Eye gaze collaboration with Brain-Computer Interfaces – using both modalities for more robust interaction

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In this chapter, we discuss the motivation for the hybrid Brain-Computer Interface (BCI), and review progress toward more robust user interaction from existing studies. In addition, we discuss the design and development of a *hybrid* Brain-Computer Interface (*h*BCI) example that combines two symbiotic modalities: Steady State Visual Evoked Potential and eye gaze technology. By adopting a modular design, we show that it has been possible to implement such hybridisation by integrating mostly existing software components and, indeed, facilitate future updates to the system that will be necessary as hardware, software and interfaces continue to evolve.

1.0 INTRODUCTION

Brain-Computer Interfaces (BCI) have offered the hope of more autonomous communication and control for those with the most severe forms of muscular and neurological disability (Sellers, Vaughan and Wolpaw, 2010). BCIs are also emerging as a supplemental technology for Human-Computer Interaction (HCI) (Allison, 2011; Allison, Millan, *et al.*, 2012; Brunner *et al.*, 2015). Interaction with computing systems and embedded smart devices is typically achieved through a set of tailored BCI paradigms that in some way instigate an intended and measurable activity within the electroencephalogram (EEG). Historically, BCI paradigms fall into two categories. The first category is Motor Imagery (MI), in which the user thinks of moving a limb, a hand or foot for example, and in doing so initiates an identifiable pattern over the sensorimotor region of the cortex (Pfurtscheller and Neuper, 2001). The second category relies upon an external stimulus to evoke a response within the EEG. Although auditory (Kim *et al.*, 2012) and somatosensory (Rutkowski *et al.*, 2012) stimuli produce discernable event-related responses (ERPs), it has been prevalent for BCI paradigms to use visual stimuli in the form of flashing light emitting diodes or flickering icons on a screen. The resultant evoked cortical activity, known as Steady State Visual Evoked Potential (SSVEP), is dependent on the frequency of stimulation. This typically tends to be in the region of 6-20Hz (Müller-Putz *et al.*, 2005), although higher frequency variations, which are deemed as less annoying, have also been proposed and investigated (Durka, Kus and Zygierewicz, 2009). Higher frequency stimuli mitigate photo-sensitivity effects (e.g. people with epilepsy) but produce smaller components in the EEG. Where the stimulation occurs unpredictably, for example, a *target* stimulus that can be distinguished from a more frequent stimulus, a positivity occurs in the EEG approximately 300ms following the stimulus; this is the well-known P300 waveform. This component has been successfully harnessed for user interaction (Farwell and Donchin, 1988; Guger *et al.*, 2009; Sellers, Vaughan and

Wolpaw, 2010), as it is reliably detected in most people, reduces the processing time for feature extraction, and hence expedites classification. Other paradigms such as the slow cortical potential (SCP) have received attention by the research community but are not widely used (Hinterberger *et al.*, 2004).

Each paradigm (MI, SSVEP and P300) has its strength and weakness (Allison *et al.*, 2013). MI requires training, which is time consuming and requires significant subject compliance; it can be difficult to achieve greater than a reliable two-way classification consistently and over long durations. For example, in order to achieve a three-way communication channel, classification algorithms need to differentiate between individual imagined hand movement (left, right) and feet (the latter is often undertaken as combined imagined movement to strengthen the response). Other possibilities can be chosen specifically tailored to the most promising brain activity components of the user. For example, imagined tongue movement has also been used as a possible input (Morash *et al.*, 2008), as it can be discriminated from hands due to its location of activation on the motor cortex. Unfortunately, in some individuals it is difficult to differentiate the EEG MI activity to a suitable level for robust and usable BCI operation (Ahn and Jun, 2015).

The P300 paradigm has the advantage that a significant number of stimuli (usually in the form of icons, and more recently faces (Jin *et al.*, 2014) which tend to produce a robust response) can be placed on screen at one time. A good example of this is with the P300 speller (Farwell and Donchin, 1988; Vaughan *et al.*, 2006; Cecotti, 2011). A typical configuration contains a grid of 6 by 6 icons flashing sequentially by row and column, although variations of less or more icons have been used (Sellers *et al.*, 2006). A balance is needed between having enough icons to create a 'random' enough stimulus but not so many as to make it too slow to determine the target icon. Depending on the subject and experimental parameters, it can take from one (single trial) to multiple (up to sixteen) repeat flashes of the target icon to enhance the P300 response from the background EEG. The number of repetitions of the stimulus is dependent on both the P300 screen set up and the user, and in turn has an impact on the performance in terms of robustness (determined by sensitivity and lack of errors) and Information Transfer Rate (ITR), which equates to speed and interactivity for the user.

With SSVEP, there is also a tradeoff in these performance metrics. The choice of discriminable frequencies for the icons is important and is often dependent upon the user. Furthermore, the greater the number of distinct icons flashing on screen the greater the challenge in differentiating between frequency characteristics of the EEG. Furthermore, improved discrimination could depend on tuning an algorithm to tailor the threshold power values in the EEG for each frequency associated with each user. Such choices have an impact on the duration of recording before a decision can be made with a certain degree of confidence. Ware *et al.* (2010) reported a gap in what was considered an acceptable accuracy by some users (77-81%), and what they were able to achieve using SSVEP (16-95%). This highlights the importance of a minimum viable accuracy before such systems can be deemed usable. To be accepted by users, BCI systems need to have a high enough accuracy to be robust in terms of errors, and with a suitable speed and performance to alleviate frustration. Consequently, Accuracy and ITR have been applied as metrics to indicate this overall system performance of a BCI. Performance metrics are further addressed in section 3 of this chapter, and described in more details in Chapter 7 of this book.

Conventional BCI systems have been impeded by an extensive list of constraints, such as intersubject performance variability, robustness, and comfortable EEG acquisition, that prevent ubiquitous distribution and widespread adoption (Abdulkader, Atia and Mostafa, 2015; Brunner *et al.*, 2015). Consequently, *hybrid* Brain-Computer Interfaces (*h*BCI) (Vilimek and Zander, 2009; Allison, Millan, *et al.*, 2012) is an emerging research area that has the potential to address many of the limitations and associated hindrances by combing two or more BCI paradigms within a single system (e.g. MI and sensory stimulation) or by combining a BCI system with other input/output modalities. Allison, Leeb, *et al.* (2012) provide definitions of different classes of *hybrid* BCIs. Based on these definitions, Figure 1.

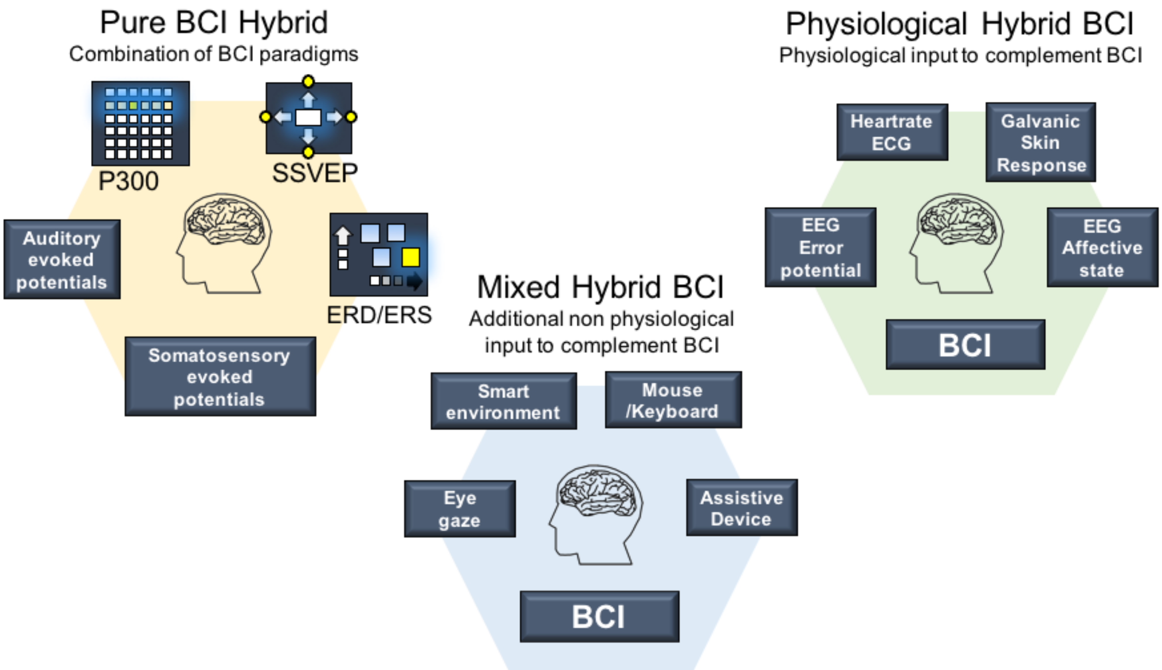

Figure 1: Hybrid BCI Approaches: Pure BCI Hybrid, which combines a number of existing BCI paradigms; Mixed Hybrid BCI, which employs non-physiological sensors as an additional input modality to the BCI system; Physiological Hybrid BCI, which combines physiological-based sensor input with a BCI system

