ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2015

An Enhanced SSVEP BCI Application through Emotion: Preliminary Results

Hadi Mohsen M. Oqaibi[1] and Anas M. Ali Fattouh[2,3]

[1] Teaching Assistant, Computer Skills Unit, FCIT, King Abdulaziz University, Jeddah, Kingdom of Saudi Arabia

[2]Associate Professor, Dept. of C.S., FCIT, King Abdulaziz University, Jeddah, Kingdom of Saudi Arabia

[3]Associate Professor, Dept. of Automatic Control and Automation, FEEE, Aleppo University, Aleppo, Syria

ABSTRACT: Steady-state visual evoked potential (SSVEP) is a well-established paradigm of brain computer interface (BCI) where the interaction between the user and a controlled device is achieved via brainwave activities and visual stimuli. Although SSVEP-based BCIs are known to have high information transfer rate (ITR), wrong feedback reduces the performance of these applications. In this paper, we investigate the possibility of enhancing SSVEP-based BCI applications by incorporating the user's emotions. To this end, an SSVEP-based BCI application is designed and implemented where the user has to steer a simulated car moving in a maze to reach a target position. Using standard flickering checkerboards, the user has to select one of two commands, turn right or turn left. After each selection, a visual virtual feedback is shown and the emotional state of the user is estimated from recoded electroencephalogram (EEG) brain activities. This estimated emotion could be used to automatically confirm or cancel the selected command and therefore improve the quality of executed commands.

KEYWORDS: Steady-state visual evoked potential (SSVEP); emotion recognition; brain computer interface (BCI); visual stimuli; Emotiv EPOC neuroheadset

I. INTRODUCTION

Brain-Computer Interface (BCI) is an application of pattern recognition systems that interprets the intention of the user, expressed by brain activities, as a control signal [1]. It provides an alternative communication way between the user and a device that does not relay on standard pathways of the brain such as muscular peripheral [2]. The main objective of BCI research is to develop systems that allow people with motor disabilities to communicate with others or to control their environment [3]. To achieve this goal, numerous BCI aspects have been investigated. Research areas include, for example, the extension of the application fields of BCI [4,5], the discovery of new physiological nature of the experimental paradigms [6,7], the invention of new prediction algorithms to enhance the speed and accuracy of BCI applications [8-10] and the evaluations of these applications, specifically for disabled users [11,12].

The proposed work aims at improving the applicability of BCI applications by integrating SSVEP paradigm and emotion. In the following section, we briefly explain the SSVEP paradigm, the emotional BCIs and previous attempts to use emotion with other BCI systems.

II. RELATED WORK

2.1 Steady-State Visual Evoked Potentials (SSVEPs). Steady-state visual evoked potentials (SSVEPs) are oscillations in the electroencephalogram generated in the visual cortex when a user looks at periodically flickering stimulus [13]. Fig. 1 shows the standard block diagram of an SSVEP application.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2015

