Looking Around with Your Brain in a Virtual World

Danny Plass-Oude Bos*, Matthieu Duvinage†, Oytun Oktay‡, Jaime Delgado Saa§, Huseyin Guruler¶, Ayhan Istanbullu‖, Marijn van Vliet*, Bram van de Laar*, Mannes Poel*, Linsey Roijendijk**, Luca Tonin††, Ali Bahramisharif**‡‡, Boris Reuderink*

*HMI group, Faculty of EEMCS, University of Twente, The Netherlands
†TCTS Lab, Electrical Engineering University of Mons, Belgium
‡Electronics and Communications, Corlu Engineering, Namik Kemal University, Turkey
§Faculty of Engineering and Natural Sciences, VPA Lab, Sabanci University, Turkey
§IEE Group of Robotics and Intelligent Systems, Universidad del Norte, Colombia
¶Department of Electronics and Computer Education, Faculty of Technical Education, Mugla University, Turkey
‖Faculty of Computer Engineering, Balikesir University, Turkey
**Radboud University Nijmegen, Donders Institute for Brain, Cognition and Behaviour, Nijmegen, The Netherlands
††CNBI, École Polytechnique Fédérale de Lausanne, Switzerland
‡‡Radboud University Nijmegen, Institute for Computing and Information Sciences, Nijmegen, The Netherlands.

***Abstract*—Offline analysis pipelines have been developed and evaluated for the detection of covert attention from electroencephalography recordings, and the detection of overt attention in terms of eye movement based on electrooculographic measurements. Some additional analysis were done in order to prepare the pipelines for use in a real-time system. This real-time system and a game application in which these pipelines are to be used were implemented. The game is set in a virtual environment where player is a wildlife photographer on an uninhabited island. Overt attention is used to adjust the angle of the first person camera, when the player is tracking animals. When making a photograph, the animal will flee when it notices it is looked at directly, so covert attention is required to get a good shot. Future work will entail user tests with this system to evaluate usability, user experience, and characteristics of the signals related to overt and covert attention when used in such an immersive environment.**

***Index Terms*—Multimodal interaction, brain-computer interfacing, covert attention, eye tracking, electroencephalography, electrooculography, virtual environment.**

I. Introduction

So far, most brain-computer interfaces seek to replace traditional input modalities, like mouse or keyboard. However, current electroencephalography-based brain-computer interfaces (EEG-based BCIs) have considerable problems: low speed, low detection accuracies varying highly between users, low bandwidth, sensitivity to noise and movement, often requiring training, and expensive and cumbersome hardware [1]. These make it difficult to make BCIs an interesting input method for able-bodied users. Allison et al. mention a number of considerations for BCI applications for this healthy user group [1]. In this report we touch upon some of them (extending the term BCI to interface using neurophysiological signals):

- **Hybrid BCI**: using BCI in combination with other input signals, either as independent command signal or as a modifier of commands from other inputs.
- **Induced disability**: in circumstances where conventional interfaces are not usable, BCI could function as a replacement, or when they provide not enough bandwidth, BCI could function as an extra input channel.
- **Mapping between cognition and output**: making systems natural in their use by letting the system respond in a way that corresponds to what the user would expect. The interaction does not only consist of the system response however, but also of the user action [2]. Therefore, we propose to extend this definition to include: to use brain activity or mental tasks that come naturally given the situation. This ensures that the system is most intuitive in the interaction, requiring no user learning or memorization.
- **Accessing otherwise unavailable information**: some processes have no outside expression (whether it is only a mental process, or the user is purposefully inhibiting such expressions), but could be detected from brain signals.

We have developed a system that makes use of naturally-occurring neurophysiological activity in a natural way, to augment the user interaction with a virtual environment, which already uses conventional mouse and keyboard controllers. The main mode of feedback from any computer system is visual, through the computer screen. Thus, for natural interaction, it makes sense to look into tasks that are related to vision: overt and covert attention. Jacob and Karn mention that it is difficult to have the system respond to eye gaze in a natural way, as also happens in the real world [2]. The only example they give is human beings: people respond to being looked at, or what other people are looking at. In our prototype, we use this natural response by letting an animal flee when looked at directly. This induces a situational disability (animals cannot be looked at directly), which is solved by using covert attention to get a good view of the creature. But we also show another option for the natural mapping of eye input: when we move our eyes, our view changes. This natural mapping can be translated to adjusting a first person camera in a virtual environment based on the user's eye movement.

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The paper first dives into covert and overt attention, providing background information, design and evaluation for the signal processing and classification pipelines. As the pipelines are planned to be used in an online, real-time setting, issues that are relevant in such a situation are investigated. Finally, the whole system is described, including the game application, followed by conclusions and future work.