There are many reasons why additional inputs could provide a more robust and usable system. In combining the different mechanisms (Pfurtscheller, Allison, *et al.*, 2010) discuss how systems can be combined to enhance the quality of the decision making (*simultaneous processing*), as also highlighted by (Millán *et al.*, 2010); or so that one component can act as a '*switch*' to initiate the control while the other is used to determine the ongoing action (*sequential processing*). For further detail on *h*BCI control mechanisms, please see Henshaw, Liu and Romano (2014). In their work, they provide a review of *h*BCI since 2011, putting the example of *h*BCI into the categories of *simultaneous* and *sequential* processing, and highlighting in their overview the key benefits that the combinations provide over pure BCI systems. In addition, they reported associated improvements, such as an increase in accuracy (Allison *et al.*, 2014), specificity (Spüler *et al.*, 2012), performance (Yin *et al.*, 2014) and function (Choi and Jo, 2013).

Such examples demonstrate how multiple BCI systems can be combined to provide a purely EEG reliant interaction. These fall into the traditional concept of a BCI (Pfurtscheller, Allison, *et al.*, 2010) in which there must be an element of determined patterns detectable in the EEG in response to the user's goal-directed behavior. Zander and Kothe provide an alternative argument through studying BCI technology as a passive input for human-machine interfaces (Zander and Kothe, 2011). Other examples combine physiological inputs with EEG components to provide a level of classification reinforcement (Leeb *et al.*, 2011; Shahid, Prasad and Sinha, 2011) or to extend the number of classification targets (Lin *et al.*, 2016). Passive BCIs (Zander and Kothe, 2011) utilise the modulating EEG, for example due to affective state of the subject, to reinforce the active BCI.

Millán *et al.* (2010) discuss the combining of all the individual decisions from each component of the *h*BCI in such a way as to assign a confidence or certainty on the classifications. The result would be a 'weighted' fusion of the incoming information and classifications. Consideration is given to a number of factors: from the reliability of the systems and channels through to the inclusion of supervision signals such as mental states (e.g. fatigue, Error Potentials (ErrPs), which may occur when a subject realizes that an incorrect classification occurred) and physiological parameters (e.g. muscular fatigue). Ongoing performance monitoring could also play a beneficial role. Incorporating evidence of error occurrence from the EEG using ErrPs has also been applied to *h*BCI design (Buttfield, Ferrez and Del R. Millan, 2006), with (Schmidt, Blankertz and Treder, 2012) showing that including automatic error detection enhanced the writing speed of their BCI speller.

The future of BCI has been envisioned in a roadmap (Brunner *et al.*, 2015). The roadmap categorizes BCI from the most extreme cases, whereby using EEG within the BCI offers the only route for communication and control, through to the inclusion of a BCI modality to supplement and guide an activity, or to be used for rehabilitation or neuroscience research. Blankertz *et al.* (2016) provide a review of examples of BCI deployment covering a range of applications, for example, monitoring alertness in safety critical situations. Another interesting example discusses combining ET technologies with BCI for implicit monitoring of the use of computing applications to enable augmentation of the HCI to the user needs. Indeed, the vision for BCI has extended beyond an assistive technology to the extent that EEG monitoring is envisaged to become a ubiquitous activity for a very wide group of users (Blankertz *et al.*, 2010, 2016; Nijboer *et al.*, 2011; Zander and Kothe, 2011; Van Erp, Lotte and Tangermann, 2012).

By broadening the scope of BCI with the addition of complementary modalities within hybrid systems, it may be possible to produce stronger more usable systems, thereby promoting greater adoption. Furthermore, as developments in wearable devices and BCI technology continues to progress, application areas will certainly extend beyond disabled user groups. This is a plausible concept, albeit the technology still being in the 'Innovation Trigger' phase of the Gartner 2016 Hype Cycle (Gartner, 2016). The report envisages that '*technology will continue to become more human-centric to the point where it will introduce transparency between people, businesses and things*'. As part of this vision they highlight BCI, human augmentation, affective computing and connected home (among others) to be key driving technologies.

This potential increase in widespread user acceptance and interest from commercial developers should in turn have a positive impact on the availability of BCI technology as an assistive device for those that it was originally designed for. Indeed this market stimulus can additionally reinforce further BCI research into hardware, algorithms and synergies with user groups (Saproo *et al.*, 2016).

This chapter's focus is on combining eye gaze with BCI paradigms. In section 2, we review the current BCI literature in SSVEP, and in BCI mechanisms in which Eye Tracking (ET) has been used in a complementary way to enhance performance and usability. Section 3 provides an overview of the challenges and techniques in developing a *h*BCI. This is demonstrated through an example which combines SSVEP with eye gaze to create more robust navigation through a user interface for control over a virtual smart home. This includes an experimental protocol and evaluation. Section 4 concludes with a discussion on the subtleties in operation of the hybrid design and provides commentary on future developments in the area.

2.0 Overview of current SSVEP and ET advances

This section provides an overview of the state of the art in SSVEP systems, which will set the background for the algorithm used in the hybrid example in section 3. We also investigate the application of ET metrics into EEG and BCI systems.

2.1 SSVEP

The Visual Evoked Potential (VEP) can be detected in the in the EEG in response to external visual stimuli. The stimuli can be pattern reversal (e.g. a checkerboard on computer screen), flashing icons on a computer screen or externally modulated flashing lights, usually light emitting diodes (Zhu *et al.*, 2010). The VEP component is prominent in the visual region of the occipital cortex (Regan, 1988). If the visual stimulus is presented at a rate greater than 6 Hz, an oscillatory response is evoked. This response is termed steady-state visual evoked potential (SSVEP). If users pay attention to one or more stimuli that oscillate between 6-50 Hz, corresponding frequencies may be measured over visual areas of the brain. Users can thus communicate by focusing on one stimulus while ignoring others. Different frequencies elicit different SSVEP activity across different subjects (Gao *et al.*, 2003; Kelly *et al.*, 2005) Allison *et al.* (2008) showed that SSVEP sufficient for BCI control may be elicited by selective attention to one of two overlapping stimuli. Thus, some SSVEP-based BCI approaches may not depend on gaze control and could function in severely disabled users (Allison *et al.*, 2010; Pfurtscheller, Solis-escalante, *et al.*, 2010; Volosyak *et al.*, 2011).

Hwang *et al.* (2013) surveyed the percentages of each BCI paradigm used in EEG-based BCI articles published between 2007 and 2011. For a review of these paradigms please refer to (Amiri *et al.*, 2013). In 2011, SSVEP comprised 10% and hybrid BCI comprised 4% of these articles. The main paradigms were Motor Imagery (56%) and Visual P300 (18%).

The SSVEP component is maximum for 10Hz stimulation. The EEG activity has peaks at the fundamental frequency and its harmonics; thus, 10Hz stimulation enhances activity in the EEG at 10Hz, 20Hz, 30Hz, etc. These components of the EEG are best measured in the frequency domain using signal processing techniques, typically by analyzing the power spectrum of the EEG (Gao *et al.*, 2003; Lalor *et al.*, 2005; Friman *et al.*, 2007). In order to operate as a BCI, the user focuses his/her attention on a target stimulus (possibly attending to one of many stimuli).

Most SSVEP-based BCIs use stimulation frequencies in the 6-30Hz range (classified as ‘low frequency stimulation’ up to 12 Hz and ‘medium frequency’ stimulation up to 30Hz). The SSVEPs elicited by frequencies in this range have high amplitude but can induce visual fatigue and may not be suitable BCI devices for people who are photosensitive, e.g. people with epilepsy (Fisher *et al.*, 2005). Although SSVEP systems may allow excellent control without training, the flickering stimuli typically produces a degree of annoyance and fatigue. Presenting stimuli above 30Hz (to approximately 50Hz) can provide a better user experience as it is prone to less flicker and, therefore, annoyance (Volosyak *et al.*, 2011) but with a lower signal-to-noise ratio (Pastor *et al.*, 2003) for the SSVEP components, thus requiring improved signal processing tools. One of the challenges that continues is finding the best stimulation frequencies for a user. Gembler, Stawicki and Volosyak (2015a) proposed a wizard based approach to address this. If this could be reliably deployed in practice it would be a big advance.

