Exploiting EEG-extracted Eye Movements for a Hybrid SSVEP Home Automation System

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Abstract: Detection of eye movements using standard EEG channels can allow for the development of a hybrid BCI (hBCi) system without requiring additional hardware for eye gaze tracking. This work proposes a hierarchical classification structure to classify eye movements into eight different classes, covering both horizontal and vertical eye movements, at two different gaze angles in each of four directions. Results show that the highest eye movement classification was obtained with frontal EEG channels, achieving an accuracy of 98.47% for two directions, 74.38% with four directions and 58.31% with eight directions. Eye movements can also be classified reliably in four directions using occipital electrodes with an accuracy of 47.60% which increases to around 80% if three frontal channels are also included. The latter result was used to develop a hybrid SSVEP home automation system which exploits the EEG-extracted eye movement information. Results show that a sequential hBCI gave an average accuracy of 82.5% when compared to the 69.17% obtained with a standard SSVEP based BCI system.

1 INTRODUCTION

Electroencephalography (EEG) is the recording of brain signals using non-invasive electrodes, typically used for the development of EEG-based brain computer interface (BCI) systems. One of the most promising BCI systems is that based on steady-state visual evoked potentials (SSVEPs) which are elicited in the occipital region of the brain when the subject attends to a set of flickering stimuli. When making use of such a system the user carries out a series of eye movements to saccade from one stimulus to another, selecting a sequence of command functions in the process. Eye movements have been used in hybrid BCI systems aimed to improve the BCI performance either by recording electrooculographic (EOG) signals (Padfield, 2017) or through a vision based eye gaze tracker (Saravanakumar, 2018). The former however requires an extra set of electrodes placed around the subject's eyes whereas the latter requires additional hardware.

This work investigates the possibility of classifying eye movements typically carried out during the use of an SSVEP-based BCI, using standard EEG signals only, thus allowing for the possibility to design a simple hybrid BCI requiring only the use of an EEG cap. Some researchers (Gupta et al., 2012; Hsieh et al., 2014) took this approach but the classification of the eye movements was limited to horizontal eye movements, typically distinguishing between left and right eye movements only. Belkacem et al. (Belkacem et al., 2013; Belkacem et al., 2015) however attempted to classify both horizontal (left vs right) and vertical (up vs down) eye movements, obtaining an accuracy of 98% for the horizontal and 46% for the vertical eye movements in their most recent work (Belkacem et al., 2015). Dietriech et al. (Dietriech M. P., 2017) also considered the classification of four extreme eye movements and the central position and obtained a true positive rate of 96.6% for one subject using a KNN classifier.

In (Gupta et al., 2012; Hsieh et al., 2014; Belkacem et al., 2013; Belkacem et al., 2015; Dietriech M. P., 2017), frontal and temporal electrodes were used but none of the works investigated the possible detection of the eye movements through occipital electrodes, which are the standard set of electrodes used in SSVEP-based BCIs. Furthermore, eye movements were limited to left, right, up and down move-

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ments. This work thus aims to investigate the extent at which eye movement information can be extracted from the frontal region, occipital region, or both, and whether it is possible to classify a saccadic eye movement of different visual angles. These results are then exploited within an SSVEP-based home automation system where a comparative analysis is carried out to assess the performance of a hybrid BCI which fuses EEG-based eye movement information with SSVEP information and compare it with that of a standard SSVEP-based BCI system.

This paper is divided as follows: Section 2 presents the experimental setup, the processing of data and the method used to classify eye movements, Section 3 presents and discusses the results related to the EEG-based eye movement detection, Section 4 presents the hybrid SSVEP-based home automation system with the results obtained for both an offline and an online study and finally Section 5 concludes the paper.

2 METHOD

2.1 Experimental Setup and Data Acquisition

A computer system with a 22 inch monitor, a resolution of 1920×1080 pixels and a refresh rate of 60Hz was used. The g.USBamp from g.tec was used for EEG data acquisition. The visual stimuli were designed using PsychoPy (Peirce et al., 2019), an open-source Python toolbox, which permits control of the timing of the stimuli with very high precision.

EEG data was recorded at a sampling frequency of 256 Hz from a total of 19 channels: O1, Oz, O2, PO7, PO3, POz, PO4, PO8, T7, FT7, F7, AF7, Fp1, Fpz, Fp2, AF8, F8, FT8 and T8. This set of electrodes was chosen in order to carry out a thorough analysis of which combination of frontal channels is best to extract eye-movement related EEG and to determine to what extent is the occipital region capable of providing such information.

Five healthy subjects participated in this study which was approved by the University Research Ethics Committee (UREC) of the University of Malta. Every participant was seated in front of an LCD monitor, placed approximately at eye-level with the subject. Participants were advised to limit their physical movement to avoid EMG artifacts. A chin rest was provided to restrict head movements. This setup was used to ensure that for this preliminary study the data is not confounded by artifacts.

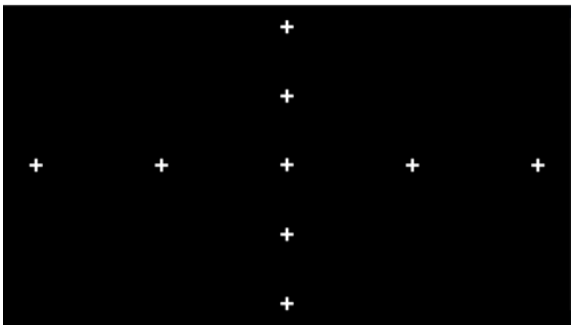

Figure 1: Positions considered on screen for 8 different saccadic movements.

