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Augmented Reality Interface for Smart Home Control using SSVEP-BCI and Eye Gaze

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Abstract— **In this paper, we investigate the integration of eye-tracking and a Brain-Computer Interface into an Augmented Reality system to control a smart home environment. Through a head-mounted display, we present context-dependent control elements which the user selects by directing attention towards them. We show that the combination of both modalities leads to the most robust detection of selections and an interface which is accepted by its users.**

I. INTRODUCTION

Augmented Reality (AR) interfaces make their way into many applications in various domains. While AR offers new opportunities to design user interfaces, they also come with additional challenges. One of these challenges is the limited communication channel which is provided to the user for sending input to the application. In contrast to Virtual Reality applications, users are not typically equipped with a controller as they need their hands free to interact with the physical world. For the same reason, gestures are often not suitable as input modality. Speech input is a good choice for text entry but does not convey spatial information well and is not appropriate in all use cases (e.g. when in a noisy environment or when required to stay quiet). Thus, none of the mentioned modalities on its own is appropriate in all situations and thus more options should be considered as alternatives or for combination. Great potential for this lies in the processing of biosignals, for example to capture brain activity and gaze.

One of the most successful paradigms for implementing Brain Computer Interfaces (BCIs) is the SSVEP-BCI, which induces Steady State Visually Evoked Potentials (SSVEPs) in the brain through the presentation of a flickering visual stimulus at a specific frequency. The frequency-specific SSVEP response, which occurs when such a stimulus is attended, can be captured by measuring and evaluating an electroencephalography (EEG) signal. These responses can be used for a user interface by tying different options to different frequencies and asking the user to overtly or covertly direct their attention towards to the desired option. SSVEP-BCI have been used successfully to control a music player [1] and other user interfaces, for human-robot interaction [2], for text entry [3], game control [4], and many other applications.

Another modality to explore as user input, which also responds to the user attending a certain stimulus, is eye gaze. Gaze can be captured through an eye tracker, which in the case of an AR head-mounted display (AR-HMD) has to be mobile and lightweight. As BCI and eye tracker measure very different correlates of attention, a combination of both modalities has the potential of increased classification performance compared to the individual modalities.

In this paper, we transfer the SSVEP-BCI approach, supported by a mobile eye tracker, to an AR scenario. For this purpose, we explore the control of a smart home environment through this user interface. When the user navigates through the environment, the AR blends context-sensitive virtual control elements into the field of view which allow the user to control the environment by simply attending the appropriate element. This leaves the user's hands and voice free for other tasks.

Our contributions in this paper are 1) the systematic integration of a training-free, self-paced SSVEP-BCI in an AR-based smart home control, 2) the combination of BCI with eye tracking for increased robustness in a mobile setting, and 3) the evaluation of an end-to-end system for classification performance and usability.

II. RELATED WORK

In recent years, different BCI paradigms have been investigated as interfaces for AR. Si-Mohammed et al. [5] give an overview over different approaches and their analysis showed that mostly P300- and SSVEP-based BCIs have been employed for this purpose. The dominant application is robot and prothesis control, as well as neurofeedback. Most of the identified systems used video-see-through AR, which is based on capturing the real world through a camera which is then presented to the user through a virtual reality HMD. Only a few systems employed optical-see-through, as would be necessary for a mobile system which depends on natural vision and field-of-view.

As an example for a BCI-based environment control through AR, Wang et al. [6] used an SSVEP-based AR interface to control the flight of a drone. Escobedo et al. [7] overlayed a grid for a P300-based BCI for telepresence control of a robot. Si-Mohammed et al. [8] used an AR interface to control the movement of a robotic platform. In their study, they systematically explored different ways of integrating SSVEP stimuli in the environment in relation to the robot and also investigated the effect of motion on the BCI performance, given that an AR scene is rarely static.