For detection, spatial filters may be used to enhance the response (Garcia-Molina and Mihajlovic, 2010). Principal Component Analysis (PCA) seeks uncorrelated components with maximal variance, while Independent Component Analysis (ICA) decomposes signals into statistically independent components.

ICA, PCA, and combinations of both methods have been applied to BCIs based on SSVEP (Friman *et al.*, 2007; Allison *et al.*, 2008). However, Canonical Correlation Analysis (CCA) (Hardoon, Szedmak and Shawe-Taylor, 2004), has become a key algorithm choice for SSVEP (Lin *et al.*, 2007; Zhang *et al.*, 2014). See Chapter 7 for an overview of other spatial filters.

Various techniques have been proposed to enhance the stimulation paradigm. The approaches are similar to the techniques adopted in communication modems to enhance effective bit rate. Multiple stimulation frequencies can be combined into one time-locked stimulus (Cheng *et al.*, 2001; Mukesh, Jaganathan and Reddy, 2006) evoking more SSVEP component power for detection (assuming that the signal processing can decode these components). Another approach adopted is to use the same stimulating frequency but with different phase (Kluge and Hartmann, 2007; Wang *et al.*, 2008). The SSVEP response is phase-locked with the stimulus facilitating target identification. If the Fourier Transform is used to produce a spectrum, the epoch length for analysis should be a multiple of the stimulus period. This reduces the communication throughput (Wilson and Palaniappan, 2009). Garcia-Molina, Zhu and Abtahi (2010) used the Hilbert transform to detect phase, after narrow band filtering of the EEG. The difference between the instantaneous phase of SSVEP and the stimulation-signal reference phase was calculated in order to identify the stimulus. Such phase difference is dependent on the user's SSVEP response to the frequency. Phase synchrony analysis can extract the phase difference between the SSVEP and the reference light signal. The difference between these two values deviates slightly from the expected value, but the difference is sufficient for detection. Bit rates greater than 70 bits/min were reported.

More recent performance results demonstrate a higher ITR in the range of 100 bits/min (Volosyak, 2011). Cited improvements in the signal processing and feedback modules constituted the basis for achieving this accuracy. In their study five out of seven subjects spelled all copy spelling words without errors. SSVEP has also been used for assistive technology application. Gollee *et al.* (2010) developed a LED panel system that allows the control of an FES-based neuroprosthesis. The system is robust, achieving accuracies of typically over 90%. Volosyak, Gembler and Stawicki (2017) explored the effects of age on SSVEP usability. The mean ITR of the young age group was 27.36 (6.50) bits/min while the older age group achieved a significantly lower ITR of 16.10 (5.90) bits/min, showing that the subject age must be taken into account during the development of SSVEP-based applications. ~ less commercilly viable

2.2 *h*BCI with Eye Gaze

This section provides a review of BCI hybrids in which the BCI is combined with an additional input modality coming from eye gaze metrics. Consideration is given to how eye gaze can be combined with BCI methods to enhance the robustness of the BCI decision making (*explicit use*) or to infer (*implicit use*) information about user engagement with computer-based applications through associating gaze location onscreen to EEG responses. **Error! Reference source not found.** illustrates eye gaze combined with BCI for both explicit and implicit interaction. In (a), the Eye Tracker signal is employed for search activity with subsequent use of BCI signal to provide command decisions; in (b), classification employs explicit use of BCI signal and Eye Tracker signal as feature vectors in a combined classifier in which each input reinforces the output classification; in (c), the Eye Tracker signal is implicitly used to identify onscreen components of interest. By analyzing the epochs of the BCI signal which correspond temporally to the spatial onscreen component of interest then some output decision can be made.

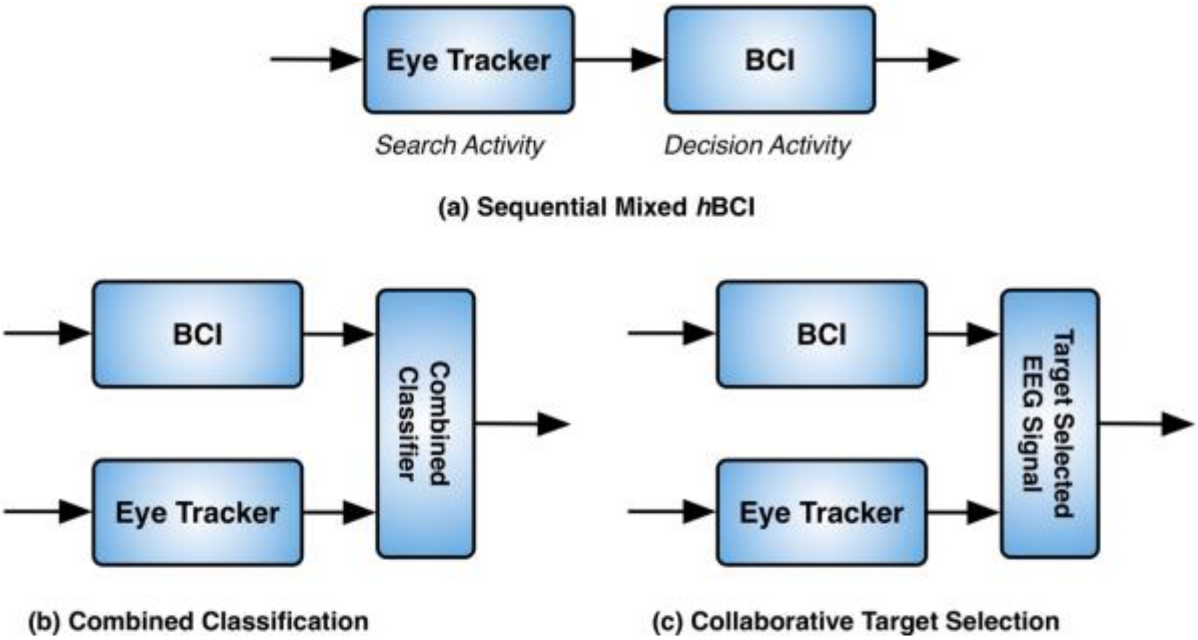

Figure 2: Explicit and Implicit use of eye tracking and BCI: (a) Sequential mixed *h*BCI (b) Combined classification; (c) Collaborative target selection

One of the benefits with BCI systems relying solely on EEG is that they require no peripheral movement by the user, in particular, eye movement. Although the extent to which this is true for visual evoked potentials is under some debate (Brunner *et al.*, 2010) and (Treder and Blankertz, 2010) observed a drop in performance within ERP-based BCI when attention was not overt, i.e. with a user unable to shift their gaze to the object of interest. For a review on eye-gaze independent auditory and tactile BCI please refer to Riccio *et al.* (2012).

In contrast, ET is an assistive technology relying on gaze direction and is widely accepted by users up to the point when gaze control has been lost (Pasqualotto *et al.*, 2015). Combining active eye gaze technology with BCI can bridge the gap between the two systems. In particular, eye trackers used to navigate on screen commands can meet challenges when a decision or action needs to be confirmed.

Dwell-time[1] is an example technique used to activate a command. Here a subject gazes at an object for an intended length of time, notably longer than natural gaze behavior and thus indicating an desired action. However, this interaction can lead to unintended selection if the duration of the dwell time is too short. Alternatively, BCIs could lend themselves to performing this 'switch' (Zander *et al.*, 2010; Amiri *et al.*, 2013) operation to perform the selection, thereby providing a greater level of intentional control to the user (Figure 2a).

Early EEG responses referred to as Eye Fixation-Related Potentials (EFRPs) have been investigated as a method to provide insight on '*the cognitive processes that occur during a single eye fixation'* (Baccino and Manunta, 2005). The combination of analysing ET with EEG is of great interest in the research of lexical processing with ERP components (P1, N1 and P2, between 100ms and 200ms post-stimulus) offering potential understanding of the cognitive processes (Sereno and Rayner, 2003). Such insight can subsequently be utilised to automatically augment the HCI in response to ET and EEG patterns to enhance usability and personalisation to the needs of the user.