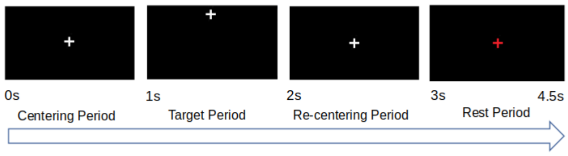

Figure 2: Timing protocol of a single trial.

EEG-based eye-gaze data was recorded for offline analysis. Five sessions were recorded and in each session, 10 trials were allocated for each position, amounting to a total of 80 trials. In a trial, the subject was instructed to look at the center of the screen for 1 second, saccade to one of eight positions on the screen as shown in Fig. 1 for another 1 second and saccade back to the center in the next 1 second. Subjects were instructed to blink only during rest periods which were indicated by a red stimulus at the last 1 second of each trial. The timing protocol of a single trial is shown in Fig. 2. A rest period of 1.5 seconds was allocated after each trial.

2.2 Data Processing

EEG data was filtered with a 4^{th} order infinite impulse response bandpass filter having cut-off frequencies of 0.5 Hz and 7 Hz. Common spatial patterns (CSP) (Ramoser et al., 2000) was then used as the feature extraction method. CSP applies a joint diagonalisation on the covariance matrices of two classes, resulting in a transformation W. This is applied to the EEG data, $X \in \mathcal{R}^{N \times T}$, where N represents the number of channels and T the length of the data, to project this to $Z \in \mathcal{R}^{N_1 \times T}$ with a reduced number of channels $N_1 < N$., The variance of each channel is then used as a feature vector, i.e. $\underline{v} = [\sigma_1^2, \dots, \sigma_{N_1}^2]^T$ where σ_i^2 is the variance of channel i of Z . A support vector machine as in (Bishop, 2006) was then applied to classify features into two classes. Since both the CSP and SVM algorithm require training, the recorded data was divided into three sets; one was used to train the CSP, the other to train the SVM and the third was used as test data. A three fold cross validation approach was then adopted to quantify performance.

2.3 Classifying Eye Movements

A hierarchical classification system was used to classify an eye movement into one of eight possible classes. As shown in Fig. 3, the hierarchy consists of three tiers. At the top tier, epochs are classified as either horizontal (H) or vertical (V) saccadic eye movements. Once labelled, epochs are passed down to the second tier where the H labelled saccades are passed to the 'Left (L) vs Right (R) vs Others (O)' classifier while the V labelled saccades are passed to the 'Up (U) vs Down (D) vs Others (O)' classifier. It must be noted that although three classes are present from the second tier downwards, both the CSP algorithm and the SVM classifier were executed by performing independent pairwise classifications between all pairs of classes and assigning the majority class to the trial (Johannes M. G., 1999), known as the 'One vs One' approach. Epochs labeled as 'Others' within the second tier are passed on to the sibling class on the same tier. For example, a saccade labelled as O by the 'L vs R vs O' classifier is passed to its sibling class, specifically to the 'U vs D' classifier within the 'U vs D vs O' block.

Finally, at the third tier, epochs are classified according to the visual angle of the horizontal or vertical saccade where a visual angle of 23.9° from the screen centre is labelled as 'far' (F), while a 12.5° visual angle is labelled as 'near' (N). For example, trials labelled as L from the second tier are passed to a 'Near Left (NL) vs Far Left (FL) vs O' classifier. Similar to classifiers at the second tier, eye movements classified as O are passed on to their sibling classifier within this third tier.

2.4 Performance across Different Scalp Regions

Part of the analysis carried out was to investigate how the eye movement classification performance varies when considering EEG channels at i) frontal channels, ii) occipital channels and iii) both frontal and occipital channels combined. For the frontal channels, subsets of 11, 7, 5 and 3 channels were also considered as in Table 1.

Table 1: Subsets of considered frontal channels.

Number of Frontal Channels	Frontal Channels
11	*T7, FT7, F7, AF7, Fp1, Fpz, Fp2, AF8, F8, FT8 T8*
7	*F7, AF7, Fp1, Fpz, Fp2, AF8 F8*
5	*AF7, Fp1, Fpz, Fp2 AF8*
3	*AF7, Fpz, AF8*

3 RESULTS

3.1 Hierarchical Classification

Initially, the testing trials were passed through the hierarchical structure and labelled into one of the 8 possible classes. Table 2 shows the classification accuracy of the 7 classifiers within the hierarchy while Table 3 shows the results at each tier. Clearly, the performance is very high at the first tier, with results of the combined or frontal channels exceeding 98%. Hence, classifying between horizontal and vertical eye movements can be done at a very high accuracy using these channel combinations. If occipital channels are used instead, the performance is 71.11%.