There exist some earlier approaches to employ an SSVEP-BCI in an AR setting for mobile smart room control. An early example is the work by Takano et al.[9], who demonstrated the feasibility of SSVEP classification with targets presented through an AR interface. They showed that classification performance was no worse than for targets presented on

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a normal computer screen. Another feasibility study by Faller et al. [10] investigated how SSVEP markers can be situated in an AR scene and used for controlling a table-based navigation task. Their result showed that participants could navigate variable mazes successfully. Saboor et al. [11] implemented a mobile SSVEP-BCI for smart home control in which controllable targets were identified by automatically detected QR codes attached to them. They showed that participants were able to identify the majority of physically situated targets (e.g. controlling lights, an elevator) distributed throughout the building, i.e. requiring mobility. Angrisani et al. [12] performed a similar analysis for a hands-free robot operation in an industrial setting. Coogan et al. [13] combined Unity and the BCI2000 software to provide a template for control of Internet-of-Things devices (such as smart light, television, or thermostat) via BCI interfaces in virtual reality. The authors claimed that this approach allowed the rapid integration of additional tasks (due to the use of established software components) and a higher motivation for users compared to traditional BCI interfaces. Evain et al. [14] showed that an SSVEP-BCI could be used even when the user was distracted by a different task that induces additional mental workload. This is an important prerequisite for using BCI for mobile smart home control, as such a scenario will often comprise operating smart room components as part of a more complex task.

A number of researcher have looked into the combination of SSVEP BCI with gaze tracking for improved classification performance. While in many cases, a gaze-based approach may simply be superior to an SSVEP-BCI, this may not necessarily be the case in situations where we use a mobile eye tracker, such as when using a HMD for virtual or augmented reality, due to challenges in maintaining a valid calibration. Kishore at al. [15] showed that both eye tracking and BCI can be employed for reliable target detection to control a humanoid robot. Ma et al. [16] showed that the combination of both modalities for text entry in VR resulted in a significantly higher information transfer rate compared to the individual modalities.

III. SYSTEM DESCRIPTION

The *HoloSSVEP* system is an smart home control using the Microsoft HoloLens AR device (see Figure 1). It employs the camera of the AR-HMD to locate the positions of controllable elements within the environment, which are marked by visual identifiers that can be automatically detected. As AR-HMD, we chose the HoloLens device, as it can act completely stand-alone as required for a mobile smart-home control application.

For recording EEG, we use a the wireless g.Nautilus headset with active g.SCARABEO Ag/AgCl electrodes. Three electrodes at the ocipital cortex, in locations Oz, O1, and O2, were recorded at 500 Hz, with reference to the right mastoid. Impedance was kept below $20k$. During placement of the AR-HMD, it was ensured that its head strap did not touch the electrodes to avoid artifacts.

Fig. 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.

For eye tracking, we used the Pupil Labs binocular eye tracker with its compatibility add-on to the HoloLens. 6-point calibration of the eye tracker was done directly through the AR-HMD, using a Unity component provided by Pupil Labs[1]. Eye tracking within AR-HMDs is challenging: The employed eye tracker is mounted bellow the glasses of the HMD and thus captures the eyes at a steep angle, with eyelashes often occluding a clear image of the pupil. This is especially challenging for users with glasses. Additionally, even small movements of the AR-HMD after the calibration can impede tracking performance.

The graphical user interface was implemented with Unity and compiled and deployed as a standalone application for the Universal Windows Platform. To ensure stable refresh rates for presenting the flickering selection targets, we implemented these as a custom blink shader at frequencies of 4, 6, 10, and 15 Hz. For the placement of selection targets, we used the Vuforia plugin to Unity which allows the automatic detection and 3D localization of preregistered images through the world camera of the AR-HMD. This allows the convenient placement of selection targets on any surface in the room.

The communication between all components of the *HoloSSVEP* system was realized using the Lab Streaming Layer[2] middleware (LSL). One challenge was that the LSL cannot be directly compiled for the Universal Windows Platform, due to limitations of the provided programming interface. To solve this issue, we implemented a *HoloBridge* component which provides a custom LSL interface. The HoloLens uses LSL to send markers indicating the activation and deactivation of selection markers as well as their relative position in the user's viewport. The actual classification (as well as data collection) is performed on a separate computer to which EEG and eye tracker are connected. The classification result is send to the smart home controllers as well as back to the HoloLens to trigger a visual feedback indicating the detected choice.

