# Attention-Aware Brain Computer Interface to avoid Distractions in Augmented Reality

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## Abstract
Recently, the idea of using BCIs in Augmented Reality settings to operate systems has emerged. One problem of such head-mounted displays is the distraction caused by an unavoidable display of control elements even when focused on internal thoughts. In this project, we reduced this distraction by including information about the current attentional state. An multimodal smart-home environment was altered to adapt to the user's state of attention. The system only responded if the attentional orientation was classified as "external". The classification was based on multimodal EEG and eye tracking data. 7 users tested the attention-aware system in comparison to the unaware system. We show that the adaptation of the interface improved the usability of the system. We conclude that more systems would benefit from attention-awareness.

## Author Keywords
Attention; BCI; EEG; Eye-Tracking; Augmented Reality

## CCS Concepts
•**Human-centered computing** → **Mixed / augmented reality; Interactive systems and tools;** *User interface management systems;* Ubiquitous and mobile computing systems and tools;

**Figure 1:** Window blinds control via AR using the SSVEP-BCI paradigm in a room where the menu allows for four operations: blinds up, blinds down, blinds close (fins), blinds open (fins) – the operations are automatically executed via the building's intelligent control system.

## Introduction

Both, Brain-Computer Interfaces (BCI) and Augmented Reality (AR) devices, have been of growing interest to the industrial and scientific community. While AR is a way to merge real and virtual content in many different scenarios and thereby offers interesting applications, BCIs allow for a new way of communication between humans and machines. The combination of the two technologies offers the possibility of designing an implicit, voice-free and hands-free, adaptive user interface.

In recent years, BCIs that control a person's environment have found several applications - controlling robots, spellers, smart-home environments or any other remotely controllable system. The advantage of combining such a system with AR is an intuitive display and control of control elements, which makes a remote control unnecessary. However, AR devices that use a Head-Mounted Display (HMD) face one major problem: the continuous visibility of the screen makes distractions by the virtual content hard to avoid. When the content does not support a task the user is currently pursuing, it might interfere with the user's goals and inhibit or prolong task solving. A task in this context can be diverse, from following or participating in a conversation, over logical or mathematical reasoning, to memory recall and planning. Depending on the task, setting, and the controlled system itself, the possibilities of distractions vary. In general, the sudden display or change of AR content in times of internal attention can be very distracting. *Internal attention* is defined as focus on thoughts, memories, and problems that don't require a sensory input. It relies on internally produced information. *External attention*, on the other hand, describes a focus on information produced in one's surroundings (including AR).

In this study, users control a previously published smart-home system using AR-HMD and a BCI [13]. The user can turn on lights or control blinds by shifting their attention to certain fields, displayed in AR. These control elements appear in the field of view, as soon as a visual real-world marker is detected and flicker with individual frequencies, producing a Steady-State Visually Evoked Potential (SSVEP)(See Figure 1 from Putze et al. [13]). Electroencephalography (EEG) and eye tracking (ET) data is then used to classify the choices and the classification triggers the respective operation. The system will always display the control elements at the recognition of a marker. Thus, if a user is wearing the device in an everyday situation, an unexpected appearance of virtual content might disrupt other ongoing internal, cognitive processes. Our approach in this paper is to supply the AR application with information about the attentional state of the user and limit the situations in which virtual content may be displayed to times of external attention. The real-time classification of the attentional state will also be based on EEG and ET data and was introduced in Vortmann et al. [18]. If this approach proves successful, it could be transferred to a large number of AR applications in which distraction through AR elements during times of internally directed attention should be avoided.

Overall, we hypothesize that a restricted system behavior based on the classified attentional state improves the usability of the Smart-Home system in AR by reducing the distractions caused during times of internal attention. Explicitly, our hypotheses are as follows: (1) During internal attention, changes in the virtual visual field cause distraction from the internal task. (2) A higher level of distraction decreases the usability rating of a system. (3) An attention-aware system will be rated better in terms of usability. Our contributions in this paper are (1) the combination of a real-time attention classifier with an SSVEP-based self-paced Smart-Home system (SHS) as a realistic application for such a classifier, (2) a BCI that is used both implicitly and explicitly in the same system, (3) an attention-aware end-to-end system,

**Figure 2:** The setup of the EEG cap, the eye tracker, and the HoloLens on the participant

and (4) the evaluation of the system for usability and performance.