II. Covert Attention

Covert attention is the act of mentally focusing on a target without head or eye movements [3]. While overt attention is said to be an indication of place of focus, covert attention is a possible confound. By detecting both, all options for spatial attention are covered. There is also a theory that covert attention guides saccadic movement, and that it is possibly a mechanism to scan the visual field for points of interest [4].

Offline experiments have shown that when attention is directed to the left visual hemifield, alpha activity decreases in the right posterior hemisphere while increasing in the left hemisphere (and vice versa) [5]–[8]. It is also shown in [9]–[11] that not only left-right but also other directions of covert attention are strongly correlated with the posterior alpha.

Covert attention was measured using EEG, which is one of the most suitable methods for healthy users at the moment, because no surgery is required, the equipment can be used outside of a laboratory setup, and the equipment is relatively portable and affordable [1].

Besides evaluating two potential pipelines, this section also addresses another important question: does this correlation of spatial attention with posterior alpha depend on whether a participant fixates centrally, or is the same pattern observed irrespective of the location the participant's fixation point? While a central fixation point has been the norm in clinical laboratory experiments, in a practical application, this may only rarely be the case. Finally, some other research questions that are relevant for the online situation were looked into: what directions can we detect, how many trials are needed for training, and how long the trial window needs to be for classification?

A. Methods

The experiment is covert attention to the four directions of visual hemifields with three different fixation points. The task is to fixate at each fixation point in the screen which is 70 cm away from the eye of the participant and covertly attend to the direction of the pre-specified arrow. See Figure 1 for a screen shot of the situation. There are three fixation points: left, middle, and right, with six degrees of visual angle distance between them. The target focus can be one of five positions: either the fixation point itself (neutral), or one of the four diagonal directions. The focus targets were placed diagonally as earlier research indicated that this is best discriminable [11]. Distance from the diagonal targets from the center is about seven degrees. It was verified that when focusing on one of the diagonal targets, the other diagonal targets did not disappear in the blind spot.

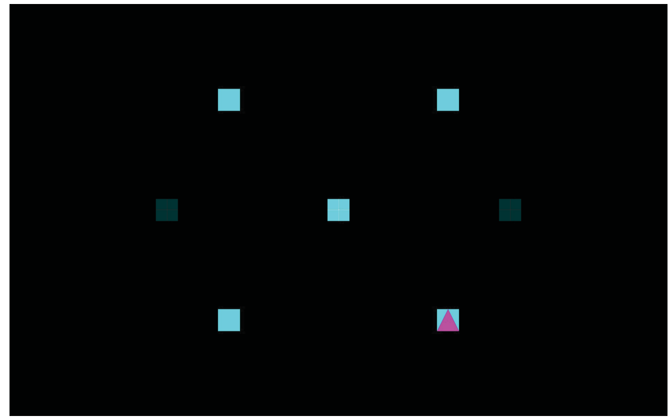

Fig. 1. Covert attention screen with fixation point in the center, potential target squares (distractors), and the arrow on the actual target. The darker squares to the left and right would normally not be visible, but indicate the alternative fixation positions.

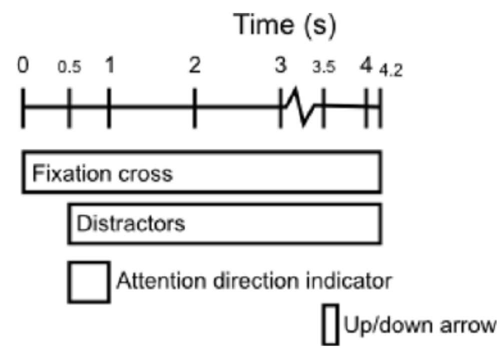

Fig. 2. During a trial first the fixation cross is shown, then the diagonal positions appear, after which the focus position for covert attention is indicated. After a little while an up or down arrow is shown in the focus position. The participant then presses the corresponding button.

Fifty trials were recorded for each of these conditions consisting of a fixation position and target position. A trial starts with half a second showing the fixation cross, then for half a second the focus position for covert attention is indicated with a yellow circle inside one of the five potential positions. The other positions remain visible as distractors. After a period of 2 seconds plus a random duration of up to half a second, an up or down arrow is shown in the focus position. The participant then has a short period of time to press the corresponding arrow button (arrow up or down). This task ensures that the focus area is relevant to the participant, which may increase the effect on the brain activity for this paradigm. The trials were split up in five blocks, each containing ten repetitions for each condition in randomized order. The breaks in between blocks lasted until the participant pressed a key to continue.

Brain activity is measured during the task using the BioSemi ActiveTwo EEG system, at 512 Hz sampling frequency, with 32 electrodes according to the montage shown in Figure 3. Electrooculogram (EOG) was also recorded to control for confounds in eye movements.

