EVALUATION OF AN SSVEP AND EYE GAZE HYBRID BCI

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ABSTRACT: An evaluation of a *hybrid* Brain-Computer Interface that combines input modalities of Steady State Visual Evoked Potential (SSVEP) and eye gaze is provided. Thirty volunteers participated and all but one could use the BCI, eye-tracker and hybrid system. The *hybrid* BCI was compared with SSVEP alone for navigating to four domotic tasks issued via a graphical user interface. Mean performance metrics of *Accuracy (Acc.)*, *Efficiency (Eff.)* and Information Transfer Rate (ITR) all improved (mean *Acc.* = 93.3% to 99.84%, mean *Eff.* = 89.56% to 99.74%, mean ITR = 23.78 to 24.41 bpm). While the absolute improvements are small, better performance may contribute to user acceptability, as the eye-gaze component adds minimal additional user effort to the interaction yet provides control that is more robust.

INTRODUCTION

The electroencephalogram (EEG) provides a recording of electrical activity within the brain. As complex as this activity is there are methods to extract meaningful information from the brain waves. By developing certain paradigms intentional modulation of brain activity can be established and used as a mechanism for communication and control. Known as Brain-Computer Interfaces (BCI), this technology has been explored extensively for over two decades as a mechanism to provide an input modality to a computing system that does not require the involvement of peripheral nerves and muscles [1]. Recording normally takes place under controlled laboratory conditions; in more recent years there has been an objective to extend the technology to users in the community, placing more emphasis on reliability, robustness and ease of use. Reliance on EEG features only is one of the key attributes with BCI systems, particularly important for users who have lost peripheral movement including eye gaze. However, BCI is recognized as a difficult assistive technology to establish for a user as successful deployment requires substantial tailoring to the user's needs and individuality within their EEG.

In contrast, for potential users with residual eye movement, eye-gaze technology has been deployed as an effective assistive technology, albeit with its own challenges in terms of attaining robust decision making. In particular, eye trackers have been used to navigate on-screen commands; when a decision or action needs confirmed, features such as 'dwell-time' may be used to activate the classification.

Combining active eye-gaze technology with BCI can bridge the gap between the two systems [2][3][4], creating a *hybrid* BCI (*h*BCI) system. BCI paradigms lend themselves to performing this confirmation or 'switch' operation [5][6], providing complementary intentional control for the user. In some cases, the searching activity, can be employed to items and locations within the user's physical environment, and this information provides a context to the decision to be made by the BCI system [7]. Meena *et al.*, 2015 [8], proposed a *h*BCI combining motor imagery (using the event related desynchronization component) with eye tracking, aspiring to increase the number of available command choices. The eye gaze is used to detect (search for) the spatially located device, while the BCI (motor imagery) is used to select.

Additionally, eye tracking has been used to provide the selection of 'on-screen' icons, with a BCI component confirming a choice. Galway *et al.*, presented eye tracking selection of directional arrows to gain navigation through a Graphical User Interface (GUI) for control of domestic appliances [9]. The arrow icons flash to initiate Steady State Visual Evoked Potential (SSVEP) responses and thus perform the switch operation to activate the desired movement through the GUI or to activate a command on an external device.

Kalika *et al.* [10] combined a P300 speller with eye tracking. Instead of a sequential search and select protocol, complementary inputs were combined and a Bayesian classifier enhanced the accuracy of selecting a character in the speller. Dong *et al.* [11] used a similar approach to combine motor imagery with eye gaze. Évain *et al.*, [12] combined eye gaze and SSVEP inputs to enhance classification accuracy and demonstrated a speed up in operation and performance over existing BCI systems.

