Eye Movements as Information Markers in EEG Data

Sherif M. Abdelfattah, Kathryn E. Merrick, Hussein A. Abbass
School of Engineering and Information Technology, University of New South Wales, Canberra, ACT2600, Australia

***Abstract*—Artifacts such as voluntarily and involuntarily muscle movements are usually seen as a source of noise in EEG signals. In this paper, we see artifacts as a source of information in a signal. For example, eye movements can generate a traceable change in the EEG signals. We use eye movements as an effective marker for direction of movement. We propose two experiments for classification of four eye movement directions (left, right, up and down). In the first experiment, we utilize feature partitioning method based on J48 decision tree to tackle the effect of concept drift in the training dataset resulting from dynamic non-stationarity characteristics of EEG signals. Afterward, we feed the extracted partitions to three different classifiers: multilayer perceptron (MLP) (with 10 hidden layers), logistic regression (LR) and random forest decision tree (RFDT) respectively, while comparing their classification accuracy. In the second experiment, we explored an ensemble learning mechanism as an alternative criterion to deal with the dynamic nature EEG signals. We trained the last three classifiers simultaneously on each training example, followed by a voting method to determine the dominant class label. The ensemble approach increased classification accuracy from 86.2% in the first experiment to 90.1% in the second.**

I. Introduction

Brain-computer interfaces (BCIs) are changing the communication theme between humans and machines. With the opportunity of controlling computers using a form of thoughts, the technology can be considered as the future of human-computer communication that enables the computers to understand and respond to the human mind's cognitive state. A brain-computer interface can be defined as a system that aims to reinterpret the output of the central nervous system (CNS) in order to replace, restore, enhance, supplement or improve the interactions with the internal or external environment [1]. To intercept the output of the CNS, BCIs utilise two primary methods. First, invasive methods, which work by surgically implanting electrodes in the target tissue for recordings, such as brain tissue or muscle tissue. Second, non-invasive methods, which are based on recording CNS activities without implanting electrodes inside the target tissue.

Electroencephalography (EEG) is one of the most applicable, non-invasive methods utilized by BCI applications to record brain electrical activities [2]. EEG works by placing electrodes on the scalp that can detect and record electrical potential reflected from neurons firings in the brain surface tissue [3]. The EEG signal spectrum consists of five basic bands [4]: delta waves (0.5-3.5 Hz) usually generated during deep-sleep in adults, Theta waves (3.5-7.5 Hz) associated with drowsiness or idling, Alpha waves (7.5-12 Hz) reflecting cognitive relaxation such as thinking of something peaceful with eyes closed, Beta waves (12-30 Hz) generally associated with active thinking and Gamma waves (30-100+ Hz) representing the highest frequency that can be recorded from brain activity. Gamma waves are associated with memory matching activities.

Signal analysis techniques for EEG utilize various methods such as event-related potentials (ERPs), frequency-domain analysis or time-domain analysis. These methods were summarized by [5] into four groups: first, P300 evoked potentials, which is a positive potential generated about 300ms after a subject is exposed to specific stimuli such as a flashlight. Second, Steady State Visually Evoked Potentials (SSVEP), reflected from visual stimulation at specific frequencies. When the retina is excited by a visual stimulus with a specific frequency, the brain generates electrical activity at the same (or multiples of) frequency of the visual stimulus. Third, Slow Cortical Potentials (SCP) commonly referred to as brainwaves (alpha, beta, mu, and gamma rhythms). These rhythms involve the synchronisation of a ring of large numbers of neurons and are associated with changes in the state of consciousness such as attention and sleep. Fourth, Sensorimotor Rhythms (SMR), they are oscillations [8-12] Hz and [18-26] Hz in the EEG recorded signals over the sensorimotor cortices. The sensorimotor cortices are an area of the cerebral cortex which is involved in the processing of sensory information, planning, control, and execution of voluntary movements.

Control BCIs have wide potential applications. On the one side, it can help people suffering from movement disabilities to interact with their environment by intercepting their sensory-motor electrical activity and decoding into control commands for control [6]. On the other side, it can be used to augment the human's controlling capabilities with additional resources, such as controlling a robotic arm or a drone only by thoughts [7].

There are many challenges for the development of reliable EEG-based control BCIs such as low signal-to-noise ratio, non-stationarity, training phase can be demanding for subjects and high dimensionality [5]. The feasibility of any classification method of EEG signals can be significantly affected by its ability to deal with these challenges. Accordingly, we took into consideration the need to deal with the dynamic nature of EEG signals during the design of our classification experiments.