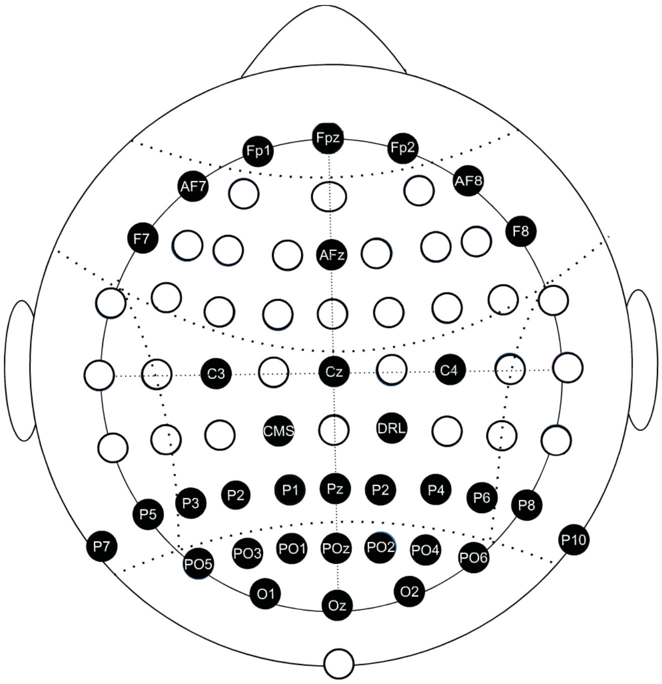

Fig. 3. Electrode positioning for EEG measurement: 32 electrodes positioned mainly on the parieto-occipital area as this is where the relevant alpha modulations for spatial covert attention are expected, and some others to look at artifacts and to offer the possibility to apply certain spatial filters.

TABLE I
DETECTION ACCURACIES OF THE COVERT ATTENTION PIPELINES PER PARTICIPANT, FOR FOUR AND TWO CLASSES.

4 classes	CA1	CA2	2 classes	CA1	CA2
S1	33%	31%	S1	62%	60%
S2	31%	31%	S2	57%	59%
S3	52%	42%	S3	78%	85%
S4	44%	35%	S4	72%	62%
Avg	40%	35%	Avg	67%	67%

B. Results

a) Which pipeline performs best?: The two pipelines that were tested both used the occipito-parietal EEG channels as input, and they also used the same time window: from 0.5 to 2.0 seconds relative to the focus indication stimulus. The difference is in the feature extraction and classification. Pipeline CA1 consists of the following steps: downsampling to 256 Hz, CAR (Common Average Reference), bandpass 8-14 Hz, whitening, covariance, logistic regression. Pipeline CA2 is: CAR, bandpower 9-11 Hz STFT (Short-Term Fourier Transform), z-score normalization, SVM (Support Vector Machines, error cost set to 2.0).

Table I shows the performance accuracies per pipeline on average but also per participant. CA1 gives the highest performance with 67% and 40% on average on the same datasets for two and four-class classification respectively. The difference in performance between CA1 and CA2 is not significant, however.

b) Does the position of the fixation point matter, with respect to the correlation of focus direction with parietal alpha, and with respect to detection accuracy?: To answer this question, scalp plots were computed for each participant for each fixation position (left, middle, right), showing the relative difference in the alpha band (8–12 Hz) of each diagonal focus direction with the fixation point, see Figures 4-6. A time window from 0.5 to 2 seconds after the cue was used. The scalp plots were averaged over four participants. The lateralization pattern is in line with what has been shown in literature [8], [9], [11]. As the eyes fixate on a different position, the excitation of the retina remains the same, and the mapping of the image to the occipital cortex is not expected to change. However, surprisingly, the patterns are a bit different for the different blocks, showing a migration of the alpha sources from one side to the other.

On average, there did not seem much of an accuracy difference between each of the fixation point conditions (28%, 30%, 32% and 30% for left, center, right, and pooled fixation points). When looking at our best participant however, we see an increase for the center fixation: 36% for left and right, 40% for pooled, but 45% for center fixation cross only.

c) Which directions can be detected?: Results based on datasets recorded from 4 different participants analyzed with pipeline CA1 indicate a performance above random. For a 4-class situation (each of the four directions) yields a 40% performance accuracy on average, and 52% on our best participant. The samples for the three different fixation points were pooled, so the classes indicate the covert attention direction relative to fixation. Random for four classes would have been 25%. For the two-class situation the bottom and top targets were merged to result in one class with samples to the left, and one class with samples to the right. For this, the average performance accuracy over 4 participants with pipeline CA1 was 67%, with 78% for our best participant, against a random performance of 50% for two classes. The other pipeline shows a similar pattern in performance.