In this paper, we provide an evaluation of an *h*BCI, which combines input modalities of SSVEP and eye gaze, and uses a similar signal processing approach as [13]. The aim was to evaluate the performance and usability of SSVEP for healthy participants and indicate improvements, that *h*BCI offers. The SSVEP paradigm provides a natural and intuitive procedure to collaborate with an eye-tracking algorithm. Users interacted with an existing menu system [9], which provided navigation of a virtual smart home, on a desktop computer. They were required to observe and fixate on the navigation icon they wished to select; as the icons were collocated with frequency-modulated stimuli, the technique for interaction does not change from a user perspective.

MATERALS AND METHODS

Ethical approval was granted by the Ulster University Research Ethics Committee (UUREC ethics number REC/16/0053). Thirty healthy volunteers (16 males and 14 females), from staff and students at Ulster University and members of the public over the age of 18 years participated. Participant age ranged from 21-73 years, average 37.6 (SD 14.73). Exclusion criteria prevented volunteers from participating if they were sensitive to flickering lights, had substantial problems with left-right discrimination, and hearing or visual impairments, which could not be corrected. Prior to beginning, participants undertook a practice run to familiarize themselves with the control paradigm and the GUI of the menu system. The assessment required participants to complete tasks to initiate domotic control, multimedia playback, communication, and free control of a smart-home environment. Participants completed a pre-questionnaire to indicate expertise and their perceived level of tiredness/arousal and a post-questionnaire to provide some qualitative feedback.

Setup time ranged between 4-26 mins, (average 13m:53s, SD 5m:35s) and total experiment time ranged from 50 mins to 2 hours and 29 mins, dependent on the number of sessions that the participant completed, (average 1 hour and 25mins, SD 20m:07s). From the 30 participants, 12 had prior experience with eye tracking technology, nine had prior experience with SSVEP BCI, and 28 were experienced computer users. Eight participants required vision correction; six of which removed their glasses for the duration of the experiment to account for reflections, which may have adversely affected eye tracking performance.

The experimental setup comprised dual LCD displays (refresh rate 60 Hz), an EyeTribe eye tracker, g.USBamp, g.LADYbird passive electrodes, g.GAMMAcap, and a Raspberry Pi home-automation server (for interaction with external devices such as lights). The experiment was controlled by monitor one and participants were required to interact with the GUI displayed on monitor two. Participants were seated approximately 70 cm from this monitor. The EyeTribe Tracker was utilized to record gaze at a sampling rate of 60Hz, with a latency of <20 ms. The device was calibrated on 9 points and with an accuracy in the range 0.5 – 1 degree. On-screen gaze coordinates were derived from the EyeTribe application programming interface.

For SSVEP generation, four unique flickering stimuli (6.67 Hz, 7.5 Hz, 8.57 Hz, 12 Hz) were presented by modulating pixels on screen (rather than through external LEDs, which was adopted in previous studies). The four stimulation areas were set at the default size of 150 x 150 pixels and by focusing attention on flickering stimuli, users could traverse through the menu structure by issuing a succession of *left*, *right*, *up*, and *down* commands. The *down* command selected an item or navigated to a lower level in the hierarchical structure, and the *up* command returned to the previous (higher) level. In addition, spoken feedback was provided after each command to reinforce the user experience by confirming the command. The four stimulators were surrounded by a 250 x 250-pixel border, representing the maximum size that each stimulator could increase to without classification occurring. As an additional method of feedback, the stimulators were designed to grow dynamically in relation to the SSVEP amplitude of the respective frequency. This design was for two reasons: 1) it provides user feedback allowing participants to know when they have issued a command; and 2) larger stimuli produce a greater SSVEP response. In the second case, real-time SSVEP visualization relating to the power estimation of the relevant frequency, decreases the time to select, as the response becomes increasingly more prominent in the EEG due to the increasing size of the stimuli; it is a positive feedback loop.