Literature used to deal with eye movements and eye blinks as pervasive sources of noise that affect the quality of EEG signals. However, we find eye movements a rich source of information that can be useful for EEG control BCIs. In this paper, eye movements are used as an effective indicator of the direction of movement to develop an EEG-based control BCI.

The main contribution of this paper can be summarized in three main points. First, it proposes eye movements as an information marker for the movement intention, that can be used in EEG-based BCI applications. Second, it selects effective EEG features that can provide sufficient discrimination for the direction of eye movements. Finally, it introduces two classification methods that can classify direction of eye movements from EEG signals with high classification accuracy.

The rest of this paper is organized as follows: Related Work, introduces the literature in the field of EEG-controlled BCI; Experimental design, describes the design and flow of the experiment used to collect the data; Methods, illustrates the EEG data pre-processing and processing procedures; Discussion, explains the research findings; finally, the conclusion summarizes the findings and indicates directions for future work.

II. RELATED WORK

An algorithm for game control was introduced in [8], the authors focused on the alpha rhythm as an indicator for attention along with Electrooculography (EOG) signals that come from four electrodes placed around eyes to identify movements and blinks. Authors hypothesized that the identification of eyes state in terms of movements or blinks can give insights on the level of subject's attention. Wireless hardware for measuring EEG and EOG signals was proposed. Through estimating the sight angle of the subject using EOC, the proposed architecture could identify the movement direction with an average accuracy of 96%.

A hybrid BCI from EEG and electrooculography (EOG) was introduced in [9]. Authors used continuous wavelet transform (CWT) to detect the time domain characteristics for five eye movement classes (left, right, up, down and centre). The experimental design involved five subjects (4 males and 1 female) with an average age of 26.2 years. During the experiment, the subjects were asked to move a ball centred on the screen to the four basic directions using their eye movements and to change the colour of the ball by eye blinks. The experiment involved 10 runs per each subject, divided into 2 settings: 5 runs with the eye open and 5 runs with eye closed. Each run takes 60 seconds to execute, starting by 10s for fixation on the centre of the screen, then 10 trials to move the ball in four directions (up, down, right and left) each trial takes 4s, then the last 10s the subject is asked to blink his eyes three times to change the colour of the ball from white to yellow. In the eye closed runs, the subject is directed to imagine the needed movement direction using voice commands. The results summarized over both settings showed an average 95% of classification accuracy for left, right and centre commands and 50% for up and down based on an experiment of controlling a 2D computer game. The authors designed the game to be controlled by three eye movements commands (left, right and stop) probably to overcome the low classification accuracy of Up and Down commands by the proposed algorithm.

While utilization of EOC sensors can increase the accuracy, it limits the real-life application for disturbing the subject as it requires placing electrodes around the eyes to detect facial muscle movements.

A 2D game was designed by [10] to help people with severe disabilities to control mouse and keyboard of a computer. The mu rhythm sometimes called signal rhythm was utilized to identify the movement potential. It can be observed in the central derivations of the motor band, C3, and C4 of the international 10-20 electrode location system. Authors used Butterworth filtering followed by FFT to prepare the signal that comes from 4 channel EEG device with recording periods lasting 1000ms every 125ms. The proposed algorithm used thresholds learned through a training phase to identify three basic movements Up, Down and No Movement. The experiment done on 4 subjects showed a minimum accuracy of 80% and a maximum of 92.6%. Although the proposed algorithm achieved high classification, it depends on thresholds acquired from initial training phase. Due to the non-stationary characteristic of EEG signals, the thresholds values can deviate from its learned configuration over time, a situation that will cause a decrease in classification accuracy.

A game control BCI was introduced in [11]. It is based on Steady-State Visual Evoked Potential (SSVEP) of the signal. SSVEP working procedure is based on demanding the user to focus on a visual stimulus that flickers at a sufficiently high rate, which will drive the individual transient visual responses to overlap, resulting in a steady state signal observable mostly in the occipital area [12]. During the game, a flickering stimulus was shown on the left bottom corner of the screen, every 2 seconds a movement option will be shown to the user (right, left, up or down) to select a specific option. The user has to focus on the stimulus, so SSVEP can be detected on the EEG signal. To robustly detect the presence of SSVEP signal, authors adapted an approach by An Luo and Thomas Sullivan [13] called Stimulus-Locked Inter-trace Correlation (SLIC). This approach determines the presence of SSVEP signal in the time domain based on correlation analysis of independent components (ICs) of the time window. The SSVEP is an effective method for building BCIs, however, it has a limitation as it needs to provide the control interface with a separate graphical user interface (GUI) for the visualization of the flickering effects. For example, if the SSVEP BCI objective is to control a game, the game interface will need to adapt the GUI for flickering effects visualization.