Implicit selection of relevant onscreen content was demonstrated by (Eugster *et al.*, 2016) through their development of a natural interface for reading onscreen text and inferring the user's interest in the content that their eyes were focused on. Their system used a combination of eye gaze and 'semantic' ERPs to classify if the particular words onscreen had relevance to the reader. By gathering this information from user's interaction with online material, they developed a participant-specific single-trial prediction model based on word relevance. This model was then used to search for more relevant online content and provide recommendations to the user. For all their participants, they found it possible to distinguish between two classes of relevant versus irrelevant words by looking at the grand-average-based ERP between 300 ms and 600 ms. This extends beyond the initial window for EFRPs (Rama and Baccino, 2010).

One of the challenges that faces the combination of ET and ERPs is that user recognition of an onscreen target can occur in the foveal or peripheral vision. Wenzel, Golenia and Blankertz (2016) investigated this variability of the latency between the recognition of the visual target object and the corresponding evoked response. They performed a gaze search task in which there were targets and distractors. EEG epochs were captured over 800ms after fixation-onset. They found that despite such variability ET data can be effectively correlated with brain activity to provide '*appearance aligned EEG features'* to determine user interest of visual online material.

Hild *et al.* (2014) show that the use of ET and EEG to allow spatio-temporal event selection. Their system, (Putze *et al.*, 2016), combined eye gaze with BCI to enable the implicit selection of onscreen objects from non-target objects within a graphical user interface without the need for manual user intervention. By using eye gaze to determine where on screen the user is looking and combining this with ERP changes in

[1] Dwell time is the time that a user focuses on a screen object, with gaze set stationary

brain activity, they found it possible to determine the onscreen object of interest to the user, and hence the user's selection. They did not suggest their method as a sole selection mechanism for a user interface but instead for it to be part of a combined approach (Putze, Amma and Schultz, 2015).

The concept of '*Cortically Coupled Computing'*, presented by (Gerson, Parra and Sajda, 2006), uses the ability of the human brain to rapidly analyze a visual scene at a glance for the purpose of triaging images. Through EEG analysis during *rapid serial visual presentation* (RSVP) of a series of images they can determine those images of greatest relevance. A more recent review of Cortically Coupled Computing is provided by (Saproo *et al.*, 2016). They make the distinction between BCI systems in which the user actively performs a task which leads to a decision classification and the implicit or explicit monitoring of brain states to infer the decision through machine learning without a priori information. They provide the example of cortically coupled computer vision in which eye gaze is used to determine the object that the user is viewing while their associated brain state information is being analysed to determine or infer some condition, for example, a target image selection. Their goal for this process is to allow the images to be automatically '*tagged'* through the response from the EEG. By collating large amounts of data, machine learning approaches can be employed using supervised learning to tag patterns in unknown data.

From these examples, it can be determined that ET can be effective in associating temporal EEG, and hence user brain state information, with spatial objects such as images or onscreen text. Achieving this is not without challenges but offers a promising input modality (Nikolaev, Meghanathan and van Leeuwen, 2016; Ušćumlić and Blankertz, 2016). The main challenge, as always is decoding and understanding the EEG given the high levels of competing sensory, motor and cognitive processes. The human and software form a closed loop, and the software may have to adapt to continue to extract information. The EEG activity is non-stationary and may change over time, due to attention, tiredness, familiarisation and habituation effect, and the use of alternative interaction strategies.

Eye gaze is a natural interaction method for an onscreen application; however, users have free eye movement and may unintentionally fixate on undesired areas, thus implementing unwanted actions. This is referred to as the *'Midas Touch'* problem in which free eye movement can cause unintentional selection. Methods such as setting a certain dwell time on a fixation point or using intended eye blinks have been used to help make the selection with ET-based interfaces (Holmqvist *et al.*, 2011). Combining ET with another form for making the decision can help resolve unintentional actions. This is demonstrated by (Shishkin *et al.*, 2016) in which they combined ET with EFRPs to enable control over a game solely using eye movement. By analyzing the EEG they were able to differentiate between intentional fixations and spontaneous fixations. Finke *et al.* (2016) also demonstrate the possibility of using EFRPs combined with ET for HCI.

Combining ET with a more explicit BCI decision mechanisms, namely SSVEP (or MI and P300), can also help make a more robust system. Huang, Lo and Shi (2013) present a hybrid BCI with ET to perform a continuous cursor control task. Here, the user is asked to navigate a cursor around on screen obstacles towards a target position. They use MI to decide if the cursor movement is an intended action, thus providing more control over the cursor movement.

Yong *et al.* (2011) propose an ET and BCI hybrid which incorporate on/off states for intentional control. When on, BCI operation is active and selection can be made using a MI task. If off, no BCI interaction is used. This is done to restrict possible false positives when operating the BCI in a self-paced manner. The system demonstrated is for a speller operation in which the ET points to the letter or word, the user would fixate on this item for a certain dwell time, then activate a selection through BCI interaction based on the MI paradigm. They report a lower true negative/false positive ratio with their system as compared to similar systems, highlighting the additional computational load and the importance of choosing a suitable dwell time so not to impact speed performance.

A combination of SSVEP with ET is presented by (Hwang *et al.*, 2012) for a spelling application. This example incorporated a web camera for ET with a custom made QWERTY keyboard in which each letter displayed an associated LED key with a unique frequency. The SSVEP speller in this example is not screen based but through a combination of the ET and SSVEP classification between each of the characters is obtainable, reporting a mean accuracy over 5 subjects of 87.58% and a mean ITR of 40.72 bits/min.

In general, the search and select combination of ET and BCI offers a promising solution to the difficulty in robust selection through ET alone. Naturally, as the previous examples demonstrate, ET is used to locate an object of interest on the screen. A BCI paradigm such as MI can then be used to activate the command (Zander *et al.*, 2010). There are examples, however, where the eye gaze is used to determine spatial locations within an environment in order to select a device that the user will then communicate with via the BCI (Valbuena *et al.*, 2011). This is an example of how the environment in which the user is situated can provide context to the decisions available to the user. Comparably, a simultaneous BCI combining MI with ET has been proposed by (Meena *et al.*, 2015) with the goal to increase the number of available command choices. As with (Valbuena *et al.*, 2011) the eye gaze is used to detect (*search*) the spatially located device, while the BCI (MI) is used to perform selection.

3.0 EYE GAZE AND SSVEP HYBRID BCI

The versatility and usability of ET as an input metric to complement EEG and BCI systems has been demonstrated in section 2. The example presented in this section details the method in which ET is employed to navigate (*search*) a computer screen for a target object, while the BCI, which in this case is SSVEP, is then used to instigate a command (*selection*). In this specific example, the ET has been used to provide the on screen selection of directional arrows for navigation through a user interface to control domestic appliances (Galway *et al.*, 2015). The SSVEP then performs the switch operation in order to activate the desired movement through the user interface or to activate a command on an external device.

This allows us to understand the interplay between eye gaze and SSVEP components in the decision process for a task-based user interface comprising four possible on-screen selections. The following sections provide an overview of the design of the hybrid architecture. It includes the combination of an existing SSVEP solution with a commercial ET collaborating through a custom designed user interface, displaying both navigational options and visual stimulus (Volosyak, 2011; Galway *et al.*, 2015). An example experimental protocol is provided, and a study to measure ITR, accuracy and efficiency was carried out on healthy volunteers (Brennan *et al.*, 2017). The evaluation aims to highlight the intricacies of combining the two modalities into a usable system.

3.1 Concepts for the Inclusion of ET into the *h*BCI

Due to collaborative decision making, a *h*BCI may be endowed with slower information throughput in comparison to a single modality BCI, however, we hypothesise that it will provide more robust HCI by enhancing accuracy, we can reduce the number of incorrect decisions and hence improve efficiency.

Typically, it is considered that an increase in accuracy can lead to a slower speed of operation, thus a reduction in efficiency while increasing effectiveness. However, by making a more robust system with a higher accuracy we hypothesise that there will be a reduction in incorrect decisions and hence an overall reduction in total decision classifications needed to perform a set of tasks. Thus, this can offer a reduction in the overall duration for these tasks. This aligns with the ISO 9241 (ISO, 1998) definition of efficiency which relates to the resources expended with regards to the accuracy and completeness of the goals achieved. The full extent of this improvement depends on any increase duration of an individual classification versus the duration needed to correct failed decisions within a set of tasks.

Our *h*BCI architecture, described herein, comprises two complementary modalities: (1) SSVEP-based BCI; (2) ET using a low cost eye tracker (EyeTribe). The BCI software component, similar to (Volosyak, 2011), was employed for onscreen frequency modulated stimulation and signal processing.

The introduction of ET as a complementary technology removes the need for the precise tuning of EEG parameters, in addition to potentially overcoming the Midas Touch problem that would occur with the use of ET alone, as the *h*BCI will only make a selection when the gaze-fixation point corresponds with the SSVEP decision. Consequently, this permits SSVEP parameters that would normally lead to usage instability with an SSVEP-only BCI to be used successfully. Furthermore, the command classification decision is now a collaborative one. Of course, the eye tracker should also be calibrated, however, this is a more straightforward and generally more stable process.