As the trials flow through the hierarchy, the labelling of left vs right trials is done with a higher accuracy than that involving up and down trials. Taking the frontal channels option as an example, the L vs R vs O classifier achieved an accuracy of 89.17% while the U vs D vs O classifier reached 73.82%. This work further investigated the possibility of distinguishing between two visual angles, referred to as near and far, in each of the four directions. The results of Table 2 show that left and right trials are more accurately classified as near and far eye movements, than up and down trials. For the former, classification reached 70.83% (left) and 68.06% (right) while

Table 2: Classification accuracies of the 7 classifiers within the hierarchical structure at combined (C), frontal (F) and occipital (O) channels.

	Scalp Region		
	C	**F**	**O**
H vs V	98.61%	98.47%	71.11%
L vs R vs O	88.96%	89.17%	50.21%
U vs D vs O	74.40%	73.82%	53.40%
FL vs NL vs O	64.17%	70.83%	53.40%
FR vs NR vs O	65.42%	68.06%	46.25%
FU vs NU vs O	49.24%	52.50%	37.71%
FD vs ND vs O	47.78%	50.97%	37.08%

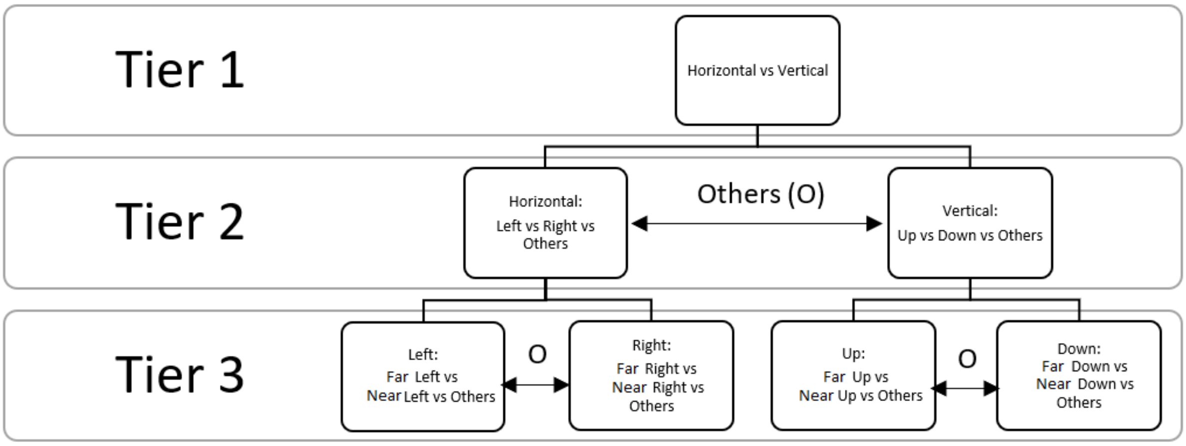

Figure 3: 3-Tiered hierarchical classifier used to classify EEG-based eye movement potentials into one of eight classes.

Table 3: Classification accuracies at each tier of the hierarchical classification structure at different scalp regions.

	Scalp Region		
	Combined	**Frontal**	**Occipital**
1st Tier	98.61%	98.47%	71.11%
2nd Tier	76.51%	74.38%	43.85%
3rd Tier	54.87%	58.31%	28.02%

for the latter the performance was of 52.5% (up) and 50.97% (down). Table 3 also gives a clear indication of how the performance varies across each tier. For the combined channel option the classification is decreasing by around 20% as the number of classes increases from 2 (tier 1), to 4 (tier 2), to 8 (tier 3).

This work also aimed to investigate, for the first time, at which accuracy can such eye movements be classified considering only the standard occipital channels used in an SSVEP-based BCI. These results show that horizontal and vertical movements can be classified with an accuracy of over 70% but this performance decreases to around 43% if classification is carried out between 4 classes, specifically left, right, up and down. Classifying eye movements based on the visual angle becomes more challenging from this set of electrodes with the resulting classification accuracy of the third tier going down to 28% among 8 gaze directions. This means that if such a system is to be used for a hybrid BCI, recordings from frontal channels would be highly desirable to boost performance. The actual number of frontal channels required is further analysed in Section 3.3.

3.2 Distinction between Visual Angle

Given that eye movements corresponding to small visual angles are characterised by small saccadic displacements in the EEG signals, this part of the analysis investigates whether the performance would improve if trials corresponding to only large visual angles are considered. The hierarchical system would now only consist of two tiers and involve a distinction between four classes, specifically left, right, up and down. The results of this analysis are shown in Figure 4 and they are being compared to the classification accuracy obtained when trials of both small and large visual angles progress through the same two tiers in the hierarchy. It must be noted that the first and last block of bar graphs correspond to the classification at the first and second tier respectively. The results show that for combined or frontal channels, the accuracies obtained are comparable for all trials, with and without the inclusion of small visual angles. This demonstrates that trials with small visual angles do not adversely affect the accuracy of detection of eye movement direction.. However, if occipital channels only are used, as in a standard SSVEP-based BCI system, the eye movement accuracies not only decrease substantially, but if trials with both small and large visual angles are used, the performance is statistically significantly lower than if only trials having large visual angles are used. These results indicate

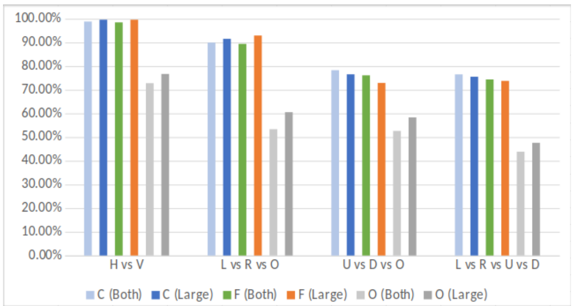

Figure 4: Classification accuracies within a two-tier structure when using trials with both small and large visual angles (‘Both’) and large visual angles only (‘Large’) for the combined ‘C’, frontal ‘F’ and occipital ‘O’ case.

that occipital channels alone may only be useful, at most, to distinguish between horizontal and vertical eye-movements.