Among different BCIs methods, P300-based BCIs [14] are very common. a P300-based BCI is working by making the subject face a screen on which visual events, used as stimuli, appear at specific locations. The subject can target any of the screen's locations by focusing on or counting the visual stimulus (e.g., flashes or changes in color and size) on this location. that occur there. This strategy will result in detection of the target location as it will generate a higher amplitude P300 than untargeted locations. Then the command represented by the target location is executed.

Mugler et al. [15] proposed a BCI for controlling a web browser based on P300 ERP. The proposed BCI was tested on 10 healthy subjects and three subjects with paralysis. The design of the browser was implemented based on Mozilla's Firefox. The EEG data was recorded using an EEG-Cap with 16 channels. During each trial, the web page's links were organized in way symmetric to P300 speller pattern. Classification of P300 ERPs was done using step-wise linear discriminant analysis (SWLDA) algorithm implemented in Matlab. The average classification accuracy for healthy subjects was 90% and for paralyzed subjects was 73%. Although the proposed methodology achieved reasonably high classification accuracy, but authors did not show how their proposed classification methods can adapt with dynamic nature of EEG signals.

In the BCI-controlled game (MindGame) poropsed by Finke et al. [16], the subject moves an object from one location to another on a 3D game board. The magnitude of the object's movement depends on the magnitude of a P300 classifier output, with a stronger ERPs to target flashes leading to larger movements and the faster achievement of game objectives, which is to move a set of objects to a preplanned set of locations on the board . In opposite to common P300 BCI spellers, the visual stimuli are not organized in cross-wise (rows and columns) but, they were organized one at a time. Principal component analysis (PCA) was utilized for dimensionality reduction and Fisher discriminant analysis (FDA) classification was applied to averaged, single-trial data.The authors reported a 66% of average classification accuracy.

In Brain Invaders BCI game [17], participants can destroy an alien invader by concentrating on him. The placement of aliens on The second experiment's classification accuracy ercentage using ensemble learning classification per each subject.the screen was in two settings: grid or arbitrary. The movement of aliens was symmetric to the original Space Invaders arcade game layout. The target alien is marked with a change in color and enlargement of size stimulus, for other aliens, only the brightness is increased. The selection of target aliens was done randomly by the game software. If the target alien was destroyed from the first trial, it will be removed from the screen. Otherwise, the game continues, until either the target alien or all aliens are destroyed. The EEG data was spatially filtered using the xDAWN algorithm [18], then a Linear discriminant analysis (LDA) was used for classification. The game required a calibration phase for 3 minutes.

P300 is an effective BCI method however, it requires the subject to focus on a screen to be able to parse the target command, which may be impractical for some real world applications such as controlling a wheelchair because the subject will have to focus on his way.

It can be noticed that there is a need to design an EEG-based BCI that can be adapted with better user comfort, minimum changes on the current application/system to be controlled and to be agile to the non-stationarity characteristic of EEG signals.

Eye movements cause variations in the EEG signal, especially in the frontal cortex. While it is widely considered an artifact by the majority of the literature, we claim that eye movement can serve as an invariant marker to the user's intended direction of movement from EEG signals. In the following section, we introduce our EEG experimental design that is based on user's eye movements as an indicator of the intended direction of movement in four basic directions left, right, up and down respectively.

III. Experimental Design

A. Hypothesis

Eye movements will pose a detectable change on EEG signals that can be used as an indicator for the intended motor direction from four basic directions of movements: left, right, up and down.

B. Data Acquisition

EEG recording was done by MindMedia™ QEEG device NeXus-32. The configured sampling rate is 2048Hz for 19 channels. Serial port communication was used to send EEG raw data to the experiment's PC for processing. This machine is running two applications. The first application controls the experiment flow including generating a new experiment profile for the subject, generating a task execution plan randomly, executing each experiment's task and saving the EEG raw data for each task. The second one is responsible for monitoring and visualizing the EEG signal quality for all electrodes. Figure 1 shows a photograph of the experimental environment.

Figure 1: A photograph representing the experimental environment. The subject is placed by 80cm from the experiment's screen (on the left side). The second (on the left side) screen was used to continuously monitor the electrodes signal quality.