*Related Work*

BCI paradigms in AR without attention-awareness have been investigated frequently. It was shown by Takano et al. [16] that the classification of targets in AR was not worse than on a computer screen. Exemplary control systems in AR were tested in Wang et al. [19] (control the flight of a drone) or Si-Mohammed et al. [15] (movement of a robotic platform). Kosmyna et al. [8] assessed the feasibility of BCI control in a realistic smart home environment with healthy and disabled participants. Both Saboor at al. [14] and Putze et al. [13] implemented SSVEP-based Smart-home control systems. The latter will be used in this paper.
Several studies have shown that it is possible to differentiate internal from external attention based on EEG or ET. Benedeck et al. were able to differentiate between the two by using the frequency power spectra [1] or in eye-tracking data [2]. The combination of EEG and eye-tracking features has been proven to work well [11, 4, 6, 7]. In Putze et al. [12], it was shown that EEG data could be classified to discriminate between internal and external attention processes on a single-trial basis. Vortmann et al. [17] showed that internal/external discrimination with EEG-data only was feasible in AR. A real-time attention classifier was first introduced by Vortmann et al. [18]. It will be used in this work.
The problem of distraction in such an AR setting was addressed in recent studies. To avoid distraction by visual clutter and masking, McNamara et al. [9] used gaze position to place labels in a mobile AR setting. Evain et al. [5] assessed the usability of an SSVEP-BCI during times of distraction and concluded that even with a higher mental workload, operating the BCI was possible.

## The System

The Attention-Aware Smart-Home System (SHS) is a combination of two systems that were tested and evaluated separately before. One is an SHS realized in an AR setting that utilizes SSVEP signals and ET data for selection. The other is a real-time attention classification system that also uses EEG and ET data to model internal and external attention. Both systems and preceding studies will be summarized in this section.

The **SSVEP-Based SHS in AR** that was used for improvement and comparison in this paper, was described in Putze et al. [13]. They used an HMD-AR device to present four context-dependent control elements that flicker in different frequencies (4 Hz, 6 Hz, 10 Hz, and 15 Hz). The flicker frequencies are different for each control element and induce an SSVEP in the brain corresponding to the attended target. The frequency-dependent response in the brain is measured by the EEG system, recorded at three occipital electrodes (in this paper: PO7, Oz, PO8). The EEG data was processed with Canonical Correlation Analysis (CCA) to calculate a correlation coefficient for each flickering frequency. The frequency with the highest CCA coefficient was returned along with the coefficient. Additionally, ET data was recorded and evaluated for proximity to the expected location of the stimuli. For classification, they employed a nearest neighbor approach (lowest euclidean distance to targets) for each gaze point and target. The target with the most gaze points assigned to it was returned as classification result, along with the sample size of gaze points and the confidence (relative frequency of selected target). The combination of both modalities proved to be most accurate in terms of classification rates. As a result, they achieved an average classification accuracy of 89.3% (chance level of the majority class: 33.3%). The System was rated by the participants on a System Usability Score

**EEG Details:**

- *Electrode Positions:* (10/20-System) CZ, FP2, F3, FZ, F4, FT7, C3, FP1, C4, FT8, P3, PZ, P4, PO7, PO8, OZ
- *Sampling Rate:* 500hz
- *Impedance:* $< 20k\Omega$

**Exemplary tasks:**

*Internal Tasks:*

1. Think of as many words starting with "m" as possible.
2. Think back in detail what clothes you were wearing two days ago
3. Solve: 12+6-14+23

*External Tasks:*

1. Concentrate on the chair in the corner.
2. Try to memorize all the details of the marker on the wall.
3. Look at the book on the table and count the occurrences of the letter "m"

(SUS) scale and reached an average of almost 75, which is considered good.
The **Real-Time Attention Classifier** described in Vortmann at al. [18] was used in this paper to add the attention-awareness to the control system. During their user study, the participants performed 6 different tasks of which 3 were considered as triggering internal and 3 were considered as triggering external attention. The tasks were displayed on a computer screen. The classifier takes EEG and ET data to generate features (i.e. mean frequency-band power, number of saccades). As the classification model, a linear-discriminant analysis with least-squares solver and shrinkage is used and trained on the training data in a 10-fold cross-validation. Vortmann et al. [18] reported that the attention states for 10 users were classified with an average accuracy of 72.73%. Furthermore, this system was able to classify the attention of one participant in the real-time-mode with an accuracy of 60.87%.

The integration of the two systems into one attention-aware BCI was mainly realized by adjusting the communication between the components via the LSL. The Real-Time Classification system was used in the online mode, where chunks of 1.5 seconds were classified on shifting time windows (shift of 10%). The classifier had to be trained on separate trails first, which will be explained in Section “Experiment Session”. The $\alpha$ (alpha, 8-14hz), $\beta$ (beta, 14-30hz), $\theta$ (theta, 4-8hz) and $\gamma$ (gamma, 30-45hz) -bands were used for feature extraction. Due to the smaller amount of training data, the cross-validation was reduced to a 5-fold cross-validation and only 16 electrodes were recorded. The rest of the setting and processing pipeline was kept in accordance with the paper by Vortmann et al. [18].
For the SHS, we altered the application so that it would listen to the classification of internal and external attention and only trigger the appearance of the virtual control fields if the real-world marker was visible, and the last classification of the attentional state was "external".