The tasks facilitated by the *h*BCI system require a 4-way command choice (*left*, *right*, *up*, *down*) that influences a menu system, which is utilised in order to actuate events in a 'smart environment'. This environment comprises a number of rooms, fitted with appliances that can be controlled by computer actuation. Metrics traditionally used to define performance are: *Accuracy (Acc.)*, *Efficiency (Eff.)* and *ITR*. There exists a degree of interplay between these measures; for example, in some cases, SSVEP-BCI *ITR* can be improved at the expense of *Acc.* and *Eff.;* but this leads to frustration for the user as task errors may have to be corrected. Correspondingly, the operator of the BCI system can tune the operation of the SSVEP by adapting the frequencies and thresholds that are used to classify commands. To add complexity to the process, these variables are typically subject specific and may also change over time due to habituation and tiredness during a long session (i.e. in excess of one hour). Due to the amount of operator intervention, it may then be difficult to compare performance across subjects or subject groups.

3.2 Visual Interface Application Design

The first component to be discussed is the design of the user interface application, which facilitates user interaction, and provides feedback and assessment of both system and user performance. In this *h*BCI architecture, we focused on the design of an interface that allows interaction and actuation of local events within a domestic smart environment. The example application was originally developed to address needs of a brain injured user group with motor impairment. It followed on from investigations as part of the BRAIN project (BRAIN Project, 2011).

The user interface design followed HCI recommendations (Nielsen, 1995) and a user evaluation from the brain injured user group (BRAIN Project, 2011; Ware *et al.*, 2014). A screenshot of the developed user interface is shown in Figure 3. The visual interface was structured hierarchically and allowed the user to navigate Left, Right, Up, or Down in order to traverse through nested menu levels to select items. Users operate devices (e.g. control home lighting or the kitchen extractor fan), interact with multimedia applications, or communicate via predefined iconography and auditory feedback. The interface was additionally designed to be controlled using standard computer input peripherals and through receipt of packets across a network.

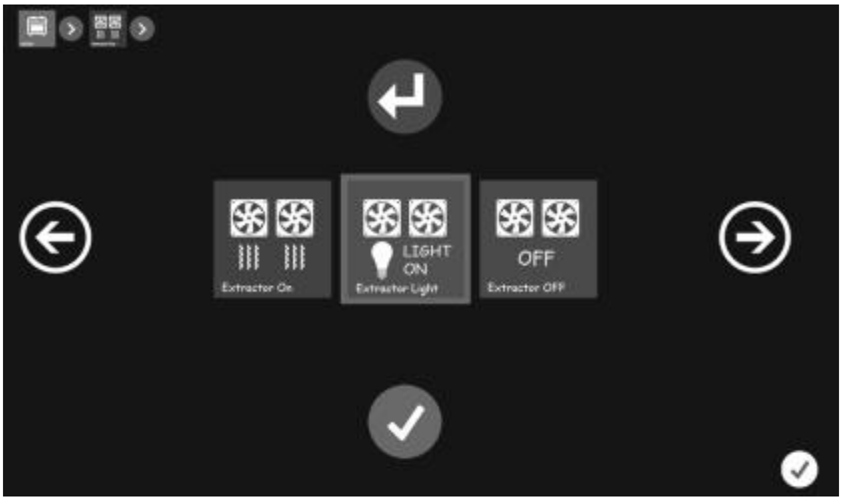

Figure 3: The visual interface comprising 4 choices: Left, Right, Up, Down. For example, at this point the user is controlling a fan within the kitchen.

3.3 The Eye Tracking Component

The second component of the *h*BCI architecture is the design of an algorithmic process to facilitate ET-based control, which should be structured around the number and location of selectable icons. In our example, there are four active icons located to the left (Left, L), right (Right, R), top (Up, U), and bottom (Down, D) of the interface. Each icon is selectable via dwell-time, (Holmqvist *et al.*, 2011), thereby allowing the selection of items based on gaze-fixation time. The approach employed divided the visual display of the interface into quadrants Figure 4. The metrics from the eye tracker provided onscreen co-ordinates for the user's gaze, and thus, which quadrant the fixation point fell within, and for what period of time during operation. Figure 4 illustrates the ET selection zones utilised by the ET control algorithm.

As may be observed in Figure 4, the screen resolution of a 'full HD' monitor (*1920px*1080px*) used for the *h*BCI was divided into four quadrants, each measuring *540px* in width and *960px in height*, along with a '*No-State Zone'*, measuring 200px in width and 400px in height, which was designated centrally. If the gaze-fixation point was situated within the no-state zone, then no decisions could occur. Such a structure allowed menu icons to be located in this area, so that a user could freely observe the changes they were affecting without accidentally triggering false positive commands. Each quadrant was then further divided diagonally based on a simple linear equation and therefore a selection could be determined based upon the portion of the quadrant that the user was fixating upon.

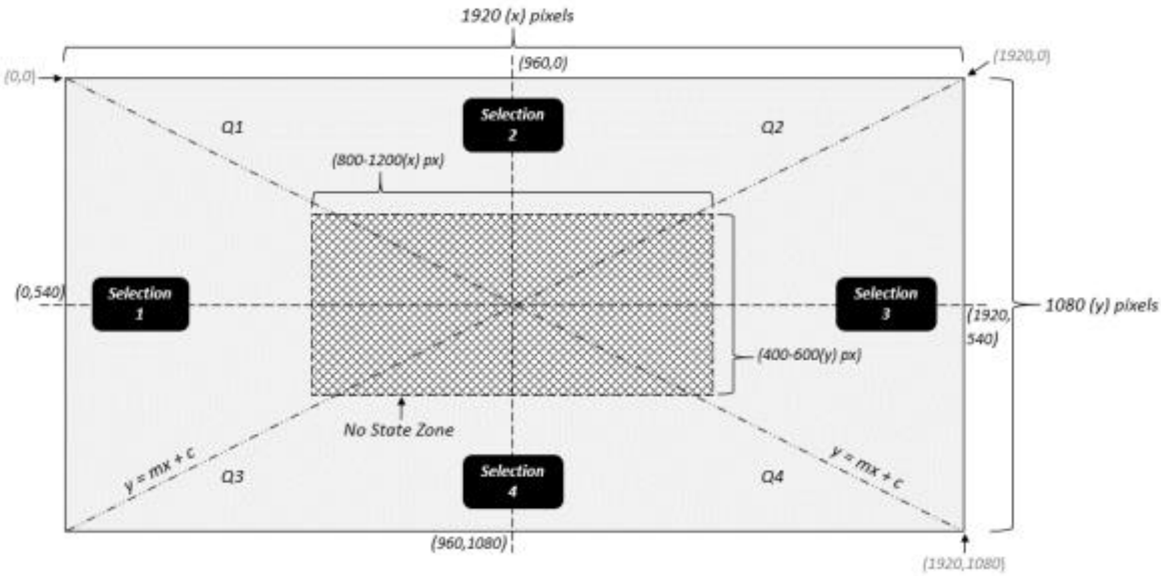

Figure 4: Eye tracking zones.

3.4 The SSVEP BCI Component

The design of the BCI component needs to consider the intended hardware which will be used to capture the EEG recordings. If utilising a low-cost commercially available EEG acquisition device, there may be a trade-off between cost and performance. In one of our early iterations, we employed the Emotiv EPOC as our method of EEG acquisition but were unable to achieve acceptable performance for SSVEP paradigms due to the restrictions on electrode placement and the low Signal-to-Noise Ratio (SNR).

Since the design of the BCI component centred on the use of the SSVEP paradigm, acquisition of EEG was handled by the g.USBamp, g.GAMMAcap, and g.LADYbird passive electrodes (www.gtec.com), which provided flexibility regarding electrode montages and a much higher signal-to-noise ratio. As the SSVEP response emanates most prominently from the visual cortex, positioning of the electrodes over the occipital region of the cerebral cortex was required. Utilising the International 10-20 system, the recommended positioning for SSVEP recordings was employed: AF_Z *(Ground)*, C_Z*(Ref)*, P_Z, PO_3, PO_4, O_1, O_Z, O_2, O_9, and O_{10}. In a passive electrode setup, it is particularly important to prepare and gently agitate the skin with an abrasive solution to reduce impedance below 5kOhms (although 10kOhms probably suffices in practice). Values for electrode impedance can be returned using acquisition tools, such as those available in OpenViBE (http://openvibe.inria.fr/), which was utilised within the work carried out herein.