C. Task Design

Two basic tasks were executed during the experiment: the baseline task and the eye movement task.

During baseline task, the subject was asked to close his/her eyes for 2 minutes and focus on his/her breathing then open his/her eyes for 2 minutes and relax by focusing on a white sheet.

While in eye movement task, which last for 6 seconds, the subject focused on a screen showing a cross shape with vertical and horizontal bars. In the middle of the screen, there is a black spot. At the beginning of task's execution, the subject was asked to focus for 2 seconds on the black spot until a direction is randomly selected by the experiment's application. When a direction, which is divided into 8 equally sized and spaced dimmed bars, is selected its bars start to be illuminated one by one till it reaches the edge of the screen. This takes 4 seconds. The subject is asked to move his/her eyes with the illuminated bar without moving his/her head or blinking.

Each experiment session consisted of 60 eye movement tasks with 15 tasks for each direction left, right, up and down respectively. Figure 2 illustrates the task's layout design.

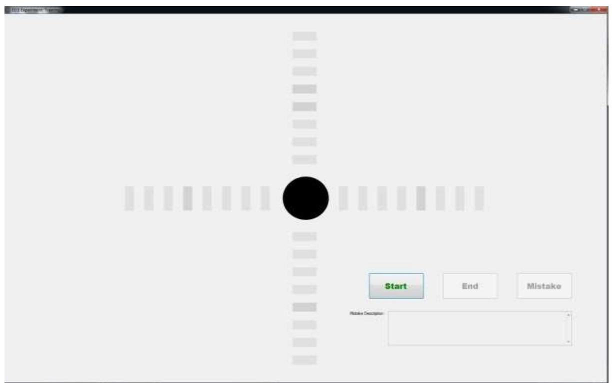


Figure 2: Eye movement task's layout design. At the middle, there is a cross shape. Each direction's branch consists of 8 bars that are illuminated one by one when the direction is selected.

D. Sample Size

The experiment's sample size is 10 subjects (5m, 5f) who were recruited on a voluntary basis. All subjects were from the graduate student community of our university's campus. The age range of the subjects was 25±4 years old. All subjects had no visual or hearing disabilities. The experiment has been approved by the university's Human Research Ethics Committee. We provided each subject with a printed participation and consent form.

E. Environment

The environment setup procedure for each subject included: placing the EEG cap on the subject's scalp, injecting the conductive gel in each electrode, calibrating the signal quality of all electrodes and adjusting the distance between the subject and the screen to be 80cm. This procedure was the same for all subjects.

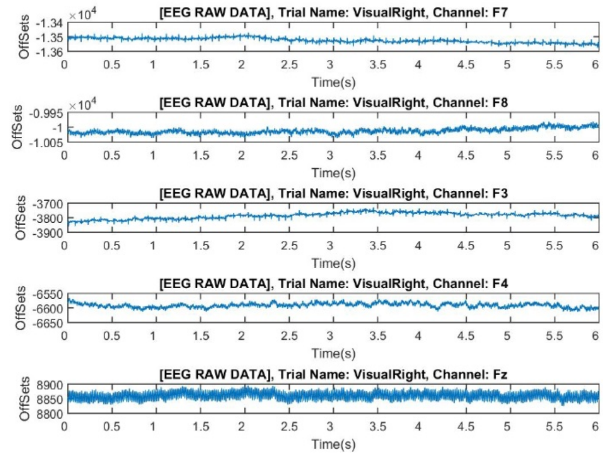
IV. METHODS

A. Signal Normalization

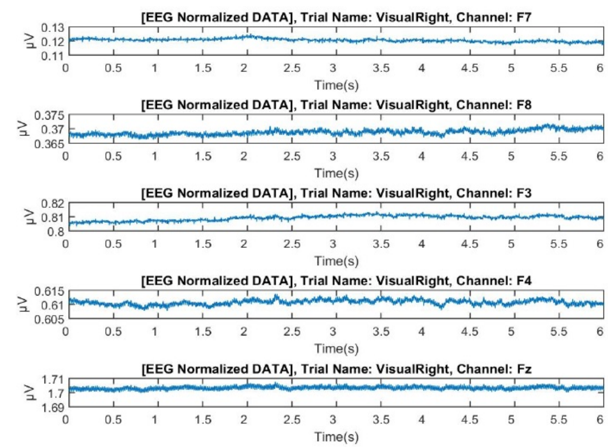
The EEG recordings received from the device are offsets. Equation 1 shows the voltage (μV) calculation by referencing to the ear lobe channels (A1 and A2).