3.3 Analysis on the Amount of Frontal Channels

Table 4 shows the classification accuracies obtained at the three different scalp regions considering a two-tiered hierarchy. Using only occipital electrodes, a classification performance of 47.60% is obtained after the second tier but the performance of the combined channels increased to 75.52%. This result however was obtained by including 11 frontal channels with the occipital channels. This analysis thus investigated how eye movement classification performance varies when reducing the frontal channels according to Table 1. Figure 5 shows that the classification performance remains very stable even when reducing the number of frontal channels down to three. This means that if 3 frontal channels were included with the occipital channels typical of a standard SSVEP setup, it is possible to classify eye movements into four classes with an accuracy of close to 80%. Results using frontal channels only indicated that a similar performance to that of Figure 5 could be obtained, with an accuracy around 80% when using three electrodes. This may be useful for any type of BCI system which needs to exploit this eye movement information in four directions with large visual angles.

Table 4: Classification accuracies of the two-tiered hierarchical system for the combined (C) frontal and occipital scalp regions, frontal (F) only region and occipital (O) only region.

	Scalp Region		
	C	**F**	**O**
H vs V	99.58%	99.58%	76.67%
L vs R vs O	91.53%	92.92%	60.56%
U vs D vs O	76.53%	72.92%	58.33%
L vs R vs U vs D	75.52%	73.75%	47.60%

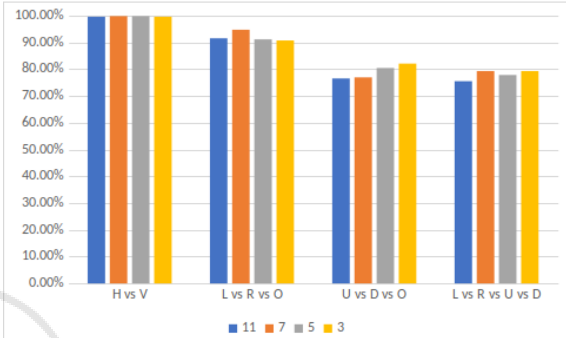

Figure 5: Classification accuracies of four different classifiers when considering 3, 5, 7, or 11 frontal electrodes only.

4 HYBRID SSVEP HOME AUTOMATION SYSTEM

Based on the results of the previous sections, a hybrid SSVEP based home automation system was designed with the main menu as shown in Figure 6. The commands at the top and bottom of the menu correspond to TV controls, those on the left control the on/off switch of a lamp and fan, and those on the right allow for the opening and closing of the blinds. Five healthy subjects (three male and two female) participated in this study. EEG data was recorded at a sampling frequency of 256Hz and based on the results of the previous sections, eight occipital channels and three frontal channels were used, specifically O1, Oz , O2 , PO7, PO3 , POz , PO4 , PO8, AF7, Fpz, and AF8.

4.1 Experimental Paradigm

A comparative analysis was carried out to compare a hybrid BCI (hBCI) which fuses EEG-based eye-movement-potentials with SSVEPs, and a conventional SSVEP based BCI. Two types of hybrid BCIs were designed, specifically a *sequential hBCI* and a *mixed hBCI*. In the former, an eye movement is first detected and classified as either horizontal or vertical and the result is used such that only the side or top-bottom stimuli respectively start flickering. Hence this reduces the stimuli by half and a final selection is then made using the SSVEP detection algorithm. In the mixed hBCI, the attended icon is selected by a fusion of the SSVEP detection algorithm and the eye-movement detection algorithm. For comparison purposes, an HCI using only EEG-based eye-movement potentials was also developed.

Prior to each session, a 72s long training session was carried out to collect EEG-based eye-movement-potentials pertaining to four classes (Up, Down, Left

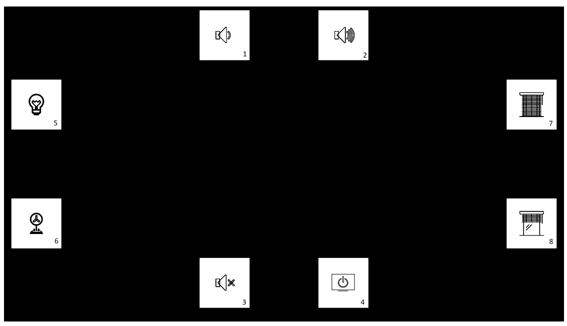

Figure 6: Menu Layout of Smart Home BCI Application.

and Right), matching the interface shown in Figure 6. Four trials of the same length as those shown earlier in Figure 2 were collected for each class and the training data was used to construct CSP and SVM models to classify the user's eye movements within the hBCI system. No training was required for the SSVEP-recognition part as an unsupervised learning technique was used in this case.