SSVEP signal detection and classification utilised the Minimum Energy Combination (MEC) (Volosyak, 2011) method to create a spatial filter and enhance the SSVEP response while reducing ambient signals and other interference. The system automatically determined the best spatial filter for each subject at each frequency. Each stimulating frequency in the EEG was detected by spatial filtering, power estimation, and a probabilistic method, which enhanced the signal at each electrode location. If classification of the input signal was not possible using the initial, shortest timeframe for the input vector, a longer timeframe was subsequently used. The adaptive windowing technique automatically extended the timeframe of the input vector in order to facilitate data processing (a maximum of four potential epochs resulting in a 'window' of approximately 4 seconds) based on the work by (Durka, Kus and Zygierewicz, 2009).

The *h*BCI uses SSVEP stimulation frequencies that are a division of the display refresh rate (100Hz) to ensure that they are reasonably constant. Verification of screen-based stimulation frequency used an external Arduino-based photodiode tool to independently measure flicker rates. Indeed, high accuracy is not necessarily a requirement here, as long as the stimulation frequencies (i) induce a feature that can be reliably detected using spatial filter/MEC approach (ii) the components are sufficiently different so that a 4-way decision can be enacted. The modulation used is rectangular (i.e. on/off) and only a subset of frequencies can be used so that division do not produce the same component. Manyakov *et al.*, (2013) have demonstrated that more sophisticated modulation techniques allow finer grained frequency coverage that is independent of refresh rate; this could allow many more stimuli for other applications or indeed reduce the need for a hierarchical menu structure. Gembler et al. (Gembler, Stawicki and Volosyak, 2015b) conducted an experiment with seven subjects and showed that six could reliably detect 28 individual SSVEP targets (22-120bits/min), and two could control a screen comprising 60 modulated targets (24-73bits/min) (Gembler, Stawicki and Volosyak, 2015a). Clearly these advances could influence the design of the interaction (beyond 4-way) and facilitate easier interaction.

3.5 The *h*BCI Architecture

The final aspect of the *h*BCI design was to create an architecture that combines the ET and BCI components, and to implement a decision-making algorithm. The ET component was implemented within the visual interface application. Consequently, the visual interface had to wait until receiving a corresponding vote from the BCI component before a selection could be made. The dataflow and overarching architecture of the *h*BCI is presented in Figure 5.

As may be observed in Figure 5, utilising functionality within the associated SDK, the Eye Tracker component repeatedly acquires screen coordinates at 128 samples per second for each eye gaze event, which are also timestamped for subsequent offline analysis. Simultaneously, the BCI component acquires and processes the raw EEG signal, resulting in a command decision, which is then encapsulated in a User Datagram Protocol (UDP) packet and transmitted to the Data Fusion Module. The EEG data can be used for further offline analysis. Once the Data Fusion Module has received the coordinates from the Eye Tracker component and the command derived from the BCI component, it performs further processing and comparative analysis in order to determine whether or not there has been a unanimous agreement in the choice of command.

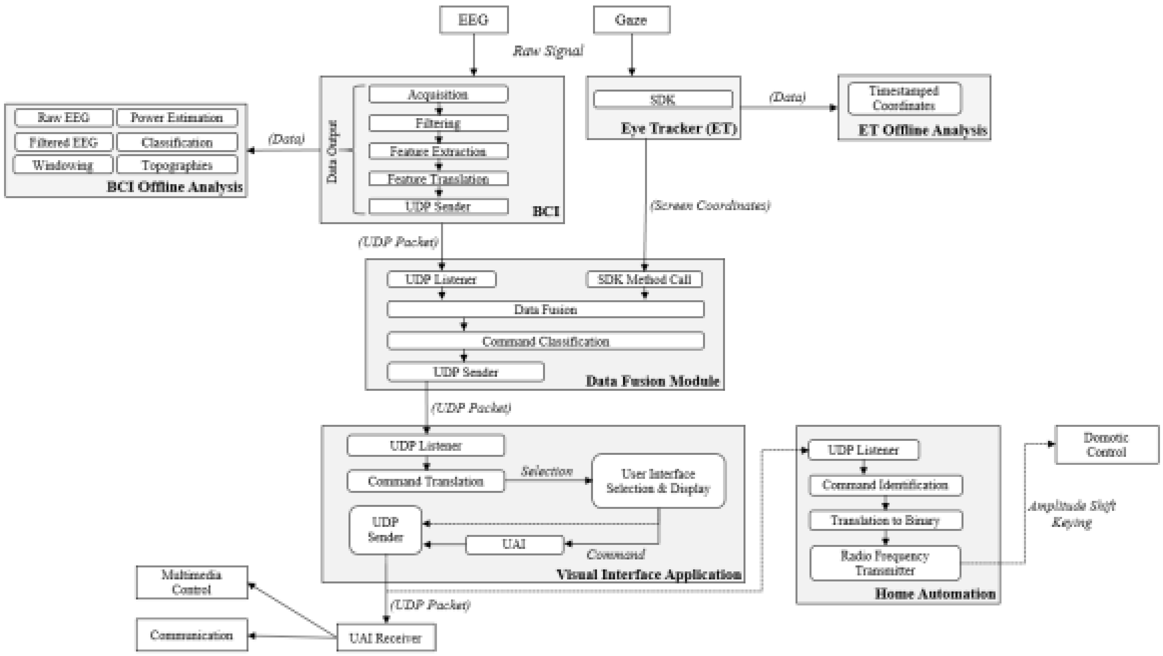

Figure 5: The *h*BCI system architecture and corresponding data flow

For both the ET and the SSVEP, determination of the current ET zone, based on the co-ordinates, or a classified SSVEP command relates to independent votes for. The ET vote for each command increments/decrements based upon the fixation point until they exceed the dwell-time threshold. When this is the case, an ET command is transmitted to the Data Fusion Module. SSVEP votes are based on the power estimation of detected frequencies, which classifies the SSVEP response and also transmits the SSVEP command to the Data Fusion Module. When both votes are in agreement a collaborative selection is performed. This is to reduce the chance of a false classification.

If agreement occurs, a collaborative command is subsequently issued by the Data Fusion Module, encapsulated within a UDP packet, and transmitted to the Visual Interface Application in order to execute the relevant command. Depending on the menu item selected within the visual interface by the agreed command, the UDP packet containing the command may be additionally transmitted to an external receiver in order to perform an action on an external peripheral, e.g. switching on/off a light via a home automation system. Table 1 provides further details.

By contrast, if no agreement occurs, no command is issued by the Data Fusion Module, and the voting levels are reset, which subsequently results in a delay occurring before the next command may be potentially issued. Consequently, a more sophisticated fusion of the SSVEP and ET components is needed to further enhance the overall operation of the system. Furthermore, through observation of the recorded EEG sessions there is evidence that the ET or SSVEP should be allowed to dominate the classification at a particular time, dependent on the current operation. In other words, if one of the components is failing then a mechanism needs to be in place to allow the operational component to lead the classification or to allow the voting level to be reduced to activate the classification earlier.

Table 1: Component of the hBCI: SSVEP and Eye Tracker

Module	**Activity**	**Attributes**	**Comment**
EEG	BCI acquisition	Acquisition, filtering, feature extraction, feature translation	Standard acquisition using gTec USB amp
EEG	BCI Offline analysis	Spatial filtering, power estimation	Signal analysis using Minimum Energy Combination (Volosyak, 2011)
Gaze	SDK	screen coordinated, timestamp	Screen co-ordinates extracted and sector determine, timestam0p added for synchronisation with SSVEP-BCI component
Data Fusion	Software component that listens to interface (UDP listener)	Which Command? SSVEP && ET	Combines BCI and eye gaze parameters to make a 'hard' decision
Visual Interface	See Figure 3	4-way choice (R, L, U, D)	Interaction between user (BCI + ET) and environment used to navigate and select
Home Automation	UAI, User application interface	Radio frequency Amplitude shift keying, can be interchanges with raspberry PI server	Interact with environment to provide domotic control, e,g. play a video, switch on a light
Communication protocol	UDP	UDP sender, UDP listener	Asynchronous activity at visual interface

3.6 Experimental Protocol

Evaluation of the *h*BCI system was performed by creating an experimental protocol and conducting user trials. With such a *h*BCI, we recommend using a dual-monitor setup, with the experimenter operating on monitor one, and the participant interacting with monitor two.