Feature detection and command translation were based on signal processing methods realized by Volosyak *et al.* [13]. The SSVEP signal detection and classification process utilized the Minimum Energy Combination (MEC) method to create a spatial filter and enhance the SSVEP response while reducing ambient signals and other interference [13]. The system was designed to automatically determine the best spatial filter for each participant at each frequency. The manifestation of each frequency in the EEG was detected by spatial filtering, power estimation, and a statistical probability method, which enhanced the quality of signal and separated channel-specific features. Furthermore, an adaptive windowing technique was employed in order to determine a suitable window length based on online performance. Stimuli induced frequencies and harmonics were estimated in the recorded EEG. When this estimation exceeded a predefined threshold, as determined during calibration, a directional vote (i.e. $SSVEP_E$ *left*, *right*, *up*, *down* or *no-control state*) was transmitted to the data fusion component of the menu system, as illustrated in Fig. 1.

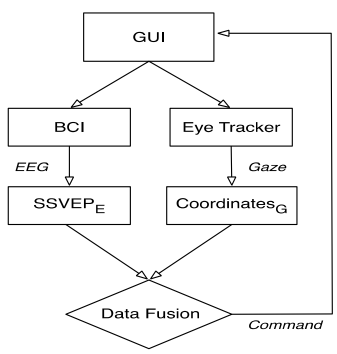

Figure 1: Conjunction-based collaborative decision making process data flow

In collaboration with the directional vote, coordinates of the participant's gaze ($Coordinates_G$) were used to ascertain an overall command and concurrently transmitted to the Data Fusion component. Employing the conjunction of the estimated location derived from the participant's gaze point and the directional vote, agreement of the intended command would occur if the conjunction was found to be true. Figure 2 illustrates the partitioning scheme utilized by the Data Fusion component, which partitioned the overall GUI along the horizontal, vertical and diagonal axes, centered on the origin of the GUI, such that gaze coordinates were easily mapped to specific quadrants surrounding the SSVEP navigation icons.

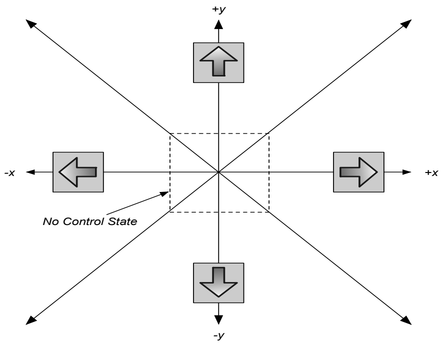

Figure 2: *h*BCI user interface partitioning scheme showing partitioning of screen along x, y and diagonal axes, placement of SSVEP navigation icon stimuli and no control state

In addition, a no-control state within a predefined area centered on the origin of the GUI was used in order to permit the participants to view the currently active menu icon, which would appear in the center of the bespoke menu system. Accordingly, gaze coordinates were not acquired when the participant's gaze was within the bounds of this zone, thus preventing the possibility of erroneous commands being issued by the Data Fusion module whenever the participant was regarding the active menu icon. Directional decisions were calculated as follows:

$$\mathrm{F}(x,y) = \begin{cases} \xi_L\Delta\,, if & \phi_1 \wedge \neg\left(y-\left(\frac{x}{2}\right)<0\right) \vee \phi_3 \wedge \neg\left(y-\left(\frac{x}{2}\right)>0\right) \wedge \left(y+\left(\frac{x}{2}\right)-\alpha>0\right) \\ \xi_R\Delta\,, if & \phi_2 \wedge \neg\left(y-\left(\frac{x}{2}\right)<0\right) \wedge \left(y+\left(\frac{x}{2}\right)-\alpha<0\right) \vee \phi_4 \wedge \neg\left(y+\left(\frac{x}{2}\right)-\alpha>0 \wedge y-\left(\frac{x}{2}\right)>0\right) \\ \xi_U\Delta\,, if & \phi_1 \wedge \left(y-\left(\frac{x}{2}\right)<0\right) \vee \phi_2 \wedge \left(y-\left(\frac{x}{2}\right)<0 \wedge y+\left(\frac{x}{2}\right)-\alpha<0\right) \\ \xi_D\Delta\,, if & \phi_3 \wedge \left(y-\left(\frac{x}{2}\right)>0\right) \wedge \left(y+\left(\frac{x}{2}\right)-\alpha>0\right) \vee \phi_4 \wedge \left(y+\left(\frac{x}{2}\right)-\alpha>0 \wedge y-\left(\frac{x}{2}\right)>0\right) \end{cases}$$