$$X(t) = X(t) - \frac{A_1(t)+A_2(t)}{2}, \forall t = 1, 2, \ldots, T \quad (1)$$

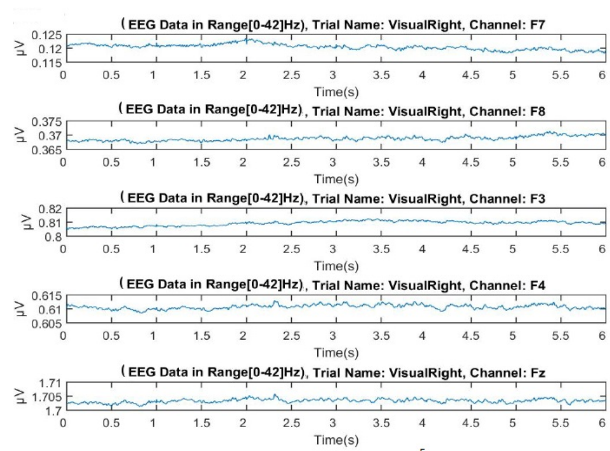
Where $X(t)$ represents one channel signal on time point t . After voltage calculation, each channel signal is normalized by common averaging normalization. FFT algorithm is utilized to filter out frequencies outside the range [0-42] Hz with three basic bands utilized: theta [4-8]Hz, alpha [8-12]Hz and beta [12-32]Hz respectively. Only the first second after eye movement was considered. Figure 3 shows the signal normalization progress on a sample from subject 1's data.



(a)



(b)



(c)

Figure 3: Preprocessing stages of the EEG signal using a sample from subject 1 data set. (a) Signal's raw offsets, (b) Signal's normalized voltage, (c) Signal filtered in frequency range [0-42]Hz.

B. Feature Extraction

Nineteen channels were selected (C3, C4, Cz, F3, F4, F7, F8, FP1, FP2, Fz, O1, O2, P3, P4, Pz, T3, T4, T5 and T6) to extract features of eye movement in each trial. For each channel, we calculate 4 features: Theta-Beta Ratio (TBR) which is the ratio between average theta band amplitude and the average beta band amplitude (see Equation 2), Average Theta Power (ATP), Average Alpha Power (AAP) and Average Beta Power (ABP). In addition, we have two features that are calculated over a whole trail period, trapezoid area under the difference curve between right hemisphere (FP1,F3,F7,C3,T3,P3,T5,O1) and left hemisphere (FP2,F4,F8,C4,T4,P4,T6,O2) channels (D) and trapezoid area under signal average curve over the 19 channels (DD). Therefore, each trial will be represented by a total of 78 features.

$$TBR = \frac{AVG(ThetaAmp)}{AVG(BetaAmp)} \quad (2)$$

C. Feature Selection

For each subject dataset (60 training examples), a J48 decision tree [19] was trained by providing a training example that consists of 78 feature vector and the assigned class label representing the direction of movement. Implementation of the decision tree was done using the WEKA data mining toolkit [20]. Ranking for all selected features among the 10 trained J48 decision trees (one per each subject) was performed by calculating the occurrence of each selected feature across all trees. Results of feature selection phase showed that TBR features had the highest ranking overall features, so we use TBR features only in the classification phase. Table I presents the ranking results indicating that TBR features accounted for approximately 90% of the selected features by the J48 decision trees.

Table I: Final feature ranking across all the trained J48 decision trees.

Feature	Rank	Occurrence (%)
TBR	1	87.59
ATP	2	4.14
ABP	3	2.76
D	4	2.76
AAP	5	2.07
DD	6	0.69

For further investigation of the effectiveness of TBR features, Figure 4 shows topographical heat maps of the average TBR values for the 19 selected channels per each direction trials (15 trials per each direction) for subject 1. The maps provide a visual prove of the discrimination ability of TBR features that is identified by four different patterns that can be clearly noticed from the graphs.

D. Experiment 1

As a preprocessing step, we partitioned each subject's dataset samples (training and testing) in a way that makes each partition has the same statistical distribution of the feature vector and the same class label. The partitioning phase enhances the discrimination ability of the classifier in the case of introduction of signal's concept drift [21]. This phase utilizes an unpruned J48 decision tree to aggregate similar observation into a partition according to its likelihood probability [22]. After this initial step, we applied three different classifiers: multilayer perceptron (MLP) (with 10 hidden layers), logistic regression (LR) and random forest decision tree (RFDT). All classifiers run with cross-validation with 10 folds. The classifiers were implemented with WEKA toolkit. Table II summarizes the results according to classification accuracy percentage for each subject.