The experimenter initialises the BCI acquisition and ET software, and launches the user interface. This displays command data, data logs containing internal values from the SSVEP algorithm and ET co-ordinates, and EEG and eye signal visualization. Monitor one is also used on BCI setup of the EEG electrodes on the user's scalp to ensure that impedances have been suitably reduced. Additionally, the experimenter launches the ET calibration tool and displays this on monitor two for user interaction. The participant focuses on monitor two; they are asked to follow the instructions to fixate on certain areas on the screen. The experimenter monitors the calibration from screen one, establishing if a suitable level of accuracy has been achieved. If not the ET calibration process is repeated. Distance from the screen, environmental light condition and the use of spectacle are all consideration for this calibration.

Once the BCI and ET have been setup the experimental protocol may begin. As with the setup, the participant should only focus on monitor two, which is employed to display the visual interface. For the set of tasks defined within the protocol, the experimenter should provide the participant with instructions on the command to issue, however, in one of the predefined tasks (Task 4) the participant is given free control of the system in order to complete a pre-set goal. Participants are instructed to complete the following set of tasks:

1. Task 1 – Lights (Total = 13)
   Navigate to Dining Room, turn on the Lamp, and return to Back Garden. The sequence of commands is: R-R-R-R-D-R-R-D-U-L- L-L-L.

2. Task 2 – Media Player (Total = 25)
   a) Navigate to Living Room, select Home Media menu, select Home Cinema, select the "Exoskeleton BCI" video, return to Home Media menu, select Controls and play video. The sequence of commands is: L-L-L-D-L-D-R-R-D-R-R-R-D (video)

   b) Stop the video and return to high level menu: U-L-L-D-R- D (stop) U-U-U-R-R-R (back to garden)

3. Task 3 – Feelings (Total = 7)
   Navigate to Talk icon, indicate you want to Eat, and return to high level menu. The sequence of commands is: L-D-L-L-D (eat) U-R (garden)

4. Task 4 - Free control
   Freely navigate around the GUI to turn off the extractor fan in the kitchen and return to the starting point (back garden icon).

Each of the tasks should be assessed in terms of *Acc*., *Eff.* and ITR. Accuracy is calculated as follows:

$$Accuracy = \frac{P_{total}}{P_{max}} * 100$$

where P_{total} is the total number of correct commands and P_{max} is the maximum number of detected commands. Efficiency as defined by Volosyak et al. (Volosyak *et al.*, 2009) 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 visual interface layout) and C_{total} is the total number of detected commands. Finally, within the BCI community, ITR is the most widely used metric for performance evaluation (Gao *et al.*, 2014) and was first defined by Wolpaw *et al.* in 1998 (Wolpaw *et al.*, 1998). ITR is calculated as follows:

$$ITR = \left(log_2 M + Plog_2 P + (1-P)log_2\left[\frac{1-P}{M-1}\right]\right) * \left(\frac{60}{T}\right)$$

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.

3.7 Post Processing

The EEG and command data can be analysed offline to further assess performance and visualize information. Plotting the ET data can provide useful information regarding performance. The graph in Figure 6, for example, shows the ET vote for each selection during Task 1. A threshold has been set at a pre-defined value, and until the vote reaches this level of confidence a selection cannot be made. In an ET-only system, the selection could be made as soon as the vote reaches this level, however, in a collaborative system the decision for a selection cannot be made until the BCI is in agreement. If a user's gaze-fixation point moves from within the area associated with the desired command then the voting confidence begins to decline, and could stall operation. From Figure 6, it can be seen that the user began by trying to select the *right* command but for the first five seconds no selection was made, as it was waiting for agreement from the BCI component. Then the second *right* command was made within the next two seconds, as soon as the ET vote met its threshold, suggesting that the BCI vote for the second selection came in before the ET had made its decision. This is particularly important as it indicates that the ET threshold may be set too high, hence a reduction of this threshold could potentially improve the time per selection, thereby the overall ITR. More statistical approaches to combining the modalities could lead to a more robust system with enhanced interaction (Dong *et al.*, 2015).

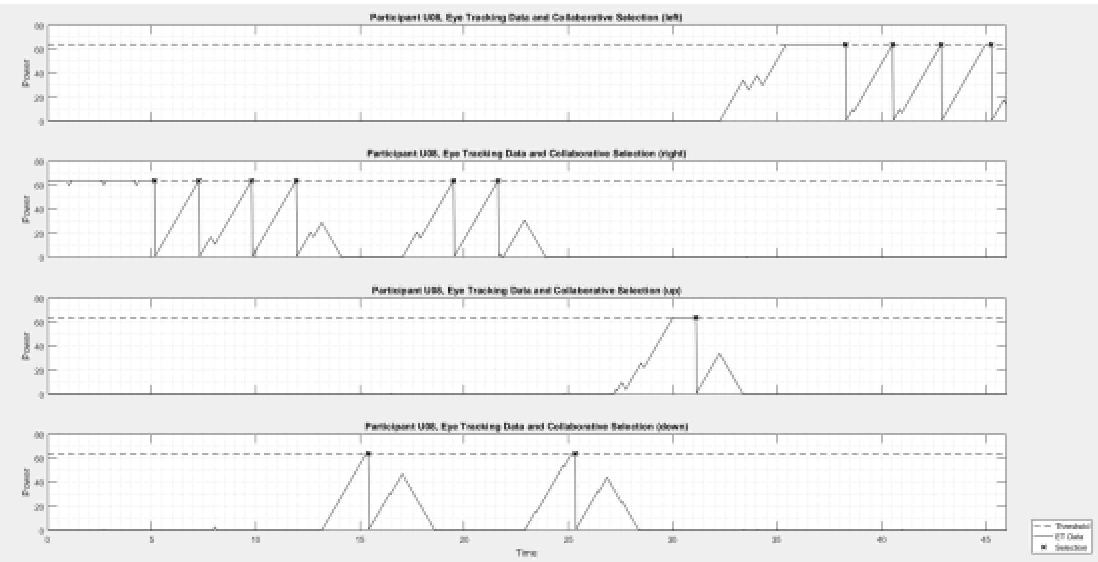

Figure 6: Eye tracking-based vote and collaborative selections for Task 1

It is equally as important to analyse the BCI command detection. In **Error! Reference source not found.**, the signal power of each frequency, left (7.5Hz), right (8.57Hz), up (12Hz), and down (6.67Hz) is displayed. The circles denote a BCI-based command, which can only be triggered once the value of the signal power reaches a pre-set threshold for the BCI decision. Like the ET component, this alone cannot make a selection and must wait for a corresponding decision. This information allows us to establish if the thresholds for BCI-based decisions are too low and classification is made based upon noise level rather than the elicited SSVEP response.

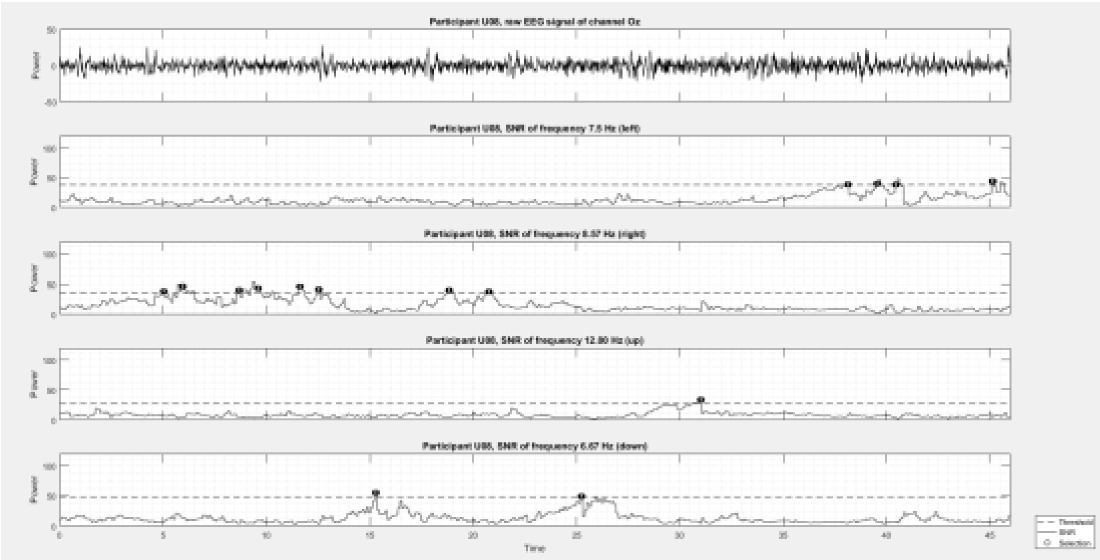

Figure 7: Signal power values and BCI-based decisions for each stimulating frequency for Task 1

To analyse the data from the *h*BCI, it is possible to utilise tools such as MATLAB in order to overlay the ET vote and collaborative selections onto the signal-to-noise ratio values and BCI-based decisions, as shown in Figure 8. Doing so provides detailed information on the experiment and allows future recommendations to be made with a degree of certainty. **Error! Reference source not found.** shows that the participant took approximately 46 seconds to complete Task 1 and executed a total of 13 selections, which is 100% accurate, 100% efficient, and resulted in an ITR of 34.67 bits/min. Further analysis of each individual selection conveys that for 10 of the total 13 selections, the BCI made a decision first, hence the performance was limited by the ET component. The average difference between the BCI and ET decision can then be calculated in order to determine the optimal values for each threshold and therefore, in this case, performance and ITR can be improved by reducing the threshold for the ET decision.