Following training the actual experiment was conducted. For the SSVEP-based BCI, 0.75s were allocated for the user to shift the gaze towards the target, 3s were allocated for the flickering of the stimuli, and finally a 2s feedback period was provided. For the hBCI, an additional 0.75s were allocated prior to the gaze shift, instructing the user to focus on a central cross. Re-centering of the user's gaze is essential for correctly classifying the user's eye movement.

For the EEG-based eye movement only HCI, an optimal cross layout as shown in Figure 7 was used. Users were instructed to center their gaze and then shift their gaze according to the location of the desired target.

Both offline and online sessions were carried out for this part of the analysis. In each case an experiment for each of the SSVEP-based BCI, the hBCIs and the eye-movement EEG-based HCI was conducted. Each exercise consisted of selecting each possible icon three times, hence obtaining 24 trials per experiment. In the online session however, subjects were asked to execute 3 different command sequences, specifically:

1. Switch on TV → Close blinds → Decrease TV volume
2. Open blinds → Switch fan → Increase TV volume
3. Switch lamp → Mute TV → Close blinds

For each command the subject was allowed three consecutive attempts to correctly select the scheduled icon. If the user did not manage to generate the necessary SSVEP and the system thus did not succeed in correctly detecting the target after three attempts, the application executed the intended command and progressed on to the following pre-defined cue.

4.2 Algorithms

Three algorithms were needed for the comparative analysis: (i) An eye-movement classification algorithm which classifies the eye-movements detected; (ii) an SSVEP classification algorithm which processes and classifies the SSVEP response of the subject; and (iii) a fusion algorithm for the mixed hybrid BCI system which fuses the output of the eye-movement classification algorithm with the SSVEP classification algorithm.

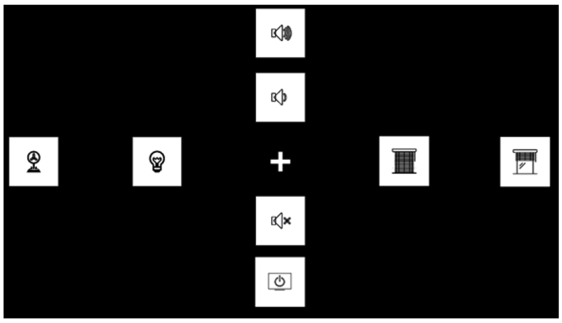

Figure 7: Interface for the EEG-based eye-gaze HCI.

4.2.1 Eye-movement Classification Algorithm

A similar approach to that discussed in Section 3.1 was adopted here. Specifically the EEG data was filtered with a 4th order IIR bandpass filter having cut-off frequency at 0.5Hz and 7Hz. The trials were then projected into CSP space. The natural logarithm was applied to the variance of the resulting signals and these were used as features to the SVM classifiers. Seven pairs of CSP and SVM models, as listed below, were compiled from the training data obtained from each user prior to the experiment.

- Horizontal vs Vertical Model
- Left vs Right Model
- Left vs Other Model
- Right vs Other Model
- Up vs Down Model
- Up vs Other Model
- Down vs Other Model

The first pair classifies eye movements as either horizontal or vertical. This is used to decrease the number of options within the BCI menu. As shown in Figure 8, the other six pairs are used to either i) categorise the horizontal eye movements as leftward or rightward eye movements ii) categorise the vertical eye movements as upward or downward eye movements or iii) through the use of the 'Others' class attempt to recover trials which are misclassified at the first tier. As shown in Figure 8, eye-movements labelled as 'Others' are passed onto the adjacent classifier within the second tier. The SVM models of these six pairs were modified with a Platt Scaling (Platt, 2000) such that the SVM classifier is converted into a probabilistic classifier giving a probabilistic estimate of how much the EEG trial pertains to a specific class. This conversion is done to aid the SSVEP detection algorithm within the mixed hBCI.

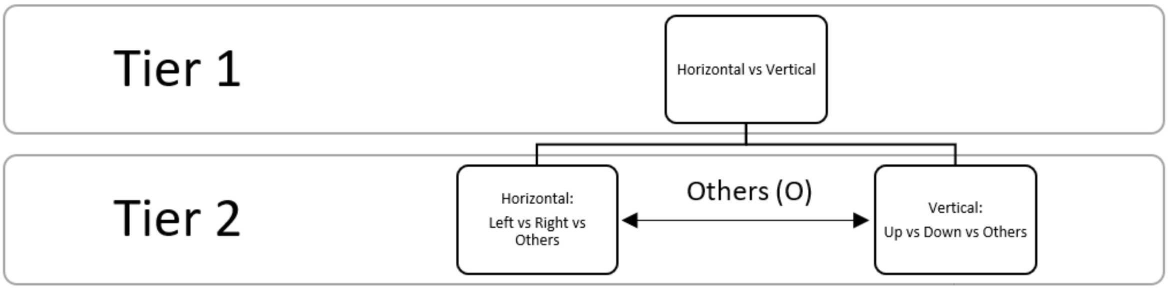

Figure 8: 2-Tiered Hierarchy for Eye-Movement Classification.