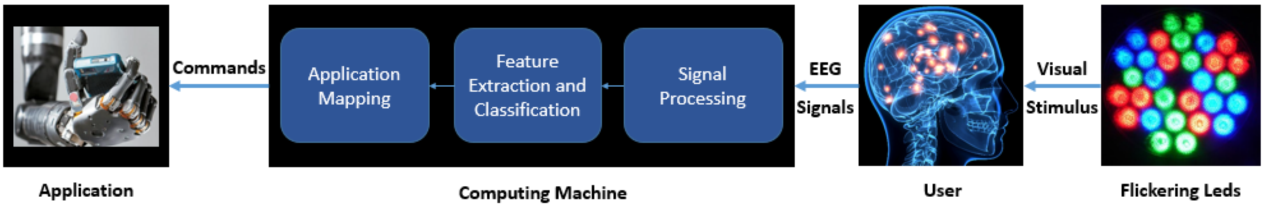
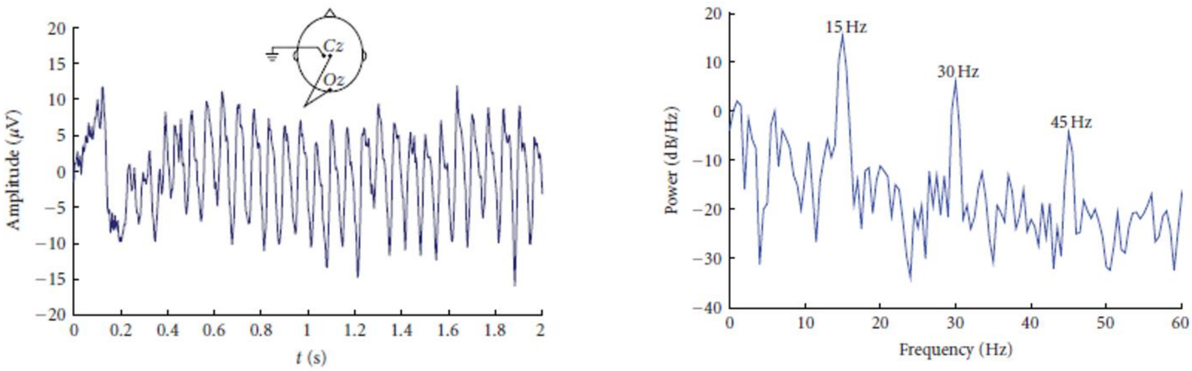


Fig. 1. Functional block diagram of an SSVEP-based BCI

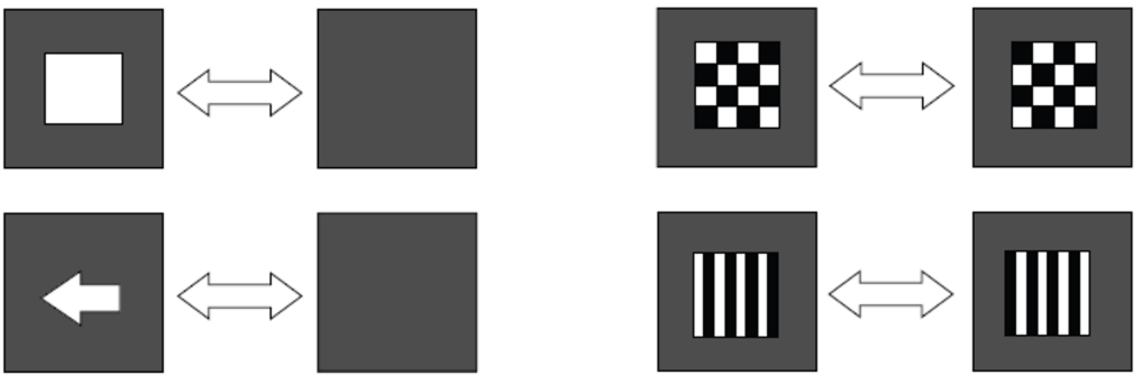
An interesting property of these oscillations is that their amplitude is modulated by the user visual attention. The amplitude of the SSVEPs is increased when the user looks at the stimulus and decreased when the user ignores it. Fig. 2 shows a typical EEG signal and its frequency spectrum acquired during visual stimulation with 15Hz flickering frequency. Fig. 2.a shows the average of ten time-aligned SSVEP signals. We clearly observe a transient visual evoked potential when the stimulation began forwarded by oscillation in the steady state. Fig. 2.b shows the ten averaged signals in the frequency domain. The oscillation at 15Hz and higher harmonics can be clearly observed [14].



(a) SSVEP-based EEG signals in time domain (b) SSVEP-based EEG signals in frequency domain

Fig. 2. Typical waveform of SSVEP-based EEG signals [14]

SSVEPs can be used in BCI applications by showing several stimuli working at different frequencies [14]. Fig. 3 shows two types of stimuli: one illustration and multiple illustrations. In one-illustration stimuli, one illustration is appeared and disappeared at specified frequency (Fig. 3.a). In multiple illustrations stimuli, at least two illustrations are shown alternately at a specified frequency (Fig. 3.b). In SSVEPs paradigm, the flickered graphical object elicits a brain signal of the same frequency or harmonics with that of the graphical object. Therefore, an SSVEP based BCI system can be implemented by detecting the basic frequency of the focused flickered graphical object from these brain signals.