where F is a function of x and y, α is the horizontal resolution divided by two, β is the vertical resolution divided by two, and ϕ_1, ϕ_2, ϕ_3, and ϕ_4 are quadrants one, two, three, and four, respectively, and ξ_L, ξ_R, ξ_U, and ξ_D are the eye tracking vote for *left*, *right*, *up*, and *down*, respectively. Upon successful command determination, the resulting command is transmitted by the Data Fusion component to the GUI resulting in continued traversal of the menu structure.

Participants were instructed to complete four tasks, controlling the GUI-based menu system, to traverse a hierarchal-menu structure and activate features and functions of a smart-home environment. The instructions, issued by trained-research staff, requested that participants navigate the menu structure executing four-way control, e.g. *left*, *right*, *up*, and *down* commands. The first task required participants to interact with smart home lighting in the dining room. The second task asked if they could select a specified video for playback on the television set and subsequently end playback when requested. The third task required users to navigate to the talk menu and communicate using predefined iconography and auditory feedback to indicate hunger (e.g., to a potential companion). The fourth task required users to freely navigate the interface to complete a predetermined goal (in this case to go to the kitchen, find the extractor fan, and turn it off), without receiving a predefined set of instructed commands and therefore permitting users to initiate different command sequences to reach the goal. Fig. 3 gives a representative example of task one, whereby participants were instructed to issue a minimum of 13 commands to traverse the hierarchal-menu structure and control room lighting. For the particulars of the individual tasks, please see [9].

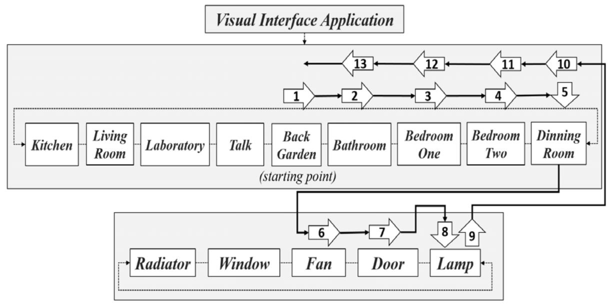

Figure 3: The minimum commands to successfully traverse the hierarchal-menu structure and complete tasks two.

In the case of an erroneous command (due to user error or misclassification), participants were instructed to rectify the mistake by issuing an additional command when required, which for subsequent analysis was considered as a 'correct' selection. In certain circumstances, however, rectifying commands were not required, e.g. when a false-positive '*up*' command was issued at the highest level of the hierarchy. Such commands did not initiate traversal of the menu structure and therefore did not require rectification. Each task was associated with a critical path (i.e. the minimum number of compulsory commands for successful completion). When completing the tasks, the total time for task completion, and the number of correct, incorrect, and rectified commands were recorded. Performance metrics for accuracy of target detection (*Acc.),* efficiency of the interaction (*Eff.*) and Information Transfer Rate (ITR) were computed offline.

In some situations, the accuracy value provides a misimpression of participant performance. Due to the structure of the tasks, false-positive commands are often succeeded by a command to rectify the mistake, which is defined as an additional correct command. The result from specific participants who issued several false-positive commands suggests performance is of a higher level than in reality. For this reason, *Efficiency*, as defined by Volosyak *et al.* [15], is calculated as follows:

$$Efficiency = \frac{C_{min}}{C_{total}} * 100$$

where C_{min} is the minimum number of compulsory commands (13 for Task 1 in our interface layout) and C_{total} is the total number of detected commands. ITR was calculated as defined by Wolpaw *et al.* in [1] and formularized as follows:

$$ITR = \left(log_2 M + P log_2 P + (1-P) log_2 \left[\frac{1-P}{M-1}\right]\right) * \left(\frac{60}{T}\right)$$

where M is the number of choices, P is the accuracy of target detections, and T (in seconds/selection) is the average time for a selection.