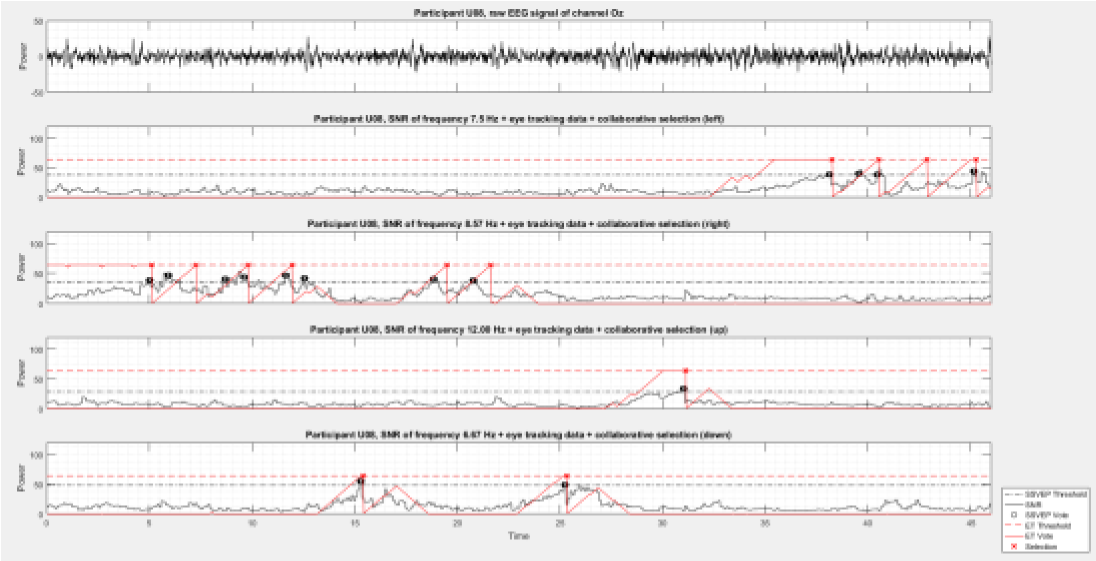

Figure 8: BCI and ET data for a representative participant completing Task 1

In summary, Figure 6 shows the simultaneous eye movement data for left, right, up and down channels and Figure 7 isolates the EEG components for 7.5Hz (left), 8.57Hz (right), 12Hz (up) and 6.67Hz (down). Command classification is based on threshold imposed on these isolated components. In some cases, as illustrated in Figure 8, the EEG makes a classification (denoted by circles) before the eye tracker (red line reaching the threshold appropriate to that zone). Agreed classification (selection) is denoted by crosses. There is, of course, still the potential for false positives and false negatives to occur.

4.0 Discussion and Conclusions

In general, *h*BCI development and different modalities (MI, SSVEP, P300, ET) and approaches (simultaneous/sequential, implicit/explicit) provide us with many possibilities for enhancing performance and for testing acceptance, usability. Figure 6, 7 and 8 serve as an illustrative example, to indicate the data that can be made available to aid the decision process. In some cases the BCI decides first, in others the ET predominates. Currently, the experimenter can influence the decision-making process by tuning thresholds. An automated process to combine these inputs appropriate to the participant and temporal changes with a more sophisticated decision making algorithms would enhance the systems, potentially improving performance metrics.

Error! Reference source not found. illustrates the interplay of some of the constituent components. Each component can utilise tools that have been developed by the BCI community such as BCI2000, OpenVibe or more general signal processing and classification tools such as MATLAB and Weka. Brunner et al. (Brunner *et al.*, 2012) provides a classification of some of these components.

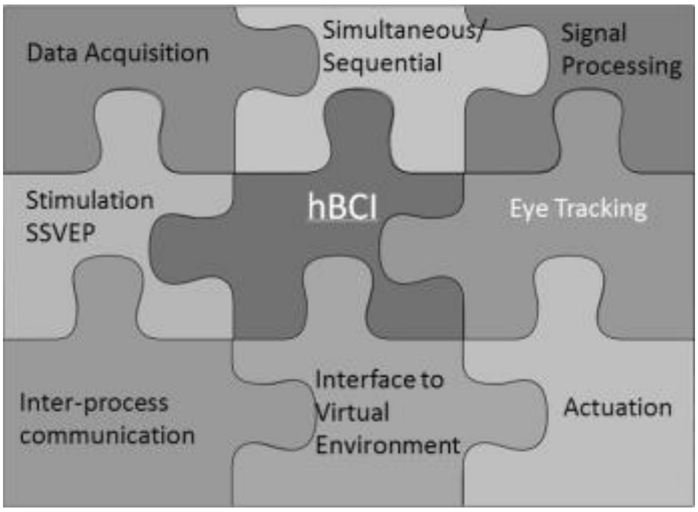

Figure 9: Components of an ***h***BCI system

Component-based modular systems allow the swapping in and out of different components for data acquisition, stimulation and analysis and allow us to test various applications. Standardisation and the use of well-defined APIs is key to expediting development. Low cost (hundreds rather than thousands of pounds/Euros) data acquisition components have become available for recording both EEG and eye tracking. Both are in a fast period of evolution.

Although we have utilised SSVEP and ET, other permutations are of course available. Examples may be found in (Amiri, Fazel-Rezai and Asadpour, 2012; Henshaw, Liu and Romano, 2014). Amiri *et al.* (Amiri, Fazel-Rezai and Asadpour, 2012) discuss the advantages and disadvantages of different EEG paradigm combinations forming *h*BCIs. They highlight that the decision to combine different BCI mechanisms influences the practicality of the data acquisition and how the control signals are isolated from the EEG. Signal processing and classification methods for the BCI mechanisms could conflict with each other. Hence, effort is needed to determine analysis and classifications strategies that are tuned for each BCI component of the hybrid system.

When we adopt more than one modality then we need fusion of the decision making process. If based on agreement to reinforce the decision, as is in the case presented here, failure to agree can cause a noticeable delay which will be obvious to the user and the command will eventually fail (time out). The experimenter may be able to pinpoint whether this was due to SSVEP or ET performance. Parameters can then be modified intuitively, e.g. reduce threshold for SSVEP 'up' command activation. This will of course be manifest in reduced ITR and diminish usability. Indeed, there is an obvious need for a more sophisticated approach to scoring classified commands rather than our existing approach that requires both systems to 'agree' within close epochs of operation.

The interaction between a MI BCI and onscreen ET has been refined by (Dong *et al.*, 2015). In their hybrid system they reinforce the decision making process by combining a 4-class MI BCI with the eye trajectories coming from the eye tracker using a probabilistic Bayesian approach. The goal with their system is to facilitate more natural interaction rather than explicit eye gaze. The paper provides a good example of how refinement of the combined systems can lead to a more elegant and robust solution.

Overall our experience and initial results indicate that the *h*BCI provides increased reliability when compared to SSVEP or ET alone (for healthy subject volunteers). Vilimek and Zander (2009) reported that this reliability came as a cost to the ITR, however, our study has shown that this may not be the case. The reason being that even though the time per individual selection may have increased, there is a reduction in the number of commands required to complete each task due to the improvement in accuracy. This, in turn, is a factor in the calculation of the ITR.

Volosyak (2011) has reported a peak SSVEP ITR 124 bits/min, which shows that development in BCI alone has further to go. Indeed, adding more 'intelligence' to the environmental devices has been demonstrated to enhance BCI function and improve self-calibration (Faller *et al.*, 2012; Cavrini *et al.*, 2014; Schettini *et al.*, 2014; Jarosiewicz *et al.*, 2015). In some applications, this reliability may be key to acceptance by users; in others, such as gaming for example, ITR and robust operation will predominate.

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