(a) Single graphic. (b) Pattern reversal.

Fig. 3. Typical repetitive visual stimuli [14]

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2015

2.2 Emotional BCIs. Emotions are internal feelings that are induced during an interaction between individuals themselves or individuals and machines. Individuals can understand the feelings of each other from speech, facial features, voice tone and body signs. Therefore, they can adapt their behaviors to improve the interaction between them. This scenario is not valid in the context of man machine interaction as machines cannot induce the feelings of individuals. In order to make this man machine interaction effective, affective computing provides the machines with algorithms that estimate the feelings of others [15].

In direct interactions, emotions can be recognized from apparent features such as facial and body signs. In indirect interactions, new features need to be estimated in order to recognize emotions. This work focuses on the recognition of emotions from EEG signals. This subsection reviews some works in this context.

Authors in [16] recognized the user's emotions from EEG signals and facial features while the user is listening to a particular song. They used brain electrodes to acquire EEG signals and video images to capture facial expressions. They found that it was not possible to differentiate between emotions from these signals. Sourina& Liu in [17] proposed an algorithm to distinguish human emotions from EEG signals using fractal dimensional model. The authors designed an experiment where the user has to listen to selected songs from International Affective Digitized Sounds (IADS). The selected songs induce certain emotions according to IADS. During the experiment, the brain signals were recorded from three channels, FC6, F4 and AF3. Level of excitement could be distinguished through the channel FC6. The valence could be classified using the channels AF3 and F4. According to the authors, feeling of positive emotion activates more power in one hemisphere of the forebrain of an individual. On the other hand, feeling of negative emotion activates more power in the other hemisphere. However, the mapping between the hemisphere and the emotion depends on each individual. Therefore, in order to use this approach, a training phase has to be first performed. The proposed fractal dimension model employed a bi-dimensional valence-arousal graph, shown in Fig. 4, to identify six basic emotions.

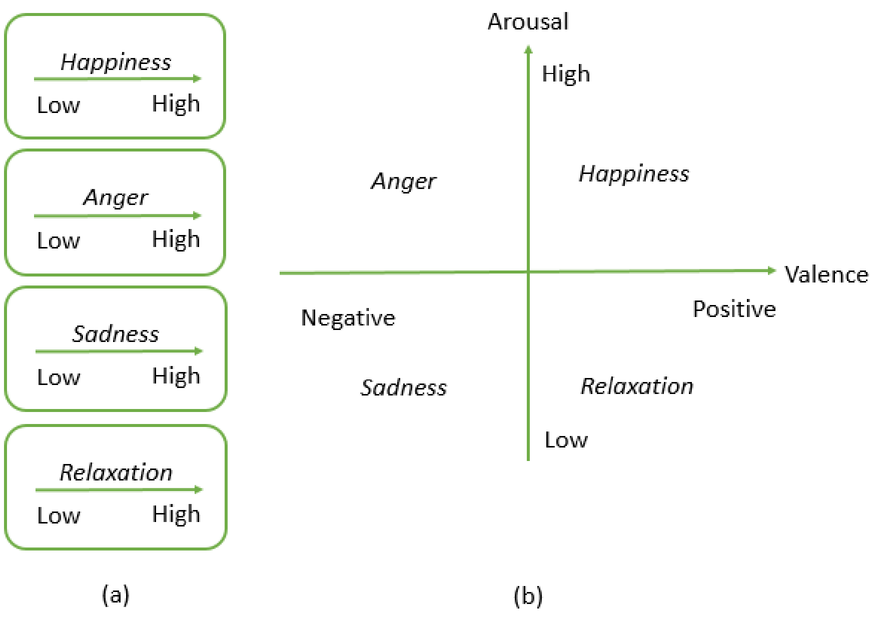


Fig. 4. Bi-dimensional valence-arousal emotion model

2.3 Emotion and BCI systems. Emotions can be used in BCI systems in two ways. In the first one, the emotion is taken into account in training the BCI systems, and, in the second one, the emotion is used to enhance the operation of the BCI systems [18]. The first approach needs extensive training of the BCI systems under different emotional states and then adapting the appropriate parameters during the online operation [19,21]. In the second approach, stimuli are carefully selected in such a way that they elicit better-featured EEG signals [22-24].