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

[2] https://gitlab.csl.uni-bremen.de/fkroll/LSLHoloBridge

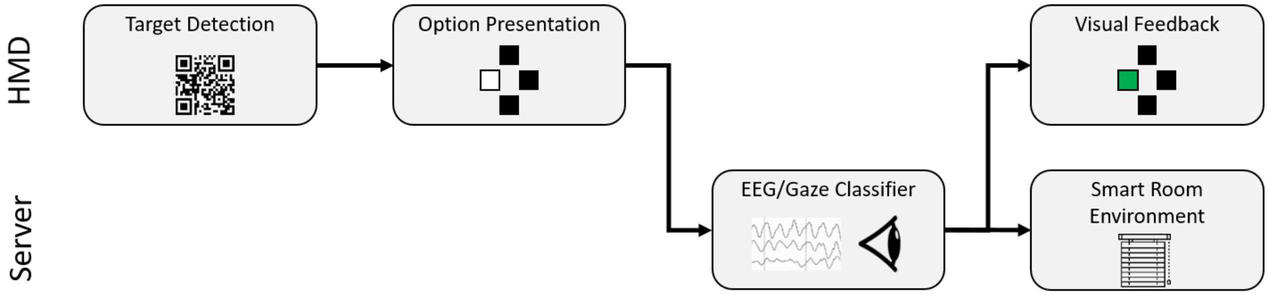

Fig. 2. System diagram of *HoloSSVEP*, components in grey run locally on the HMD, the other components run on a server connected through Wifi.

As we wanted to test not only the classification performance but also the usability of the end-to-end *HoloSSVEP* system, we created several controllable smart home components. This comprised control of the office lighting and the window blinds (both accessed through the buildings facilities automation interface) as well as control of a simulated TV and a music player. Table I summarizes the four control options available for each of these components.

TABLE I
CONTROL OPTIONS OF THE USER INTERFACE.

Light	top	Light 1 on
	bottom	Light 1 off
	left	Light 2 on
	right	Light 1 off
Blinds	top	Blinds Up
	bottom	Blinds down
	left	Blinds open
	right	Blinds close
TV/Music Player	top	Volume Up
	bottom	Volume Down
	left	Next Channel
	right	Previous Channel

IV. CLASSIFICATION

Controllable elements are detected in the visual field through preregistered printed markers. When this happens, the corresponding control elements are presented, a window with a length of 3 s is extracted, containing both EEG and eye tracking data. The window is classified into one of four classes, corresponding to the four different selection targets present in each selection. The two modalities are first processed and classified independently and then combined in a decision fusion scheme which employs the confidence of the individual modalities.

The EEG data is filtered with a bandpass filter between 1 Hz and 35 Hz and then processed with Canonical Correlation Analysis (CCA). CCA is a method that calculates linear combinations (the *canonical components*) of two sets of variables to a space which maximize the pairwise correlation between the canonical components. For an SSVEP-BCI, the two sets of variables are the EEG signals on the one hand and a group of templates for each class on the other hand. The class corresponding to the highest correlation coefficient is returned as classification result. Equation 1 shows how

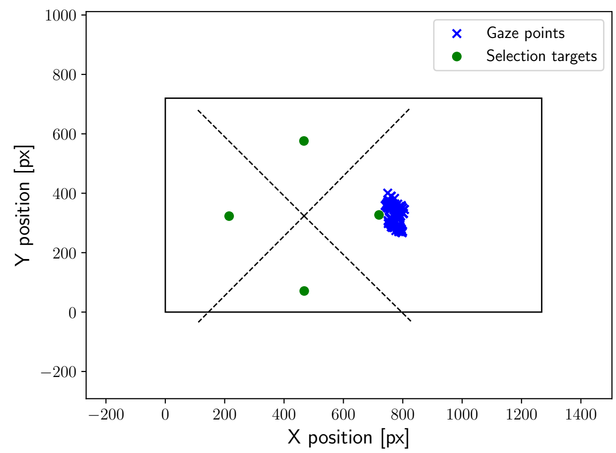

Fig. 3. Illustration of nearest neighbor classification for eye tracking data.