The classification performances for the different pairs of target directions (like top right vs. top left) were also analyzed. This confirms the information from literature that diagonally opposing targets (top left vs down right, and top right vs down left) are easier to distinguish than the other pairs.

d) How many trials are needed for training?: The two-class detection performance with pipeline CA1 was evaluated for different training set sizes using 10-fold cross validation. The results show no consistent increase in performance. After a peak at 120 trials, performance drops and flattens out.

e) What is the optimal window size?: For the online situation, preferably, the window size is minimal, because that way the data can be processed faster, which in turn could mean that updates can be computed more frequently. On the other hand, the classification accuracy is expected to be higher for longer window sizes (because you simply have more information). Windows always start at 0.5 seconds after the stimulus, and then continue for the indicated window duration, except for the two-second window which starts at

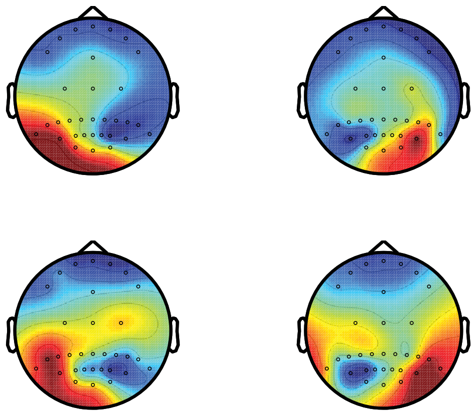

Fig. 4. Relative differences of each focus direction with respect to the fixation position, with the fixation on the left. Averaged over four participants. The positions of the scalp plot indicate the direction of the corresponding target square.The top right scalp plot shows the relative brain activity for attending to the top right target square.

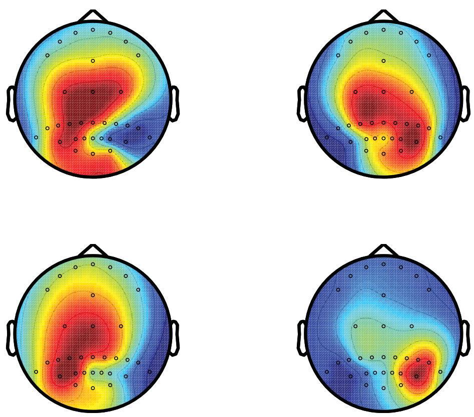

Fig. 5. Relative differences of each focus direction with respect to the fixation position, with the fixation on the center. Averaged over four participants.

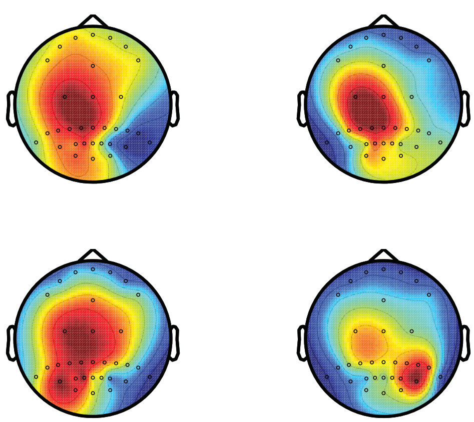

Fig. 6. Relative differences of each focus direction with respect to the fixation position, with the fixation on the right. Averaged over four participants.

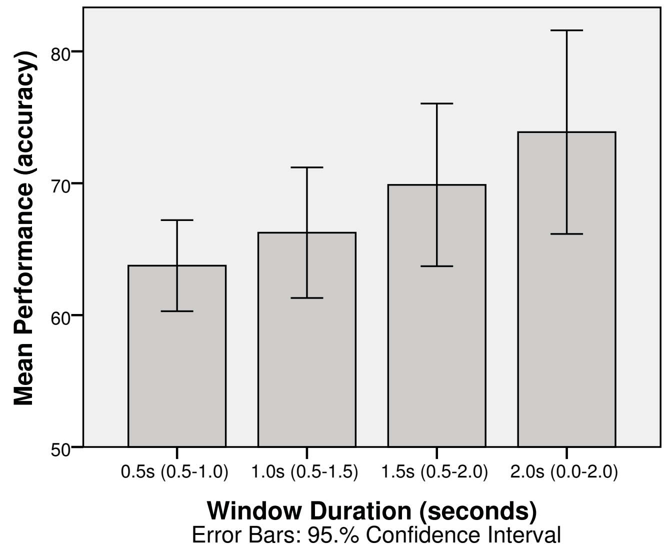

Fig. 7. Two-class covert attention performance for different window sizes, averaged over 6 participants. It shows an incremental increase for longer windows.

0.0 seconds. Figure 7 shows the average performance for the increasing window sizes: the longer the window, the higher the performance.

f) Does a blocked protocol yield a better performance?: In standard covert attention experiments there is only one fixation point, whereas in our experiment, this fixation point was randomized. To test whether this had unwanted side effects, we recorded one dataset which had the fixation points steady within each block, and one in which within a block this fixation point could jump around. The result was a 75% accuracy for both the blocked and not blocked condition of fixation points using pipeline CA1. Based on this one participant, there does not seem to be a difference between the two conditions.

C. Discussion and Conclusions

Pipeline CA1 (CAR, bandpass 8–14 Hz, whitening, covariance, logistic regression) performs a little better than pipeline CA2, on average, although this difference is not significant. It could be interesting to also investigate other variations for covert attention detection.