In this work, the emotion is estimated after each action taken by an SSVEP paradigm. This emotion is used to confirm the action or to cancel it. In the following section, we will explain the methodology developed in this research work.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2015

III. PROPOSED SOLUTION

Brain computer interfaces (BCIs) need to provide fast feedback to the user in order to be usable in real time applications. We propose in this section two serial BCI systems running in real time. The first one is a Steady state Visual Evoked Potentials (SSVEP) and the second one is an emotional system. As an application to this system, we propose a car driving system where the user has to steer the car form an initial position to a final destination. In this context, the user has to look at one of SSVEP flickers to produce a command to the car. Once the command is recognized, the emotional system is activated and the user's emotion is estimated. The estimated emotion is used to confirm or to cancel the command. Fig. 5 shows a general overview of the proposed system. Each unit will be briefly explained in the following subsections.

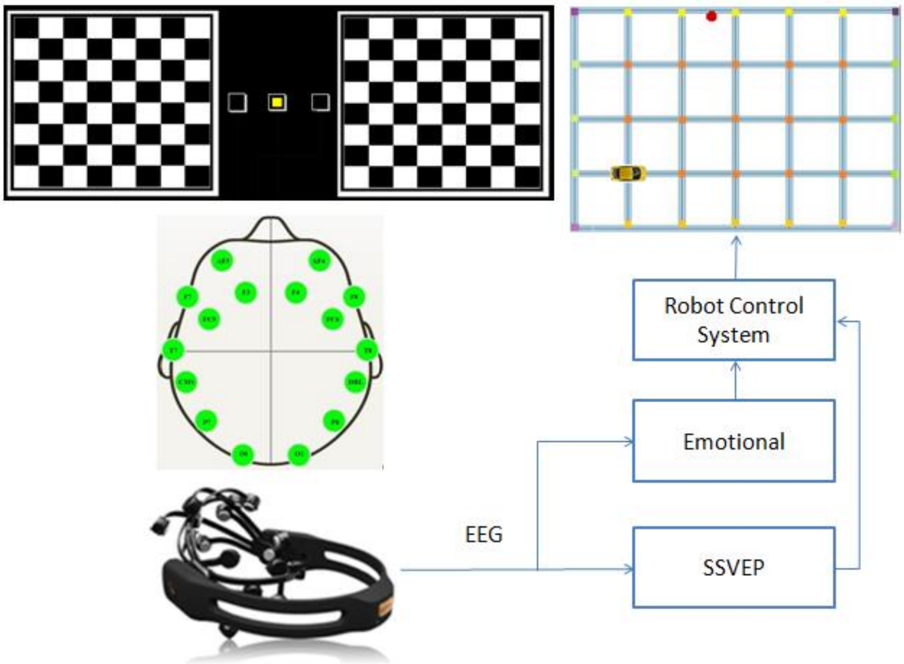


Fig. 5. General overview of the proposed system

3.1 Steady State Visual Evoked Potentials (SSVEP). Steady state visual evoked potentials are BCI systems based on generating brain signals pattern associated with visual stimuli. The visual stimuli used in our experiment are square pattern reversal shown in Fig. 3. The patterns work at frequencies 4.29Hz and 7.5Hz. The selection of frequencies is limited by the screen refresh rate (60 Hz).

The system works in two modes: training mode and online mode. In training mode, Fig. 6.a, the user is asked to look at flickers according to predefined experiment protocol. The EEG signal is recorded, filtered, preprocessed and transformed into frequency domain. The values of the signal in frequency domain at flickering frequencies and their harmonics are stored in one vector to form the feature vector. Feature vectors and experiment procedure are used to train a linear classifier. The classifier parameters are saved and used later in online mode (Fig. 6.b).