RESULTS

The experimental results, summarized in Fig. 4, provide an analysis of the individual accuracies, efficiencies, and ITRs as well as the averages across all participants. Furthermore, these results contrast the performance of SSVEP alone with *h*BCI, conveying a mean accuracy increase from 93.3% to 99.84%, mean efficiency improvement of 89.56% to 99.7%, and indeed an ITR improvement of 23.78 bpm to 24.41 bpm. The latter may be surprising as the eye tracker may be expected to somewhat dampen the responsiveness of the interaction (whether correct or incorrect), and contrast with the findings of Vilimek *et al.* in [16]. A paired t-test indicated that participants performed better using *h*BCI than BCI alone in terms of accuracy and efficiency with a significance of $p < .001$. This finding indicates that there is a statistical significant difference between the two conditions that is not attributable to chance, and likely due to the independent variable manipulation. A further paired t-test provided an analysis of the bit rates contrasting BCI-only and *h*BCI indicating a significance of $p > 0.10$. This finding suggests that there is no statistical significant difference between these two metrics, and hence the difference of the means, in this case, is likely owing to chance.
To compare these results with eye tracking-only please see the previous study in which the same tasks were employed to assess the performance of eye tracking alone on healthy volunteers (N=12), indicating an average accuracy, efficiency and ITR of 88.88%, 81.20% and 41.16 bpm, respectively.

fixed through wearable tracking glasses?

DISCUSSION

This research indicates that the *h*BCI outperforms SSVEP-based BCI alone across all considered metrics, *Acc.*, *Eff.* and ITR. Hence we believe that the *h*BCI is potentially more robust. This could go some way to addressing BCI acceptability outside the laboratory and, therefore, the additional cost and complexity of eye tracking can be readily justified. Indeed, the hardware cost in this case (a couple of hundred Euro) is minimal when compared to the BCI component as high spatial accuracy is not needed. Eye tracking is limited by false-positive selections, however, which is often referred to as the 'Midas Touch' problem [18] (i.e. selecting everything unintentionally), while SSVEP performance is not robust enough for critical applications, e.g. false-positive selections in smart environments are known to produce intolerable events in the local environment, such as lights flashing on and off, doors opening and closing, security alarms triggering etc. Therefore, the integration of both modalities as an *h*BCI has been demonstrated to improve the performance up to a level unobtainable by either modality on its own.
An analysis of the post-questionnaire responses from the 30 participants, conveyed that five preferred BCI alone, 19 preferred the *h*BCI, and six had no preference. Multiple participants stated the *h*BCI improved confidence during interaction and one user in particular stated *"the hybrid demonstrates a potential for more complex tasks"*. Other users substantiated this claim by mentioning that the *h*BCI seemingly offered enhanced robustness. A small subset of the participants contradicted these findings, however, by suggesting that SSVEP was superior as a sole input modality. In some exceptional circumstances, for example, when participant 28 achieved remarkable performance using BCI alone (*Acc. 100%, Eff. 100%, ITR 36.37 bpm*), the *h*BCI merely slowed the interaction (*Acc. 100%, Eff. 100%, ITR 33.31 bpm).* Likewise, participant 6 who also preferred SSVEP alone, achieved *Acc. 95.54%, Eff. 93.88%, and ITR 23.36 bpm* utilising BCI-only. Their qualitative feedback was somewhat surprising considering their performance improved for the *h*BCI (*Acc. 100%, Eff. 100%, ITR 21.91 bpm)* for both accuracy and efficacy, albeit with a slight reduction in ITR. While such a finding is inherently subjective, this participant was apparently more tolerant to errors than to an increase in time per selection, even if it meant 100% accuracy of target detection. Participant 8, who did not achieve 100% *h*BCI accuracy and efficacy, expressed that they found *"the hBCI control restrictive due to the fixed nature of the hardware"*. This participant highlights a known restriction of eye tracking technology whereby calibration enforces users to remain stationary; for example, adjusting the seated positioning is known to produce erratic screen-based coordinates.
The only volunteer who failed to complete the tasks, Participant 11, suffered from macular degeneration, a medical condition affecting the central field of vision, and would have been screened out if they had informed research staff prior to running the experiment. The result was labelled 'inconclusive' and excluded from subsequent numerical calculations. However, it reinforces that there will always be people that the BCI will not work with. Our intention is to assess the performance of people with brain dysfunction in the future and this will obviously pose additional challenges.
A quantitative analysis comparing SSVEP with *h*BCI is represented in Fig. 3 (A) and (B). From 30 participants, 29 completed the tasks successfully. Of those 29, only three failed to achieve 100% *Acc.* and *Eff.* and yet their

