs. CT	p-value	SSB vs. CT	p-value
1	60	72	73	0.50	0.516	0.66	**<0.001**
2	100	131	98	0.50	0.494	0.57	**0.040**
3	129	128	96	0.58	**0.036**	0.62	**0.001**
4	48	50	46	0.59	0.067	0.49	0.538
5	55	65	96	0.64	**0.005**	0.52	0.300
6	70	73	151	0.51	0.397	0.71	**<0.001**
7	181	174	163	0.59	**0.003**	0.58	**0.007**
8	156	171	169	0.53	0.17	0.59	**0.002**
9	137	138	155	0.54	0.136	0.54	0.141
10	124	139	90	0.57	**0.041**	0.68	**<0.001**
11	141	140	74	0.52	0.375	0.66	**<0.001**
14	133	137	92	0.63	**<0.001**	0.62	**0.003**
15	125	136	47	0.45	0.775	0.50	0.487
16	127	134	43	0.75	**<0.001**	0.66	**0.004**
17	123	127	69	0.61	**0.017**	0.58	**0.040**
18	101	100	32	0.61	0.054	0.43	0.836
19	117	138	43	0.66	**0.006**	0.56	0.183
20	109	135	52	0.41	0.934	0.46	0.778
M	113.1	121.5	88.3	0.57		0.58	
SD	35.7	35.1	44.5	0.08		0.06	
Med.	123.5	134.5	82	0.58		0.58	
MAD	16	6	32.5	0.06		0.06	

Table 2: P-values (uncorrected) were computed for the ROC AUC values using a permutation test ($p < 0.05$ are showing bold).

The ROC AUC increased with window length, so that the group median ± MAD was 0.75 ± 0.09 for SMB vs. CT and 0.80 ± 0.06 for SSB vs. CT when 10 trials were averaged. (Figure 4) although the window length was not allowed to be longer than a validation fold, which was likely the cause of the increased variance for the highest window length values

3.5 Sensitivity analysis and possible eye movement contribution to the classification

The highest r^2 values in the EEG channels were located between -300 ms and -200 ms as well as shortly before this interval. This pattern suggests that the EEG amplitude change between -300 ms and 0 ms contributes most to classification performance.(Figure 5)

To create topographic maps (Figure 5, right), r^2 values were averaged in the interval from -300 to -200 ms. The maps resembled the amplitude maps to some extent (Figure 1(b)), although the maxima were not at POz but at different temporal (SMB vs. CT) and occipital (SSB vs. CT) locations.

4 Discussion

4.1 General observations and previous work

Previous research by Ihme and Zander ((ZANDER et al., 2011)) and Protzak et al. ((J; O., 2013)) has shown that the E-wave can be used as a hybrid BCI system in which gaze tracking allows relatively fast and accurate detection of items available for selection. Such BCI indicates whether the user is intentionally trying to make a selection, rather than staring at an object aimlessly.

Unlike many other attempts to combine gaze-based selection with motor imagery-based BCI, the E-wave-based hybrid BCI does not require an additional cognitive task to make a selection . (from Zander et al. ((O GAERTNER M; R, 2010)) to Hou et al. ((J BEKGAARD P; S, 2020)))

The key point in these previous studies is that the E-wave helps to distinguish voluntary fixations on objects with the intention to select them even from fixations that are directed to objects because they attract attention but are spontaneous during the fixation process, so their selection would be an error.

In this work, we have shown that E-wave-based hy-

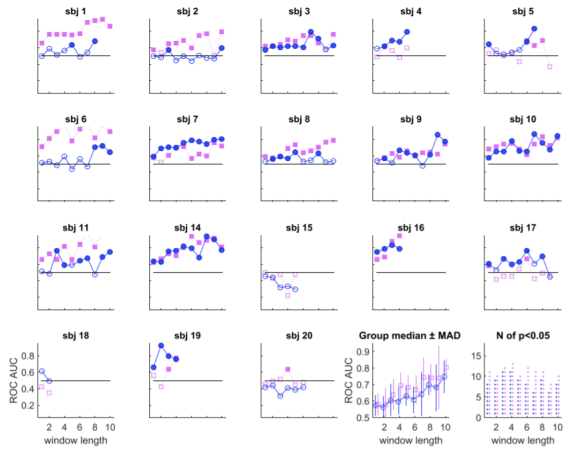


Figure 4: . Performance (ROC AUC) of the sLDA whose output was averaged over sequential trials in sliding windows. Individual ROC AUC (for 18 participants, sbj 1 to 20) are shown only if computed over at least 25 windows per class. The last two plots present the same results aggregated over the group. Blue circles are for SMB vs. CT, purple squares are for SSB vs. CT. Filed circles and squares in the individual plots indicate that ROC AUC was higher than random, according to the permutation test (p-values were not corrected for multiple tests).