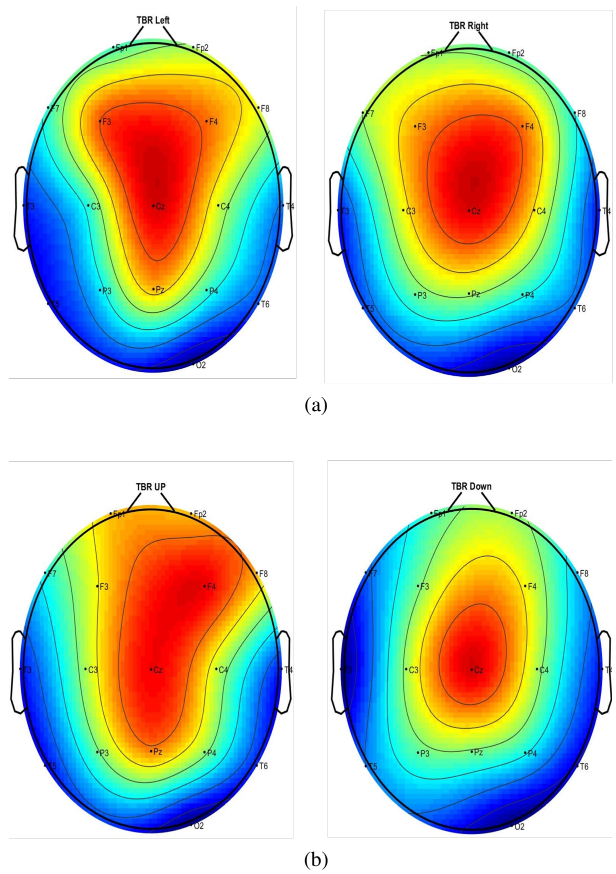


Figure 4: Topographical heat maps of the average TBR over the 19 selected channels for subject 1. (a) Left and Right eye movement trials, (b) Up and Down eye movement trials

Table II: The first experiment's classification accuracy percentage across three classifiers summarized per each subject.

Subject	MLP(%)	LR(%)	RFDT(%)
1	86.6	86.6	88.3
2	81.6	80.0	81.6
3	93.3	93.3	93.3
4	81.6	80.0	78.3
5	81.6	83.3	83.3
6	83.3	83.3	83.3
7	90.0	90.0	85.0
8	91.6	91.6	91.6
9	86.6	86.6	86.6
10	88.3	90.0	88.3
AVG	86.45	86.47	85.96
STD	4.3	4.7	4.6

The average achieved accuracy for the three classifiers was

86.45%, 86.47% and 85.96 respectively across all subjects.

E. Experiment 2

As an alternative classification method that is adaptive to non-stationarity of EEG signals, we utilized ensemble learning concepts [23]. Using an ensemble of models can reduce the impact of non-stationarity of the data by validating the classification through voting over different learning hypothesis proposed by ensemble's models. Therefore, an ensemble of models can provide a level of adaptability for dynamic changes in the input data. Accordingly, for each subject's dataset, we divided samples into 80% for training and 20% for testing. For each training example, we separately trained three classifiers: multilayer perceptron (MLP) (with 10 hidden layers), logistic regression (LR) and random forest decision tree (RFDT) respectively. During the testing phase, we take a voting for the dominant class label over the three classifiers estimates. Table III summarizes the percentage of classification accuracy for each subject.

Table III: The second experiment's classification accuracy percentage using ensemble learning classification per each subject.

Subjects	Classification Accuracy (%)
1	90.0
2	86.0
3	92.0
4	86.0
5	89.0
6	88.0
7	94.0
8	92.0
9	91.0
10	93.0
AVG	90.1
STD	2.8

Through this method, we achieved an average classification accuracy of 90.1% across all subjects.

V. DISCUSSION

The utilization of decision trees in the feature selection phase enabled us to locate the group of features that better discriminate between target class labels. Moreover, averaging the feature ranking over the ten trained decision trees gives us the best set of features that achieved high discrimination ability among the ten subjects involved in the experiment, which will be more invariant to changes in EEG signals between subjects.