The hardware of the system consists of an analysis computer running windows, a Microsoft HoloLens with a compatible binocular eye tracker from pupil labs, a wireless g.tec Nautilus headset with 16 active electrodes as EEG measuring device, and a smart home environment with control over lights and blinds. For details on the EEG measurement, see Sidebar "EEG Details".
The application for the HoloLens was implemented in Unity 3D 2018.2.14, using the Vuforia and HoloToolkit plugins. All additional scripts were written in Python 3.7. The components communicate via the Lab Streaming Layer middleware (LSL)[1] by listening to streams or feeding them with information. The eye tracker calibration happened at the start of the application directly on the AR-HMD using the HMD-eyes component provided by Pupil Labs[2].

## The User Study

A user study was performed to test the performance and usability of the system. The sessions took place in an office supporting the integration of the system to control lights and blinds. The room was not shielded to ensure that results would be reproducible in an uncontrolled setting. During the testing, only the experimenter and the participant were present in the room.

*Participants*

Participants were recruited from a pool of students. Seven healthy participants (mean age 23.4 $\pm$ 2.3; four females) participated in the experiment. All participants had normal or corrected to normal vision. All participants but one were right-handed, and all but two participants had previously

[1] https://github.com/sccn/labstreaminglayer
[2] https://github.com/pupil-labs/hmd-eyes

| No. | SUS-O | SUS-N |
|---|---|---|
| 1 | 65 | 80 |
| 2 | 75 | 75 |
| 3 | 70 | 75 |
| 4 | 75 | 80 |
| 5 | 70 | 77,5 |
| 6 | 65 | 70 |
| 7 | 72.5 | 77.5 |
| m. | 70.36 | 76.43 |
| std | 4.19 | 3.49 |

| No. | MWQ | DIS-O | DIS-N |
|---|---|---|---|
| 1 | 22 | 17 | 11 |
| 2 | 13 | 13 | 10 |
| 3 | 15 | 15 | 10 |
| 4 | 15 | 15 | 12 |
| 5 | 10 | 12 | 10 |
| 6 | 18 | 16 | 13 |
| 7 | 17 | 14 | 12 |
| m. | 15.71 | 14.57 | 11.14 |
| std | 3.82 | 1.72 | 1.21 |

**Table 1:** The questionnaire scores for each participant, mean and standard derivation. MWQ = Mind Wandering Questionnaire, SUS-O = System Usability Score of the attention-unaware system, SUS-N = System Usability Score of the attention-aware system, DIS-O = Distraction Score of the attention-unaware system, DIS-N = Distraction score of the attention-aware system

used an Augmented or Virtual Reality Device. One of the participants regularly used a smart home environment. We did not restrict the participation in the experiment except for participants with photosensitive epilepsy (due to high risk while experimenting with SSVEP). Participants were asked to wear contact lenses instead of glasses because of the compatibility with the eye tracker. The local ethics committee approved the study and written informed consent was obtained from the participants before the conductance of the measurements. All the data was fully anonymized.

*Experiment Session*

On average, the participants spent 70 minutes in our lab. After a verbal introduction and written information about the experiment and the recorded data the participants gave written consent and filled out all questionnaires (see Section “Questionnaires and Performance Assessment”). The same experimenter introduced all participants and guided them through the experiment. After the setup, the EEG system was calibrated and the eye tracker adjusted. A picture of the complete setup can be seen in Figure 2.

When all questions of the participants were answered, the application on the HoloLens started with the calibration of the eye tracker. Immediately afterward, the training of the attention classifier started. The experimenter paced the trials individually. For each condition ("internal" and "external"), 10 tasks were posed in random order. The internal task included memory, imagination and mental arithmetic, similar to the tasks used in Vortmann et al. [18]. The external tasks instead made use of the surroundings in the office. This aimed at creating an application related context. The tasks were directed at the visual real-world markers or office objects (See Sidebar "Exemplary Tasks").

After the training of the classifier was completed, each system (attention-aware and -unaware) was tested for approx. 5 minutes. The order in which the systems were tested was randomized per participant. During the 5 minutes, the participants were asked to perform different internal tasks (same concept as in the training) or control the SHS by focusing their attention on a visual marker and choosing the appropriate field of the SSVEP control elements. 10 internal trials and 5 external trails were completed by every participant. After each session, questionnaires rating the last used system were filled out by the participants. The second set of these questionnaires ended the experiment session and participants were asked for comments.