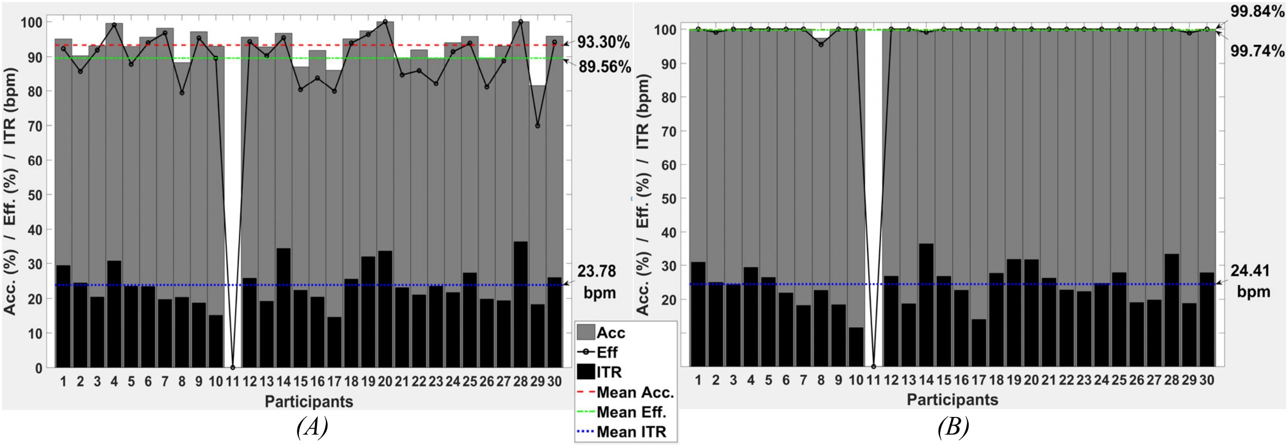

Figure 4: Data collected from 30 healthy participants. (A) The results from SSVEP-only achieved a mean *Acc. 93.3%, Eff. 89.56%,* and ITR *23.78* bpm. (B) The results from the *h*BCI (SSVEP + Eye Tracking) achieved a mean *Acc. 99.84%, Eff. 99.74%*, and ITR *24.41* bpm.