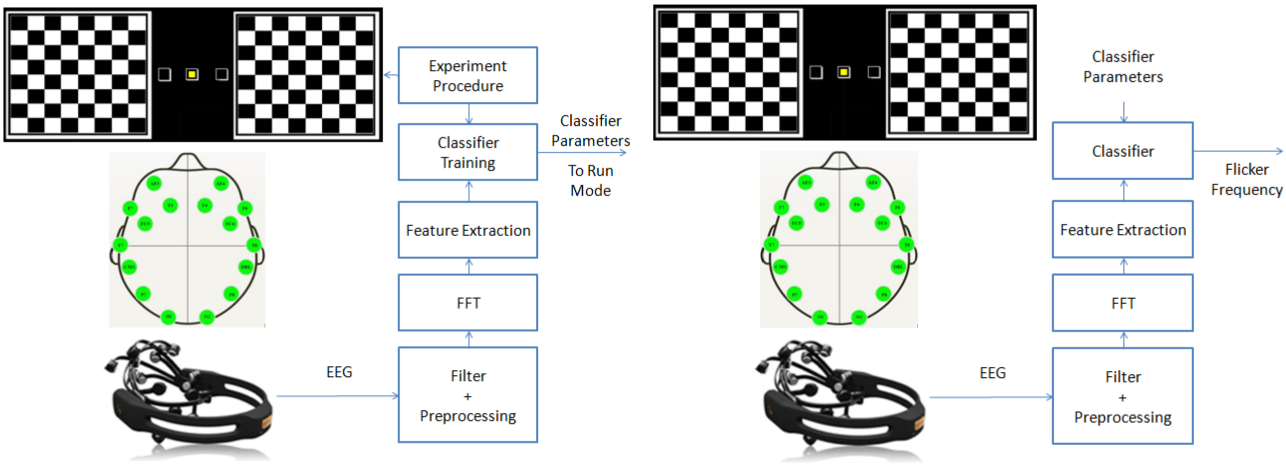
In online mode, Fig. 6.b, the user is asked to look at one flicker according to his intention whether he/she wants to turn the car to the right or to the left. The EEG signal is recorded, filtered, preprocessed, and transformed into frequency domain. The values of the signal in frequency domain at flickering frequencies and their harmonics are stored in one vector to form the feature vector. Feature vector is passed to the classifier to find its class (i.e. the flicker at which the user is looking at). The flickers and the processing are programmed in Matlab® using several toolboxes. The device that is used for recording the EEG signal is the Emotiv EPOC system (see https://www.emotiv.com/epoc/ for more details about the device).

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2015



(a) Training mode (b) Online mode

Fig. 6. Proposed SSVEP system

3.2 Emotional BCIs. Emotional BCIs is based on animation system shown in Fig. 7. It consists of a road network, a car in an initial position and a final destination. The user has to drive the car from the initial position (the current position of the car) to the final destination (the red circle on the map) using the SSVEP system explained in previous subsection. After recognizing a command, the emotion unit is activated and it will estimate the user's emotion. The emotion unit finds the user's emotions using fractal dimension approach and two dimensional arousal-valence model of emotion explained in Subsection 1.2. More details about dimension approach can be found in reference [17].

All the algorithms are programmed in Matlab®. The animation is programmed using MIT Scratch programming language (see http://scratch.mit.edu/ for more details). The communication between Matlab® and MIT Scratch software is performed via virtual ports.