we define the template representing the target frequency f and the first two harmonics, with both a sinus and cosinus term to reflect potential phase shifts. This approach has the benefit of being completely training-free as the templates can be predefined once and do not require person- or session-specific adaptation.

$$\mathbf{y(t)} = \begin{pmatrix} \sin(2\pi f t) \\ \cos(2\pi f t) \\ \sin(2\pi 2 f t) \\ \cos(2\pi 2 f t) \\ \sin(2\pi 3 f t) \\ \cos(2\pi 3 f t) \end{pmatrix}, t = \frac{1}{S}, \ldots, \frac{T}{S} \qquad (1)$$

For classifying the eye tracking data, we employ a nearest neighbor approach. For each gaze point within the classification window, we project it to the plane in which all selection targets are situated and assign it to the target with the lowest Euclidean distance. The classification result is the class to which most gaze points are assigned to.

For combining the two modalities in classification, we employ a fusion scheme which uses confidence estimates: If the maximum CCA coefficient is greater than a threshold ($t_{CCA} = 0.4$), the classifier relies on the BCI result (path A, Figure 4). Otherwise, the gaze result is returned if the sample size (SS) is high enough and the gaze confidence (path B), measured as relative frequency of the selected class,

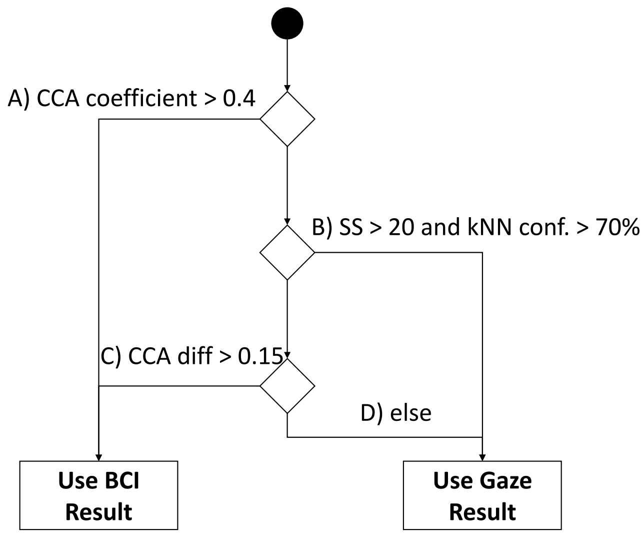

Fig. 4. Fusion algorithm for confidence-based combination of BCI and eye gaze classification.

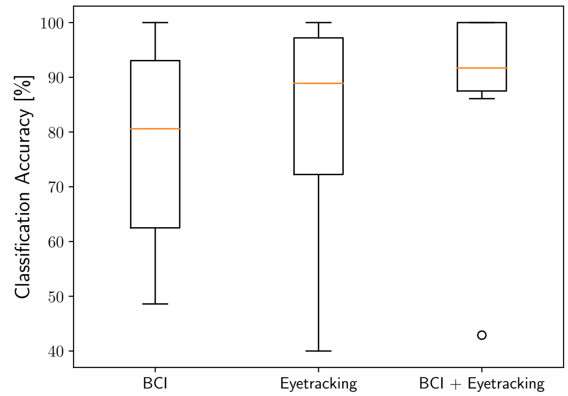

Fig. 5. Boxplot of classification accuracy for the two individual modalities and the fusion algorithm.

is above a threshold ($t_{gaze} = 0.7$). If this criterion also fails, the CCA score is again evaluated (path C), but this time the relative difference in CCA score between best and second-best option is evaluated against a threshold ($t_{diff} = 0.15$). If this criterion also fails, the fusion classifier will default to the result of the gaze classifier (path D).