performance still increased significantly in contrast with SSVEP-only. In some cases, the ITR may have dropped moderately from SSVEP control to the *h*BCI. As mentioned previously, and contradictory to prior research [16], the average bit rate improved for *h*BCI interaction. This is likely due to the ITR calculation, which is satisfied with three variables: 1) accuracy of target detection; 2) number of choices; and 3) time per selection. A system that returns perfect accuracy can account for an increased time per selection and return a higher bit rate when compared with less accurate systems that have a decreased time per selection. In an eye-gaze collaborative BCI this tradeoff is related to the dwell time of eye tracking decisions. Optimal parameters in the eye tracking algorithm will ensure interaction speed does not diminish to a level that reduces bit rate. An offline analysis of the data for a representative participant confirms this finding. Fig. 5 provides further interpretation of *h*BCI task one for a representative participant, confirming the eye tracker voted first on 12 of the 13 selections. For the most part, the eye tracker was not limiting performance, but for one of the selections, the *up* selection, the BCI had to wait for the eye tracker to agree before a selection could be issued, which increased the total time for task completion. A common assumption, may suggest this should indicate the BCI-only version will return a higher ITR, but in certain cases this is incorrect. The *h*BCI still manages to outperform the BCI alone in terms of information throughput, if it issues slower selections with greater accuracy. Comparison of the result of BCI alone and *h*BCI for Participant 2 when completing task one confirms this to be the case. From period 45-48 seconds, it is clear the BCI was confident that the participant was attempting to issue an *up* selection but the eye tracker slowed performance, and yet the *h*BCI still exceeded the bit rate of BCI alone. This is particularly interesting as it suggests that refining the hybrid system may further improve performance. A softer decision process allowing selection based on confidence level of singular modalities would likely improve the system as an assistive technology. Allowing decisions from one modality to surpass the other, however, prevents the assessment of individual components from a research perspective, e.g. eye tracking decisions that do not interact with BCI cannot be considered as an *h*BCI process, since decisions do not necessarily rely on activity from the brain.

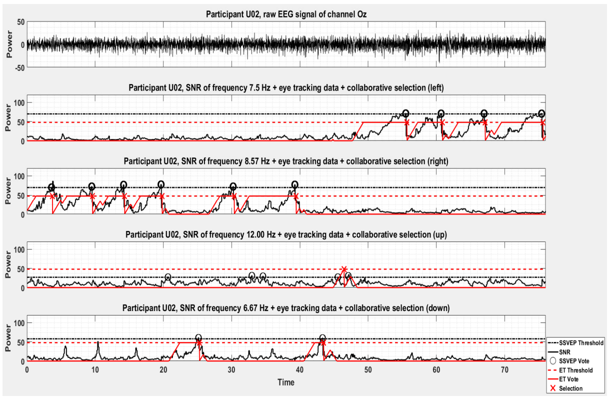

Figure 5: BCI, eye tracking, and collaborative selections for Participant 2 completing task one using the *h*BCI.

Moreover, a comparative analysis of BCI and *h*BCI *must* always consider the same number of choices in the ITR calculations. The BCIs discussed herein have four choices, the SSVEP stimuli for *left* (7.5 Hz), *right* (8.57 Hz), *up* (12 Hz) and *down* (6.67 Hz) selections. Each of these choices is reinforced with eye tracking decisions but the number of choices in the ITR calculation does not increase. In a hybrid design, the number of choices could potentially increase significantly. For example, a single frequency for SSVEP detection could be employed and 12 choices added to an interface. Each choice would be selectable via the user gaze and a BCI component. In this form the hybrid utilizes BCI as a *switch,* but unfortunately the ITR cannot consider 12/13 choices. Doing so would provide a misimpression of performance and instead the ITR should be calculated using a single choice.

CONCLUSION

The SSVEP paradigm provided a natural and intuitive procedure to collaborate with an eye tracking algorithm. Users were required to observe and fixate on the icon they wished to select, and if icons were also collocated with SSVEP stimuli, then the technique for interaction would not change at all from a user perspective. For the *h*BCI mean performance metrics of *Acc., Eff.* and ITR all improved. While the absolute improvements are small, they may contribute to user acceptability, as the eye gaze component adds minimal additional user effort to the interaction. BCI offers enormous hope for assisting communication/interaction for people with neurological disease. Further significant advances have been made in recent years. The hybrid discussed in this paper increased the performance metrics under study and generally the perceived robustness by the volunteers. Set up by an experienced user is still required, particularly regarding the thresholds to achieve best performance. Analysis of the eye tracking data and the collaborative decision process provides insight, showing that metrics can be further improved. This level of detail can also be used to quickly screen out people for whom the technology is inappropriate.

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