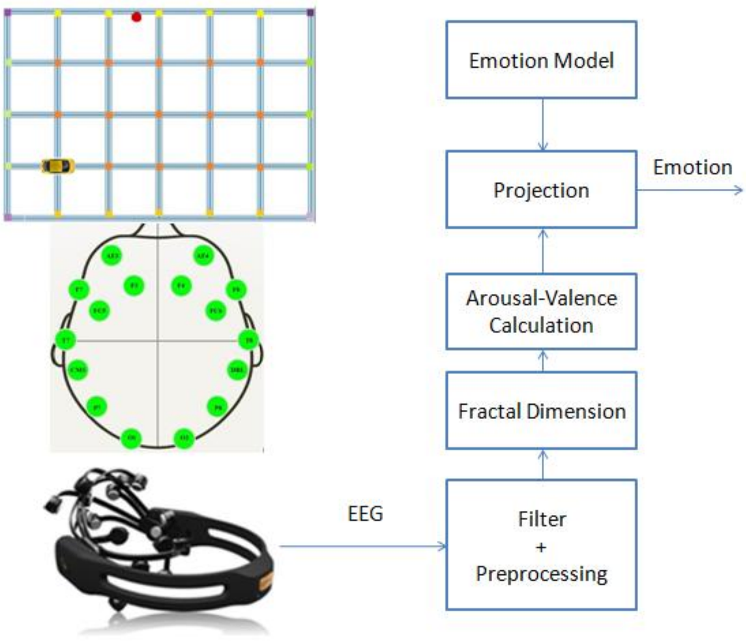


Fig. 7. Emotional BCIs

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

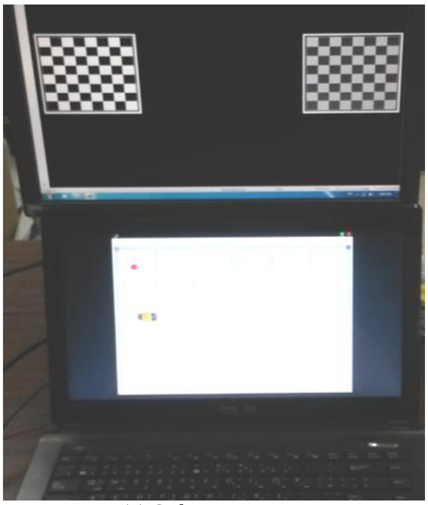
International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

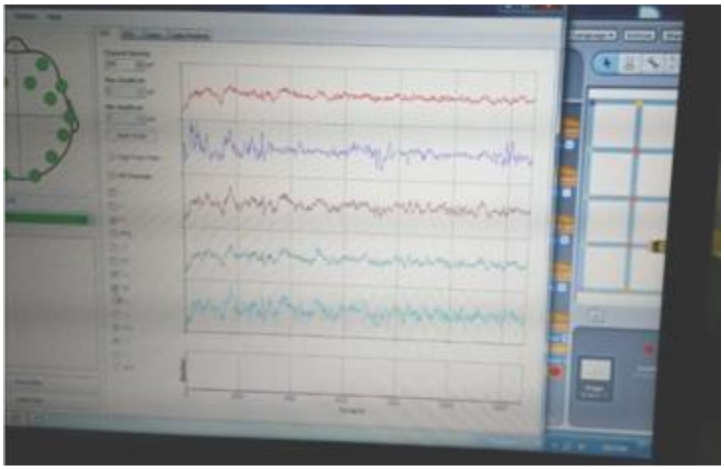
Vol. 3, Issue 12, December 2015

IV. RESULTS

In order to evaluate the proposed application, shown in Fig. 8, it was run by four users. First, a training session is performed where the user is instructed to look at one of the two checkerboards then feature vectors are extracted and used to train a linear classifier as explained in previous section. Second, an online session is run which consists of two phases, online SSVEP phase and Emotion phase. Fig. 8 shows snapshots of the hardware used in the experiment and a snapshot of the real-time EEG signals.



(a) Online experiment



(b) Snapshot of real-time EEG signal

Fig. 8. Proposed SSVEP – Emotional application

In Fig. 8.a, the lower screen shows the car that the user has to steer to the red ball by brain. The upper screen shows the flickers working at different frequencies that the user can use to generate appropriate brain signals to turn the car to the left, by looking at the left flicker, or to the right, by looking at the right flicker.