This fusion approach can be turned into a self-paced selection, i.e. one which does not operate on a forced choice paradigm between the four classes but which allows the user to avoid a selection, if desired. Similar to Cecotti et al. [17], we define a threshold on CCA score to determine no-selections, but extend this approach to cover both modalities. This can be operationalized by re-labeling path D (see Figure 4) in the fusion algorithm to "no selection".

V. EVALUATION

For evaluation, we performed a user study with 12 participants, of which one was excluded from later analysis due to technical difficulties. All participants were university students and gave their written consent to participate in the study. After EEG and eye tracking calibration, users performed a training run and then went through 36 trials in which they were asked to select a specific option of a specific target. Order of target objects and target options were pseudo-randomized. The experiment was executed in a prepared office of the Cognitive Systems Lab at the University of Bremen. Participants were standing during the experiment and switching between different target objects (light, blinds, TV, or music player) required moving through the office (ca. 4 by 5 meters). For nine of the participants, we also recorded a short segment of trials in which they were instructed to look at a target marker without making a selection. We collected this data to evaluate the self-pacing aspect of the BCI. These trials were not part of the online evaluation and the usability study but are investigated separately.

After the completion of the experiment, participants answered a System Usability Scale questionnaire [18] to evaluate the systems usability. Participation was concluded with a short interview on usage and user satisfaction.

Figure 5 shows the achieved classification accuracy for both modalities individually as well as for the fusion algorithm. Chance level accuracy (i.e. relative frequency of the majority class) is 33.3%[3].

In Table II, we further show the individual classification accuracy scores for all participants. This detailed look shows many different cases of performance combinations: For participants 5 and 6, both modalities yield a near-perfect classification performance. For participants 1 and 3, the BCI performance is substantially inferior to the eye tracking performance; for participants 7 and 10, it is the other way round. This result shows that for robust classification, both modalities are required. For these examples, the fusion scheme is able to leverage the confidence metrics of the individual classifiers to mitigate the effect of the weaker classifier. Finally, for participant 8, both modalities fail to produce an acceptable classification performance, which may be a hint at the system not being able to draw that specific user's attention towards the targets.

Eyetracking suffers from challenges of calibration, due to challenging positioning, and users with glasses. Another challenge is that the calibration is performed at the beginning of a session. Even slight movements of the HMD to which the eye tracker is attached can invalidate the calibration results.

Of course, the results depend on thresholds to chose between different paths in fusion method. To investigate whether the observed results are not just a result of the specific parameter choices in our evaluation, we performed a parameter optimization on the recorded sessions through grid search. The result shows that while not all parameters

[3]due to logical constraints (i.e. cannot move blinds up twice without moving them down in between), not all options were presented equally often.

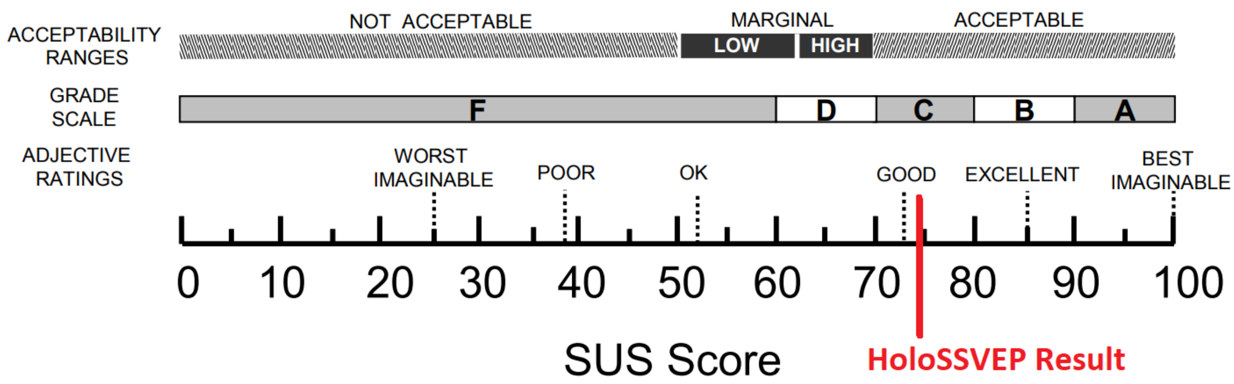

Fig. 6. SUS result on an absolute scale following [18]