In the first experiment, the partitioning preprocessing phase enables deviating the effect of concept drift in the training samples. By grouping similar samples that share the same probability density, which may vary between training samples over time due to non-stationarity of EEG signals, and target class into the same partition. This way of grouping enables the classification method to focus on the joint probability between the input feature vector and target class label, which is invariant over time. The effectiveness of this concept was proved by testing the accuracy of the three deployed classifiers, which tend to be feasibly high comparing to literature.

During the second experiment, the dependency on ensemble learning concept enabled the three deployed classifiers to share the discrimination abilities which depend on the mathematical model of each one [24]. Despite using a simple voting technique, the effectiveness of ensemble learning in adapting to non-stationarity of EEG signals was apparent from the classification accuracy achieved by cooperation of the three involved classifiers. A possible drawback of such methods is the additional computation and space complexity resulting from training multiple classifiers simultaneously. However, this could be handled through utilizing parallel processing using graphics processing units (GPUs) which showed promising breakthroughs in training machine learning algorithms [25], [26], [27], [28].

VI. CONCLUSION

This paper proposed two methods for classification of four directions of movement (left, right, up and down) based on eye movements using EEG signals. We implemented a feature selection method using a J48 decision tree to find the highly ranked features across all subjects in terms of ability to discriminate between the four classes of our experiment.

Based on our feature selection method, we found that TBR features have the highest discrimination rank for analysing visual tasks based on EEG signals. This means that it can be used to sense and analyse cognitive state in BCI applications that include similar kind of tasks.

In the first classification method, we utilized a partitioning pre-processing phase using a J48 decision tree , then we applied three classifiers multi-layer perceptron, logistic regression and random forest decision tree. An average classification accuracy of 86.45%, 86.47% and 85.96% was achieved respectively across all subjects.

In the second method, we adapted ensemble learning concepts. We trained each of the three classifiers in the first analysis method on each training example separately then, we utilized voting technique to find the dominant class label over the three classifiers estimates. The average classification accuracy for this method was 90.1%.

Comparing our methodology with literature, our methods are more applicable for two basic reasons. First, it depends on eye movements an indicator for the direction of movement, which has a clear detectable invariant effect on EEG signals rather than imaginary motor indicators. Moreover, eye movements are less demanding on the subject and require no additional modifications to the interface of the application under control rather than alternative methods such as SSVEP. Second, depending only on EEG electrodes is less annoying to the user comparing to electrooculography (EOG) methods that require placing EOC electrodes on user's face to track the eye movements.

Future work will be to close the loop by integrating one of our classification methods with an application to control such as computer game or a robot.

VII. ACKNOWLEDGMENT

This work was supported by the Australian Research Council under Grant DP160102037.

REFERENCES

[1] J. Wolpaw and E. W. Wolpaw, *Brain-computer interfaces: principles and practice*. OUP USA, 2012.

[2] V. Mihajlovic, B. Grundlehner, R. Vullers, and J. Penders, "Wearable, wireless EEG solutions in daily life applications: what are we missing?" *Biomedical and Health Informatics, IEEE Journal of*, vol. 19, no. 1, pp. 6–21, 2015.

[3] S. Xing, R. McCardle, and S. Xie, "Reading the mind: the potential of electroencephalography in brain computer interfaces," in *Mechatronics and Machine Vision in Practice (M2VIP), 2012 19th International Conference*. IEEE, 2012, pp. 275–280.

[4] M. Teplan, "Fundamentals of EEG measurement," *Measurement science review*, vol. 2, no. 2, pp. 1–11, 2002.

[5] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, "A review of classification algorithms for EEG-based brain–computer interfaces," *Journal of neural engineering*, vol. 4, no. 2, p. R1, 2007.

[6] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain–computer interfaces for communication and control," *Clinical neurophysiology*, vol. 113, no. 6, pp. 767–791, 2002.

[7] A. Astaras, N. Moustakas, A. Athanasiou, and A. Gogoussis, "Towards brain-computer interface control of a 6-degree-of-freedom robotic arm using dry EEG electrodes," *Advances in Human-Computer Interaction*, vol. 2013, p. 2, 2013.

[8] S.-A. Chen, C.-H. Chen, J.-W. Lin, L.-W. Ko, and C.-T. Lin, "Gaming controlling via brain-computer interface using multiple physiological signals," in *Systems, Man and Cybernetics (SMC), 2014 IEEE International Conference on*. IEEE, 2014, pp. 3156–3159.

[9] A. N. Belkacem, S. Saetia, K. Zintus-art, D. Shin, H. Kambara, N. Yoshimura, N. Berrached, and Y. Koike, "Real-time control of a video game using eye movements and two temporal EEG sensors," *Computational intelligence and neuroscience*, vol. 2015, pp. 1–10, 2015.