*Questionnaires and Performance Assessment*

Besides a demographic questionnaire in the beginning, all participants filled out the Mind Wandering Questionnaire [10] asking to rate their frequency of certain mind wandering related scenarios (Likert-scale). The higher the score, the more likely is the participant to start mind wandering. After each test session, two questionnaires were filled out by the participants: one asking about the distraction during the internal tasks (in analogy to the questions from the mind wandering questionnaire) and the other one rating the usability of the system in general on the System Usability Score (SUS) by [3].

To assess the performance of the system, the average classification accuracy of the 10-fold cross-validation was noted down and compared. The number of errors made by the system during the tasks was noted down by the experimenter. An error is a wrong appearance of control elements during the internal tasks and missing control elements during external tasks.

## Results

The data of each participant was analyzed for significant differences and correlation. We used an alpha level of .05 for all statistical tests.

| No. | accuracy | error |
|---|---|---|
| 1 | 72.8 | 33.34% |
| 2 | 70.2 | 53.34% |
| 3 | 66.6 | 60.00% |
| 4 | 59.7 | 66.67% |
| 5 | 60.3 | 53.33% |
| 6 | 60.3 | 60.00% |
| 7 | 70.0 | 40.00% |
| m. | 65.70 | 52.38% |
| std | 5.54 | 11.82% |

**Table 2:** Performance results of the attention-aware system for each participant. The accuracy is the average training accuracy of the fold during the 5-fold cross-validation. The reported error is the percentage of internal trails in which at one point the control fields mistakenly appeared.

Table 1 reports the results of the questionnaires for each participant. Two Wilcoxon Signed-Ranks tests were conducted to compare the attention-aware with the attention-unaware system. There was a significant difference in the SUS score of the attention-unaware ($M = 70.36, SD = 4.19$) and the attention-aware system ($M = 76.43, SD = 3.49$), with $n = 6$ (one participant rated the systems equally and was not considered) and $T_{crit} = 0 \leq T- = 0$. There was also a significant difference in the distraction rating for the old attention-unaware ($M = 14.57, SD = 1.72$) and the new attention-aware system ($M = 11.14, SD = 1.21$), with $n = 7$ and $T_{crit} = 2 \leq T+ = 0$.
The score of the mind wandering questionnaire correlated with the average distraction score for the old and new system with $r = 0.86$.

The performance of the new system was evaluated by training accuracy and mistakes during realistic usage. For a detailed report on the performance of the attention-unaware system see Putze et al. [13]. The results for each participant (see Table 2) were analyzed for correlation. During the external trails, the response of the system was sometimes delayed but displayed the control elements for all participants in all trials and was thus considered as having a 0%-mistake rate for external trials. The training accuracy and the mistakes made during usage were correlated negatively, $r = -0.79$.

## Discussion

In this paper, we combined an SSVEP-based SHS with a real-time attention classifier to reduce distraction during times of internal attention. We were able to implement an end-to-end system for a user study. It proved a significant decrease of distraction for internal tasks while wearing the attention-aware SHS compared to the attention-unaware system. We also found a significant difference in usability ratings between the two systems, with better usability of the attention-aware system.
Participants that achieved higher scores on the MWQ also rated the distraction of the two systems higher. Lower training accuracies of the attention classifier resulted in more mistakenly presented control elements during internal tasks. During external tasks, longer reaction times of the system were reported by the participants but not quantitatively assessed.
The results in this paper were comparable to the results in the papers by Putze et al. [13] and by Vortmann et al. [18]. All additional questionnaire results were as expected.
Despite the sometimes high rate of mistakes in the internal condition of the attention-aware system it already improved the usability rating and decreased the perceived distraction by the users. This allows for an optimistic outlook that an improved real-time attention classification system would highly improve the usability of BCI-AR-control systems.
More work has to be put into the comfort of the combination of HMD-AR devices, eye tracker and EEG systems. Also, the reduction or elimination of the training phase is desirable. The goal should be a self-paced, attention-aware, training-free system with a comfortable setup and short calibration times.
The described approach can be applied to several AR use cases, such as tutoring or training systems, where the user switches between taking in information and mentally processing it. Our future work will focus on improving the classification accuracy while reducing the necessary training or possibly even eliminating it. We aim at designing a person-independent attention classifier that uses very short time windows for classification. We will try to optimize task transfer and assess other features for the chosen modalities.
Overall, we conclude that more systems should consider adapting the system behavior based on the attentional state on the user.

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