TABLE II
INDIVIDUAL CLASSIFICATION ACCURACY FOR ALL STUDY PARTICIPANTS

Participant	Acc. BCI	Acc. ET	Acc. Combined
1	50%	94.4%	88.9%
2	80.6%	91.7%	88.9%
3	66.7%	100%	100%
4	80.6%	80.6%	86.1%
5	100%	88.9%	100%
6	94.4%	100%	97.2%
7	91.7%	58.3%	86.1%
8	48.6%	40%	42.9%
9	66.7%	86.1%	91.7%
10	100%	63.9%	100%
11	58.3%	100%	100%
Avg.	76.1%	82.1%	89.3%

TABLE III
FREQUENCY AND PRECISION FOR EACH PATH IN THE FUSION ALGORITHM

Path	Frequency (abs.)	Frequency (rel.)	Precision
A	137	34.7%	97.8%
B	102	25.8%	95.1%
C	59	14.9%	86.4%
D	97	24.5%	73.2%

were chosen optimally a-priori in the user study, the relation between the individual modalities and the fusion algorithm does not change. This shows that the reported results are not susceptible to parameter tuning.

Finally, we investigated whether all paths of the fusion algorithm are actually necessary for the achieved classification result. Table III presents the frequency with which the different paths are chosen to produce the fusion result, as well as the average classification precision along this path. The results illustrate that each path contributes to final result (with path C being chosen least frequently in 15% of all cases). We also observe that the secondary options C and D lead to lower classification performance, which indicates that the confidence metrics are actually able to identify the more challenging trials.

To evaluate the self-pacing aspect of the interface, we also evaluated the classifier on the additional trials that do not contain any selection. As described in Section IV, we modify the original fusion classifier such that the "default" path D is re-labeled to "no selection". As a result of this process, we achieve a classification accuracy of 72% for the original four classes and a classification accuracy of 85% for the new trials without selection. This shows that it is possible to create a self-paced selection while still achieving satisfiable performance in the original task.

For evaluation, we did not only look at the objective classification performance, but also at the subjective assessment through its participants. Figure 6 shows the achieved average score on the System Usability Scale (SUS), displayed with an absolute grade scale [18], which allows an assessment of the usability of the interface without an immediate comparison system. The SUS contains generic usability items and thus allows the evaluation of a broad range of interactive systems. The result shows that the *HoloSSVEP* system achieves a "good" usability, which constitutes the basic grade for an "acceptable" system. This means that the created interface can actually be employed in its current form for smart home control. The lowest average score was assigned to the question corresponding to wearing comfort, achieving only a score of 1.25 on a scale from 0 to 4. This was also confirmed in the closing interviews by multiple participants. A conclusion from this result is that further development into more lightweight and comfortable headsets is needed to further increase acceptance.

VI. CONCLUSIONS

In this paper, we showed the use of a multimodal user interface using EEG and eye tracking for silent, hands-free smart room control. The presented system works training-free, is quick to set up, and achieves high classification accuracy through the combination of both input modalities. Consequently, users rate the system as being of "good" usability. Results indicate that a major usability concern is the comfort of wearing two headsets; an AR headset with integrated EEG electrodes at the back of the head (to capture brain activity from the occipital cortex) would mitigate this problem.

A challenge to address in future research is the fact that the smart home environment is operated in the context of other tasks and cognitive processes. The SSVEP targets, which are superimposed on the scene for selection, are designed to draw the user's attention and thus are distracting if the user is not focusing on them. While an approach for self-paced BCI can avoid false selections, the presence of the targets alone may already disrupt internal thought processes. In future work, we will investigate approaches for attention modeling [19] to discriminate internal from external attention direction and avoid the presentation of undesired SSVEP targets in the first place.

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