4.2.2 SSVEP Classification Algorithm

The filterbank canonical correlation analysis (FBCCA) (Chen et al., 2015) was used to process and classify the SSVEP-related EEG obtained from the user in the online experiments. The FBCCA algorithm consists of three major procedures: i) filterbank analysis; ii) CCA between SSVEP sub-band components and sinusoidal reference signals; and iii) target identification. The design of the sub-bands in the filter bank was based upon a study by Chen et al. (Chen et al., 2015) since the bandwidth of stimulation frequencies used within the online experiments corresponded to that used within the study. The sub-bands covered multiple harmonic frequency bands. Each sub-band had a different lower cut-off frequency but they all shared the same upper cut-off frequency. The lower cut-off frequency of the n^{th} sub-band was set at $n\times$ 8Hz while the upper one was set at 88Hz. An additional bandwidth of 2Hz was added to both sides of the passband for each sub-band (Chen et al., 2015).

4.2.3 Fusion Algorithm for the Mixed hBCI

In this case the extended form of Bayes Rule (Kriegler, 2009), given by Equation 1, was used to fuse the predictions made by the eye-movement classification algorithm and the SSVEP-target identification algorithm for the mixed hBCI.

$$P(\omega_k|X) = \frac{P(X|\omega_k)P(\omega_k)}{\sum_{j=1}^{N} P(X|\omega_j)P(\omega_j)} \tag{1}$$

where $P(\omega_k|X)$ is the posterior probability of a specific class ω_k given the EEG trial X, $P(X|\omega_k)$ is the class conditional distribution of X for class ω_k, and $P(\omega_k)$ is the prior probability of class ω_k, the initial degree of belief in the class ω_k. The prior probability is computed by the SVM classifier modified by Platt scaling while $P(X|\omega_k)$ is computed from the FBCCA algorithm by modelling the probability distribution of the correlation given the class.

4.2.4 Performance Metrics

To evaluate the performance of the different BCI systems considered in this work, the classification accuracy, information transfer rate (ITR) and efficiency were used, all of which are common metrics in this domain. The classification accuracy determines how often a correct selection is made by the BCI and is computed by (Stawicki et al., 2017):

$$P = \frac{N_c}{C_N} \tag{2}$$

where N_c and C_N denote the number of correct classifications and the total number of classified commands.

The ITR, also known as bit rate, takes into consideration the speed of the BCI system and together with accuracy, gives a clearer picture of the system throughput. The ITR in bits/minute is calculated as (Stawicki et al., 2017):

$$B = \log_2 N + P\log_2 P + (1-P)\log_2 \frac{1-P}{N-1} \tag{3}$$

$$\text{ITR} = B\frac{C_N}{T} \tag{4}$$

where B represents the number of bits per trial and T denotes the length of the trial in minutes.

Finally, the efficiency metric gives a measure of the efficiency of the BCI system, taking into consideration the cost of errors. The efficiency in terms of the actual time taken, t, to complete a task, is calculated as (Zerafa, 2013):

$$\eta = \frac{t_{max} - t}{t_{max} - t_{min}} \tag{5}$$

The minimum t_{min} and t_{max} time that a user could take to complete a task are computed by:

$$t_{min/max} = \kappa \times t_o \times \alpha \tag{6}$$

where κ denotes the number of commands required to complete a task, t_o represents the fixed time between two consecutive commands for the system to detect an SSVEP, while α denotes the number of user attempts to execute the correct command.

Table 5: Performance Results of Offline Analysis Across all Subjects.

Method:	**SSVEP**		**Sequential Hybrid**		**Mixed Hybrid**		**Eye-Gaze HCI**	
Metrics:	Acc(%)	ITR (bpm)	Acc (%)	ITR (bpm)	Acc (%)	ITR (bpm)	Acc (%)	ITR (bpm)
S01	83.33	30.11	91.67	31.36	75	19.83	41.67	15.3
S02	41.67	6.12	62.5	13.24	75	19.83	41.67	15.3
S03	87.5	33.69	100	40	70.83	17.47	41.67	15.3
S04	87.5	33.69	95.83	35.11	62.5	13.24	20.83	1.57
S05	45.83	7.75	62.5	13.24	37.5	3.88	16.67	0.42
Mean	**69.16**	**16.17**	**82.5**	**19.06**	**64.16**	**11.32**	**32.5**	**9.58**

4.3 Results for the Offline Analysis

The results of the offline analysis are quantified in terms of the classification accuracy and ITR. The results presented in Table 5 show that the highest classification accuracy obtained within the SSVEP-based BCI was that of 87.5% with a high ITR of 33.69 bpm. For the sequential hBCI, a high classification accuracy of 100% was achieved with a corresponding ITR of 40bpm, while for the mixed hBCI, the highest classification accuracy achieved was that of 75% with an ITR of 19.83 bpm. As for the EEG-based eye-gaze HCI, the highest performance obtained was with a classification accuracy of 41.67% and an ITR of 15.3bpm. On average, the best performance was achieved by the sequential hBCI with an average accuracy of 82.5% and an ITR of 19.06 bpm.

With the exception of Subject 2, although differences in performance were noted, in general, subjects achieved their best performance for the sequential hBCI. Conversely, Subject 2 obtained poor results with an SSVEP-based BCI and achieved the best performance when using the mixed hybrid BCI, thus demonstrating the strength of this hBCI configuration when the SSVEP response of a subject is weak.