Different fixation points (left, middle, right) did not seem to have a significant impact on classification performance. When looking at the relative difference in parietal alpha between the focus direction and central fixation point, similar spatial patterns show which correspond to what is expected from literature.

Although the four-class performance is above random, for an online game situation performance should be at a usable level. For this reason we decided to use two-class covert attention in the game.

The number of windows in the training dataset, strangely enough, does not seem to have a large impact on the classification performance. The performance does increase from

20 to trials samples, but after that it drops again, stabilizing around the same performance is is shown at around 90 trials. As this is evaluated with 10-fold cross validation, about 80 trials would be enough if all trials are used.

The larger the trial window, the higher the performance. This is to be expected, but less fortunate for the online situation: the longer the window size, the longer it will take to get feedback on that particular window. However, we did not test beyond a size of two seconds, and the test for two seconds could not start at 0.5 seconds as the other windows did. This makes it possible that there are task-related eye movements in those 0.5 seconds that increase the performance.

III. Eye Movement

Using eye movement provides a number of features that make it an interesting input modality. Eye movements are not as intentional as mouse and keyboard input. This means it can provide information on an intentional but also on a more subconscious level. A side effect is the Midas Touch problem: not every eye gaze has intentional meaning, so the system should somehow discern what to react to, and what not. Eye movement is faster than other input modalities, and indicates the user's goal before any other action has been taken. Besides, no user training is required, as the relationship between the eye movement and the display is already established [2].

Bulling et al. distinguish between the following types of eye movements. Fixations are stationary states during which gaze is focused on a particular point. Saccades are very quick eye movements between two fixations points. The duration of a saccade depends on the angular distance the eyes travel during this movement. For a distance of 20 degrees, the duration is between 10 ms and 100 ms. Eye blinks cause a huge variation in the potential in the vertical electrodes around the eyes, and lasts between 100 ms and 400 ms [12]. For our application, saccades are the most relevant type of movement to detect.

There are a number of methods to determine eye movement or eye gaze, for example with special contact lenses, infrared light reflections measured with video cameras, or with electrodes around the eyes: electrooculography (EOG). These electrodes measure the resting potential that is generated by the positive cornea (front of the eye) and negative retina (back of the eye). When the eye rotates, the dipole rotates as well. By positioning the electrodes around the eyes as shown in Figure 8, one bipolar signal will be an indication of vertical eye rotation and the other for the horizontal axis.

For this system, we decided to use EOG for eye tracking. EOG signal analysis requires very little processing power, and can easily be done in real-time. Although this method is not that suitable for tracking slow eye movements (that occur when following a moving object), for fast saccades it is very robust. Slow eye movements cause slow voltage changes, which can be difficult to distinguish from signal drift. The fast voltage changes that result from saccades are easy to detect. EOG can be used in bad lighting conditions (although it works better with good lighting), and in combination with glasses. The participant does not need to be restricted in the orientation to the screen (though for absolute eye gaze, then the position of the head would need to be tracked separately), nor do they have to wear an uncomfortable video camera system firmly mounted on the head [2]. Also, it is easy to incorporate in a wearable and unobtrusive setup [12].

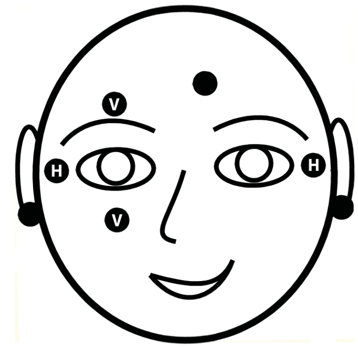

Fig. 8. Electrode positioning for EOG measurement: bipolar measurements of top minus bottom vertical electrodes around the right eye and right minus left horizontal electrodes near the canthi.

A. Pipeline

As described in [13], saccade detection can be used to construct an eye-tracker. The pipeline for eye movement is similar for both the vertical and horizontal EOG signals, is based on [13]. Itakura and Sakamoto have shown that using the integral as feature yields higher accuracies than using the maximum amplitude of the EOG derivative [14]. Our pipeline is a combination of these two algorithms:

1) High pass filter (0.05 Hz) for drift correction which is very strong in the EOG signal.
2) Low pass filter (20 Hz) to reduce high frequency noise without affecting the eye movements.
3) Derivative in order to detect the rapid variations.
4) Thresholding to detect saccades and remove noise.
5) Integration yields the regression features.
6) Linear regression between the angle and the integration result.
7) Conversion to x,y position.

The main steps are shown in Figures 9–12 and Figure 13.

B. Methods

The offline analysis protocol of the eye movement is twofold. In order to get enough data for training the linear regression, 25 trials were used. Each trial was composed of one target in the center of the screen and one of five possibilities: extreme top, bottom, left, right and center targets. For horizontal and vertical eye movement there are separate pipelines, and the regression is also trained separately – for the pipeline details refer to the Pipeline section above.