[10] E. Lopetegui, B. G. Zapirain, and A. Mendez, "Tennis computer game with brain control using EEG signals," in *Computer Games (CGAMES), 2011 16th International Conference on*. IEEE, 2011, pp. 228–234.

[11] M. Van Vliet, A. Robben, N. Chumerin, N. V. Manyakov, A. Combaz, and M. M. Van Hulle, "Designing a brain-computer interface controlled video-game using consumer grade EEG hardware," in *Biosignals and Biorobotics Conference (BRC), 2012 ISSNIP*. IEEE, 2012, pp. 1–6.

[12] B. Allison, T. Luth, D. Valbuena, A. Teymourian, I. Volosyak, and A. Graser, "BCI demographics: How many (and what kinds of) people can use an SSVEP BCI?" *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, no. 2, pp. 107–116, April 2010.

[13] A. Luo and T. J. Sullivan, "A user-friendly SSVEP-based brain–computer interface using a time-domain classifier," *Journal of neural engineering*, vol. 7, no. 2, p. 026010, 2010.

[14] G. McCarthy and E. Donchin, "A metric for thought: a comparison of P300 latency and reaction time," *Science*, vol. 211, no. 4477, pp. 77–80, 1981.

[15] E. M. Mugler, C. A. Ruf, S. Halder, M. Bensch, and A. Kubler, "Design and implementation of a P300-based brain-computer interface for controlling an internet browser," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 18, no. 6, pp. 599–609, Dec 2010.

[16] A. Finke, A. Lenhardt, and H. Ritter, "The mindgame: a P300-based brain–computer interface game," *Neural Networks*, vol. 22, no. 9, pp. 1329–1333, 2009.

[17] M. Congedo, M. Goyat, N. Tarrin, G. Ionescu, L. Varnet, B. Rivet, R. Phlypo, N. Jrad, M. Acquadro, and C. Jutten, "" brain invaders": a prototype of an open-source P300-based video game working with the OpenViBE platform," in *5th International Brain-Computer Interface Conference 2011 (BCI 2011)*, 2011, pp. 280–283.

[18] B. Rivet, A. Souloumiac, V. Attina, and G. Gibert, "xDAWN algorithm to enhance evoked potentials: application to brain–computer interface," *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 8, pp. 2035–2043, 2009.

[19] J. R. Quinlan, *C4.5: Programs for Machine Learning*. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 1993.

[20] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The WEKA data mining software: an update," *ACM SIGKDD explorations newsletter*, vol. 11, no. 1, pp. 10–18, 2009.

[21] M. Masud, J. Gao, L. Khan, J. Han, and B. M. Thuraisingham, "Classification and novel class detection in concept-drifting data streams under time constraints," *IEEE Transactions on Knowledge and Data Engineering*, vol. 23, no. 6, pp. 859–874, June 2011.

[22] E. Frank and B. Pfahringer, "Propositionalisation of multi-instance data using random forests," in *AI 2013: Advances in Artificial Intelligence*. Springer, 2013, pp. 362–373.

[23] C. Zhang and Y. Ma, *Ensemble machine learning*. Springer, 2012.

[24] T. G. Dietterich, "Ensemble learning," *The handbook of brain theory and neural networks*, vol. 2, pp. 110–125, 2002.

[25] B. Catanzaro, N. Sundaram, and K. Keutzer, "Fast support vector machine training and classification on graphics processors," in *Proceedings of the 25th International Conference on Machine Learning*, ser. ICML '08. New York, NY, USA: ACM, 2008, pp. 104–111. [Online]. Available: http://doi.acm.org/10.1145/1390156.1390170

[26] M. Van Heeswijk, Y. Miche, E. Oja, and A. Lendasse, "GPU-accelerated and parallelized elm ensembles for large-scale regression," *Neurocomputing*, vol. 74, no. 16, pp. 2430–2437, 2011.

[27] Z. Du, X. Li, and J. Wu, "Accelerating the training of HTK on GPU with CUDA," in *Parallel and Distributed Processing Symposium Workshops PhD Forum (IPDPSW), 2012 IEEE 26th International*, May 2012, pp. 1907–1914.

[28] O. Yadan, K. Adams, Y. Taigman, and M. Ranzato, "Multi-GPU training of convnets," *arXiv preprint arXiv:1312.5853*, vol. 9, 2013.