A considerable drop in performance was noted for the EEG-based eye-gaze HCI, indicating that the classification of EEG-based eye-movements, according to their visual angle extent, hinders the performance of an HCI system. In addition, the drop in performance attributes to the absence of SSVEP recognition techniques within the HCI.

Figures 9 and 10 show the relation between the classification accuracy and ITR, respectively, and the stimulating period. As the stimulus flickering time is reduced from 3 s down to 1 s, the SSVEP-based BCI, the sequential hBCI and the mixed hBCI all display a reduction in accuracy, with the SSVEP-based BCI and the mixed hBCI suffering the highest and lowest reduction, respectively. It may also be noted that the sequential hBCI remains the best performing BCI throughout. With a stimulus period of 0.5s, the SSVEP is normally difficult to detect; therefore, it is not surprising that for this stimulus period, the mixed hBCI has the highest performance, albeit at around 35%, indicating that the strength of this hBCI configuration is mainly due to the separate eye-movement detection. Similarly, for this lowest stimulus period, the EEG-based eye-gaze HCI also outperformed the sequential hBCI and the SSVEP-based BCI.

With regard to the ITR, as the stimulus flickering time is reduced from 3 seconds down to 1 second, the performance of the SSVEP-based BCI decreases monotonically. Conversely, the ITR of the sequential

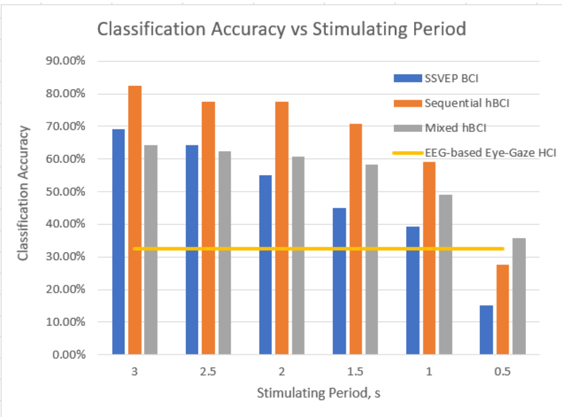

Figure 9: Classification Accuracies of Different BCI Architectures against Varying Stimulating Periods.

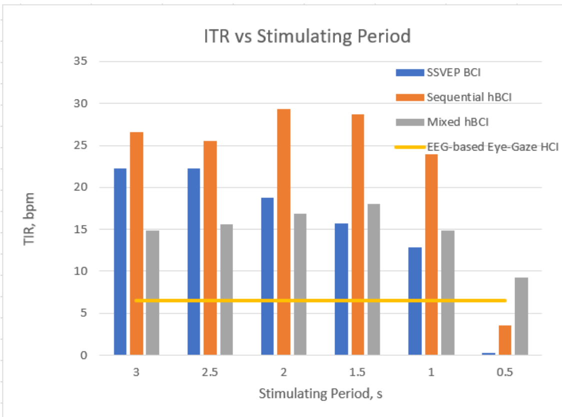

Figure 10: ITRs of Different BCI Architectures against Varying Stimulating Periods.

hBCI and the mixed hBCI tend to remain steady, even exhibiting a slight increase, down to a stimulus period of 1.5 s, with a noticeable but small reduction at 1 s. Similar to the accuracy trends, the sequential hBCI always has the best ITR throughout and at a stimulus period of 0.5 s, both the SSVEP-based BCI and the sequential hBCI exhibit a large drop in ITR, with the mixed hBCI exhibits the highest ITR at a mere 9 bpm. The EEG-based eye-gaze HCI exhibits an ITR of 6bpm and, similar to the accuracy, for a stimulus period of 0.5s, this HCI outperforms the sequential hBCI and the SSVEP-based BCI.

From the classification accuracy and ITR results of the offline comparative analysis it was concluded that a stimulation period of 2s is an adequate time window and hence, for the online experiment, whose results are presented in the next section, the stimulating period was set to 2s.

4.4 Results for the Online Analysis

An online experiment was conducted to allow the subjects to operate the smart home BCI using either an SSVEP-based BCI architecture, a sequential hBCI architecture or a mixed hBCI architecture. In contrast with the offline analysis, apart from classification accuracy and ITR, the performance of the three smart home BCI systems is also quantified in terms of efficiency. As the online experiment grants each subject a number of attempts to complete a task, the efficiency evaluation criteria was introduced to take this number into consideration.

Figure 11 illustrates the performance achieved by each subject for each BCI architecture on the basis of classification accuracy, efficiency and ITR. With the exception of Subject 4, subjects achieved their best performance when using the sequential hybrid BCI. Furthermore, relative to the mixed hybird BCI, subjects achieved better results when using the SSVEP-based BCI. However, as can be seen in the top bar plot of Figure 11, Subject 2, who achieved poor results with an SSVEP-based BCI, achieved a slightly higher classification accuracy when using a mixed hybrid BCI, demonstrating once more the advantages of hBCI configurations when the SSVEP response of a subject is weak.