For evaluation 100 trials were assessed. Because the system will be used as a kind of eye mouse, the performance evaluation was based on the accuracy of the system at N centimeters maximum deviation from the target. Although it is more common to evaluate the gaze position errors in terms

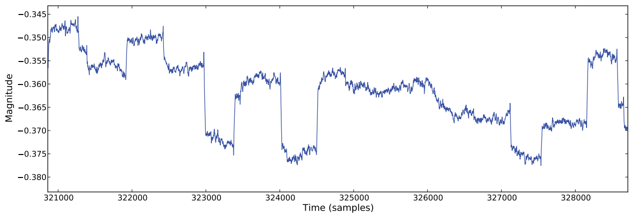

Fig. 9. EOG data is noisy and drifts over time.

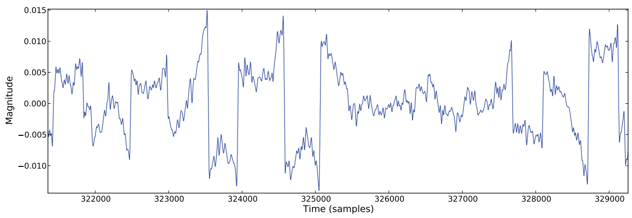

Fig. 10. Filtered EOG data without the drift and high frequency noise.

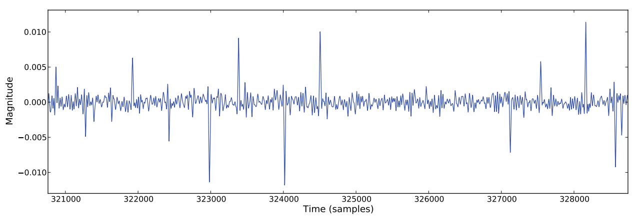

Fig. 11. The high values of the derivatives indicate saccades.

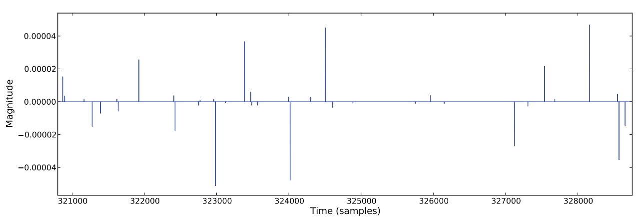

Fig. 12. Integration of the above-threshold saccade derivative provides the input for the linear regression

TABLE II
PERFORMANCE OF THE EYE MOVEMENT PIPELINE PER PARTICIPANT. HORIZONTAL AND VERTICAL ACCURACIES (HACC AND VACC) ARE FOR A PRECISION WITHIN 4CM. THE ERROR DISTANCE (HERR AND VERR) MEANS (AVG) AND STANDARD DEVIATIONS (STD) ARE MEASURED FROM ACTUAL TARGET POSITION TO REGRESSION RESULT IN HORIZONTAL AND VERTICAL DIRECTIONS.

	Hacc	Herr avg	Herr std	Vacc	Verr avg	Verr std
S1	100.0%	1.0	0.8	94.9%	2.0	6.1
S2	90.9%	2.0	1.6	57.6%	3.9	3.7
S3	70.7%	3.2	3.2	34.3%	7.9	9.4
S4	77.8%	2.4	1.8	51.5%	5.3	4.5

of angular degrees of eye rotation, looking at the resulting error in centimeters on the screen is more useful for evaluating the performance in an on-screen application. The screen was divided in a 5 by 5 grid, resulting in 25 potential target positions, which were selected randomly. To use the screen estate to the fullest, this means that the distance between the different target positions is larger horizontally than vertically, as the screen is more wide than high. The jump between the center and the target (Figure 15) of each trial is considered correct when the Euclidean distance between the EOG-based estimation point on the screen and the actual point is lower than N centimeters.

These trials were recorded using the BioSemi ActiveTwo hardware, with flat active electrodes positioned according to Figure 8. The distance between user and screen was 70 cm.

C. Results

The results are quite good for horizontal movement (Table II). Figure 17 shows the precision at N cm for four participants. The curve is sharply increasing which shows the precision of this technique. However, for vertical movement, the results are less good (see Table II, Figures 16, 18, and 14, the plots are again based on the data of the same four participants).

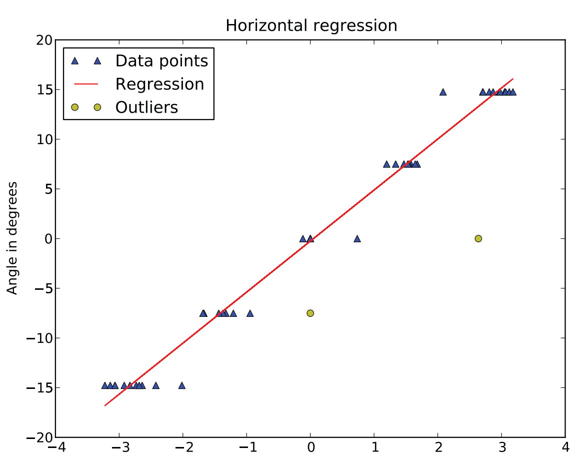

Fig. 13. The regression shows a high correlation between the parameter of each saccade and the jump in angle.