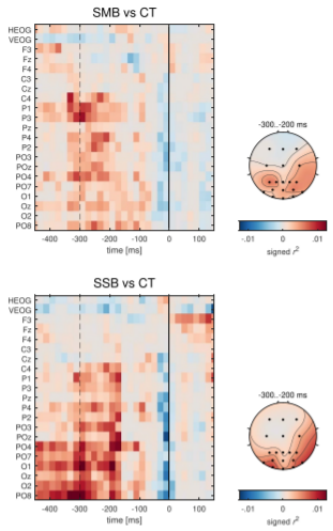


Figure 5: (Left) Spatial-temporal distribution of signed r^2 value (group medians) computed between the EEG/EOG amplitudes and class probability estimated by the sLDA, for classification of voluntary pursuit (SMB) and dwell (SSB) vs. spontaneous pursuit in the counting task (CT). (Right) Topographical maps of signed r^2 averaged over the time interval 300 to 200 ms.

brid BCI has the potential to be extended to an entirely different class of gaze behavior, namely smooth-pursuit eye movements. This class of gaze behavior can be used to select moving objects and has several advantages as an interaction technology over the use of gaze dwell/fixations (Pfeuffer et al (K VIDAL M; H, 2013), Esteves et al (A VELLOSO E; H, 2015)).

classification results for both the tracking condition in the moving selection and during gaze dwell in the static condition were remarkably similar. Thus, the study showed high flexibility and extensibility of the approach.

Because EEG under smooth pursuit is poorly studied, this study is likely the first in which the lambda wave was observed after the end of the pre-pursuit saccade.

4.2 Features used by the classier

This study shows that the classification of intentional and spontaneous pursuit data could not be strongly inflated by the contribution of electrical potentials related to eye movement, i.e., the EOG.

As a matter of fact, SMB versus CT data classification (voluntary selection versus an arithmetic task, in both conditions EEG epochs were related to fluid tracking of moving features) were remarkably similar for EEGs cleaned and uncleaned with the ICA of eye movement artifacts. Furthermore, as shown in Figure 5, the front EEG electrode features, being the most "contaminated"by the EOG components, show the weakest correlation with the classifier output. A relatively high correlation for the vertical EOG is also visible in this figure, but this could be coincidental, as the EOG features were not fed into the classifier.

4.3 Limitation and future work

Some of the limitations of this study will be described in this section, which leave room for future research and optimization. For example, during the course of this study, the BCI was not implemented in online mode, in which several factors may hinder the classification of voluntary and spontaneous gaze behaviors (Nuzhdin et al (O SHISHKIN S L; M, 2017)). EEG marker degradation after failed attempts at voluntary selection by the BCI classifier could be one such factor. In an attempt to compensate for these inefficiencies, one can try to add a second, longer dwell time threshold at which selection occurs without the use of the EEG classifier (Protzak et al (J; O., 2013)).

Online testing can as well help target another limitation of this study, which is that the conditions that modelled spontaneous pursuit could not be combined with the vo-

luntary selection conditions, yet were shown in separate blocks.
In this study, the experimental conditions were not very comfortable due to the use of a chin rest and head rest. While these provide better data, head stabilization is still undesirable. As eye tracking technology is developing rapidly, it appears likely that comparable or even better performances to the present results may soon be achievable by consumer eye trackers without head stabilization.

5 Application

Some possible applications of these results. For example, they may be useful in the case of on-the-fly EEG validation of voluntary selection of a pursued moving object. In addition, they can help optimize human-computer interaction using gaze-related EEG (Wobrock et al (D FINKE A; H, 2020)).
Furthermore, anticipation is considered an important component of social interaction (Riechelmann et al (E RAETTIG T; L, 2019)), and the anticipation-related E-wave has the potential to be used to assess the intensity of communication elements, particularly within systems used to facilitate remote video communication over the Internet.

6 Conclusion

The main focus of this work is to improve the interaction with computers, using the smooth pursuit eye movement. And effectively, the results showed that the EEG waveform can be very useful to detect gaze selection, whether in moving objects or even in video games. The use of EEG can even go further and help to estimate the degree of user involvement during gaze-based interaction.

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