When averaging the classification accuracy, ITR and efficiency across the subjects for each smart home BCI architecture, results showed that the sequential hBCI outperformed the other two systems on all performance metrics. The sequential hBCI was found to be 11.3% more accurate and 8.3% more efficient than the smart home SSVEP-based BCI. Pairwise t-tests showed that the differences between the two systems

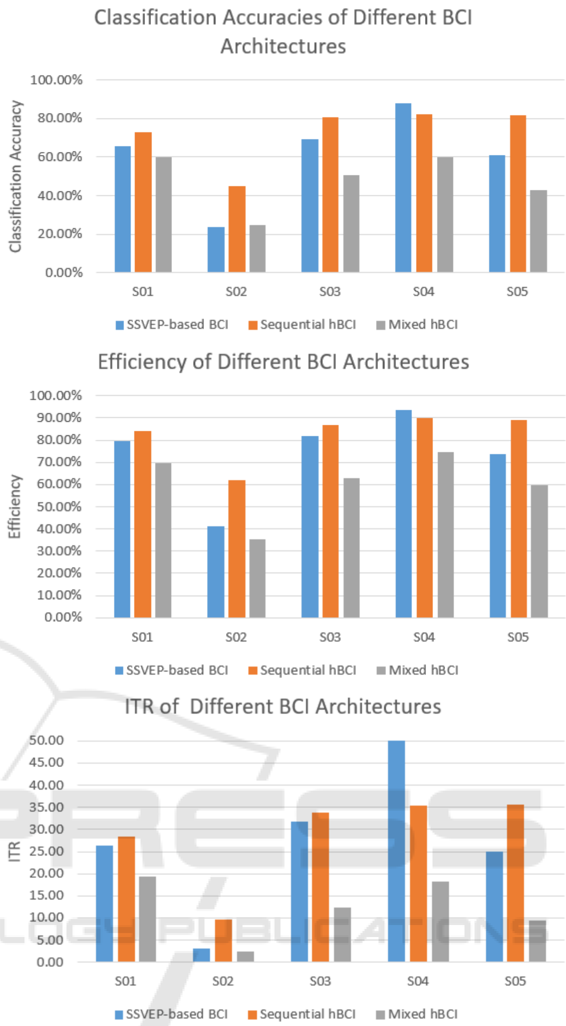

Figure 11: Performance Metrics for the Three Different BCI Architectures across Five Different Subjects.

were significant (p-value < 0.01 for both metrics). In terms of ITR, a slight difference of 1bpm was found between the two, in favour of the smart home sequential hBCI. However, this was not found to be statistically significant. The smart home sequential hBCI exceeded the accuracy, efficiency and ITR of the mixed hBCI by 25.1%, 21.9% and 16.21 bpm respectively and the differences between these two smart home hybrid BCIs were also found to be statistically significant ($p < 0.01$).

The subjects taking part in the online study were also asked to fill in a questionnaire to be able to compare the different systems based on the user's feedback. Overall users found the systems easy to control with the smart home sequential hBCI reported as being the easiest. In terms of concentration requirements, in general subjects found no difference between the three systems. Users perceived the sequential hBCI system as the least erroneous and the mixed hBCI as the most erroneous. This correlates with the quantitative results discussed earlier.

Users perceived the flickering stimuli of the hybrid systems to be less than that of the SSVEP-based BCI. This may be attributed to the fact that the hybrid systems makes use of four flickering stimuli instead of eight. In fact, users found the hybrid systems to be less tiring than the SSVEP-based BCI. Overall users agreed that the time taken to make a selection was appropriate for all systems. With regards to smart home system features, all subjects stated that the menu interface was easy to get used to and that it was adequate for a smart home system.

5 CONCLUSIONS

This work concluded that eye movements can be classified reliably into horizontal or vertical eye movements, using frontal EEG channels, with an accuracy of 98.47%. For the second tier in the proposed hierarchical structure, classification into left, right, up or down eye movements reached an accuracy of 74.38%. Finally, the eye movements could be classified into the eight considered saccadic gaze angle, with an accuracy of 58.31%. These results compare well with the limited literature in this field. Specifically (Dietriech M. P., 2017) had obtained a classification of 96.6% when classifying between 4 extreme eye movements (up, down, left, right) and the central location using a kNN classifier, and 58.4% when using a linear SVM classifier. This however was only based on a single subject as opposed to our work which was validated on 5 subjects.

The results presented in this paper also show that reliable eye-movement information may also be extracted using only the occipital EEG channels, though with lower accuracies. Specifically classification into horizontal or vertical eye movements reached an accuracy of 71.11% while classification in the second and third tiers of the proposed hierarchical structure dropped to 43.85% and 28.02% respectively. However, if three frontal channels are added to the occipital channels vertical and horizontal eye movements at large visual angles may be distinguished with an accuracy close to 80% using the proposed hierarchical classifier.

These results were then used for the development of a smart home automation system where eye movement information occurring prior to the visually evoked potential was exploited to improve classification performance of a hybrid BCI. An offline study showed that a sequential hBCI gave an average accuracy over 5 subjects of 82.5% and an ITR of 19.06bpm, while the mixed hBCI and the SSVEP-based BCI gave an accuracy of 64.16% and 69.16% respectively, and an ITR of 11.32bpm and 16.17bpm respectively. The results of the online automation system also confirmed that users performed better with the sequential hBCI and users found this more intuitive to control. These results show that eye movement information extracted from standard EEG channels typically used in an SSVEP based BCI can provide relevant information which improves the classification performance, especially for subjects whose SSVEP response is not very strong.

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