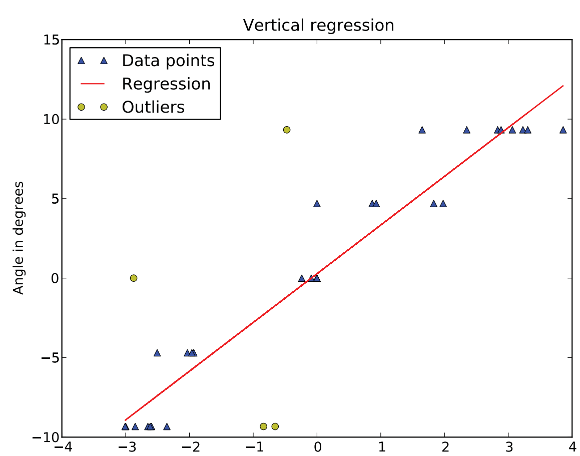

Fig. 14. Data shows less correlation between EOG features and known angle change for vertical eye movement.

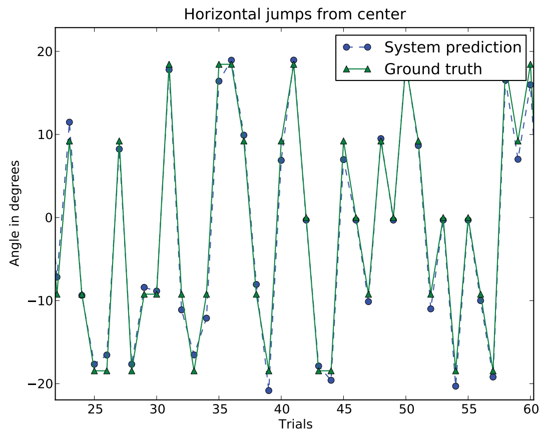

Fig. 15. The jumps between the center and the target provided by the system and the actual ones are quite similar for the horizontal axis.

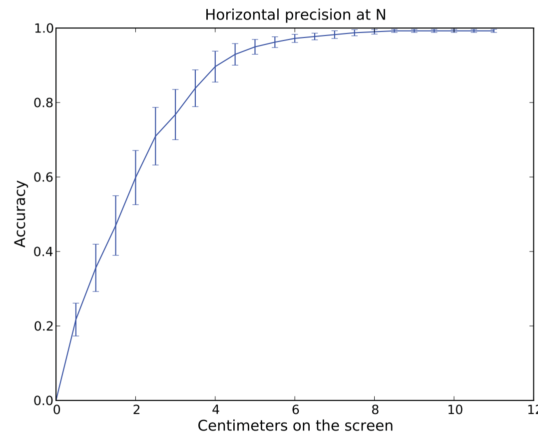

Fig. 17. Horizontal precision at N curve is sharp at the beginning which is good.

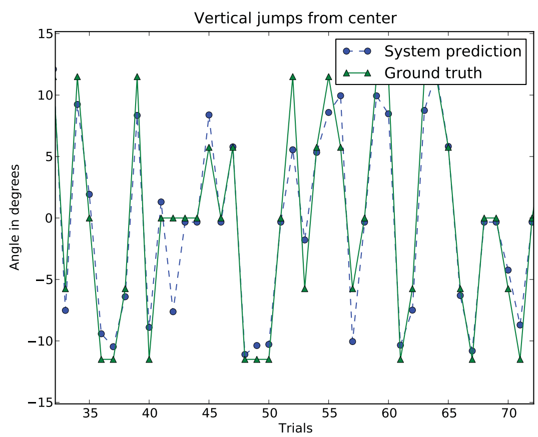

Fig. 16. The predictions of the system are quite less good than for the horizontal jumps.

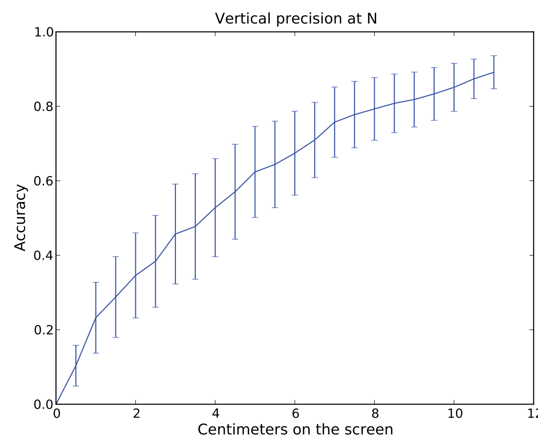

Fig. 18. Vertical precision at N curve is less sharp at the beginning than the corresponding horizontal curve.

D. Discussion and Conclusions

Horizontal eye movement appears to be easily detectable: at a precision within 4 centimeters, the accuracy is about perfect for the best half of the participants. Within 4 centimeters it is about 90%. For vertical eye movement, the performance is less good: around 50% precision within 4 centimeters.

Visual inspection of the vertical EOG data shows that sometimes there is no sign of the vertical movement when there should be one. Maybe the sensors were not positioned optimally. As the computer screen is wide screen, the vertical distance is smaller than the horizontal distance. The eyes will turn less vertically, resulting in a smaller potential change. Moreover, eye blink correction was not applied in the pipeline. This could also improve performance [12].

IV. Application and System

In the Wild Photoshoot game that was developed, you are a wildlife photographer. You take pictures of rare wild animals, but they are not that easy to catch on camera. First you have to follow animal tracks to find the creature. Then you go into photoshoot mode in which you try to get a good picture. When you look directly at the animal, it will flee and you will have to track it again. Thus you have to covertly look at the animal to focus the camera to get a good shot.

This game uses multiple input modalities: mouse, keyboard, EOG-based overt attention, and EEG-based covert attention. It also creates situational disability for eye movement by letting the animal flee when looked at directly, introducing a natural need for covert attention. The mental tasks for both overt and covert attention come naturally given the situation, and the mapping to system response is based on real-world interaction. Through covert attention, we access information about the user that would not be available through other means.

Figure 19 shows how the different system components interact. EEG is measured to detect covert attention, and EOG for eye movement. The raw data is sent over USB to the computer, where Biosemi ActiView sends the data over TCP/IP to the signal analysis software. SnakeStream reads

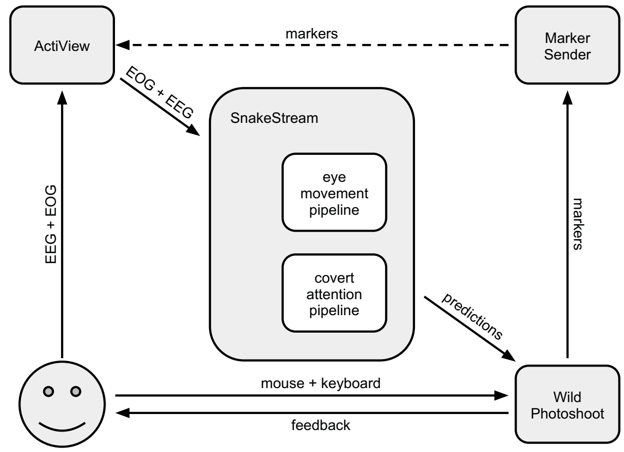

Fig. 19. The different components and communication between them within the Wild PhotoShoot system.

the data, passes it in the appropriate formats to the signal analysis pipelines, and sends the prediction results on to the game environment of Wild Photoshoot. Snakestream works together well with the Golem and Psychic Python libraries, and supports the use of different markers and different sliding windows for each pipeline. Within the game, keyboard input is used to move around, eye movement to adjust the camera angle, and covert attention to take a picture of the animal. The game can send markers to the EEG stream to give commands to the signal analysis software, and to annotate the data for later offline analysis. Because of limitations of the game engine software, it has to do this through a the marker server. This is a small application that receives marker values over TCP/IP and forwards them to the parallel port so it is added to the EEG stream. It also implements a simple queuing mechanism to ensure that markers do not get overwritten.

V. Discussion and Conclusions

We designed a prototype that uses naturally occurring neurophysiological activity for natural user tasks, applying them in a way that supports intuitive interaction, with natural system responses. Pipelines for overt and covert attention have been developed and evaluated. A game that uses them in an intuitive manner has been designed and implemented, as well as a platform that provides the communication glue between each of these components.

Covert attention into four directions is detectable, but not well enough to be used as such in a game. The current game therefore only uses left and right. Detection accuracy did not decrease significantly for different fixation points. Around 80 trials will be enough for a training set for two classes. Larger trial windows result in higher performances, but this has not been tested beyond 1.5 seconds.

Horizontal eye movement is well detectible with EOG. Vertical eye movement seems a little bit more problematic: sometimes it does not show even though it is expected. This could be an inherent problem as the vertical distance between targets is smaller than the horizontal distance on a normal computer screen. Applying eye blink correction could improve performance. Optimal window length and training protocol still need to be determined.

Future work consists of an online evaluation of the system, to investigate the influence of the immersive game environment on the signals measured and the classification performance, but also to look into the resulting usability and user experience. It is also possible to improve the online system, for example by correcting the eye movement detection for eye blinks. A template-based algorithm for the detection of eye blinks has already been designed.

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