4.1 SSVEP Results. The SSVEP method explained in Subsection 3.1 is applied on four users. Fig. 9 shows the averaged EEG signals and their FFT for left and right checkerboards for a user. It is clear from Fig. 9 that the working frequencies of the flickers can be recovered from the frequency domain. The values of Fourier transform of the left and the right SSVEPs at working frequencies and their harmonics constitute the feature vector. Table 1 shows samples of feature vectors for a user. Those feature vectors are used later to train a classifier which can discriminate between left and right SSVEPs.

Table 1. Some of feature vectors for a user

Segment	Feature Vector																Class
1	0.804363	0.102543	0.198196	0.155541	0.577931	0.857911	0.1512	0.090844	0.490836	0.027118	0.174782	0.096834	0.97763	0.21848	0.231461	0.282277	1
2	0.961674	0.471245	0.092402	0.039947	0.814005	0.443503	0.798657	0.372278	0.674493	0.400103	0.187257	0.474387	0.54017	0.415004	0.378617	0.6852	1
3	0.688543	0.45266	0.015987	0.426832	0.525245	0.500069	0.596147	0.664222	0.75201	0.090316	0.238738	0.196252	0.478224	0.463034	0.153665	0.302453	1
4	0.608946	0.72893	0.598748	0.322938	0.983851	0.949349	0.225069	0.26315	0.968229	0.349834	0.217751	0.25194	0.917486	0.42462	0.207951	0.103292	1
5	0.250281	0.651985	0.615468	0.81556	1	0.703262	0.796762	0.478	0.477062	0.579605	0.41594	0.643937	0.577507	0.577845	0.399477	0.226675	1
6	0.979462	0.423028	0.341225	0.199142	0.816525	0.853168	0.079083	0.360772	0.545819	0.530844	0.242605	0.0147	0.94096	0.035649	0.137455	0.174383	1
7	0.952623	0.46969	0.071752	0.291924	0.714688	0.210518	0.331157	0.511437	0.661518	0.396648	0.234712	0.052209	0.60923	0.590249	0.648636	0.265168	1
8	0.863226	0.305973	0.661096	0.288235	0.35355	0.428112	0.297949	0.226613	0.630787	0.755214	0.030936	0.133042	0.644589	0.030277	0.077542	0.363506	1
9	0.12603	0.604045	0.514124	0.089399	0.827258	0.724211	0.172844	0.271962	0.67907	0.223333	0.166372	0.147375	0.721223	0.235907	0.537905	0.278567	1
10	0.193678	0.482931	0.679543	0.152139	0.562939	0.765911	0.67792	0.268567	0.295019	0.870807	0.369543	0.237034	0.573171	0.748063	0.19747	0.214506	1
11	0.705967	0.780671	0.186697	0.174146	1	0.381944	0.273847	0.188183	1	0.051599	0.176615	0.080269	0.384352	0.521597	0.2309	0.056938	2
12	0.968003	0.315378	0.030406	0.05672	0.949219	0.367535	0.259152	0.099002	0.36982	0.086187	0.077298	0.046239	0.579482	0.322186	0.204125	0.072961	2
13	0.766727	0.275797	0.134234	0.061977	0.724915	0.257928	0.127039	0.147968	0.482388	0.142698	0.050981	0.016756	0.475998	0.208769	0.037557	0.036819	2
14	0.575759	0.834281	0.276907	0.187474	0.817576	0.858426	0.446316	0.434654	0.998858	0.379593	0.240185	0.093395	1	0.397026	0.388314	0.202296	2
15	0.960961	0.454234	0.346942	0.266555	0.86433	0.690564	0.399082	0.112194	0.59041	0.257662	0.038387	0.189917	0.817944	0.457034	0.229821	0.189008	2
16	0.874965	0.661933	0.140857	0.393315	0.800198	0.643658	0.08129	0.153867	0.915274	0.487183	0.468014	0.192982	0.792104	0.233059	0.0722	0.269242	2
17	0.871863	0.691135	0.144539	0.109632	0.951553	0.142452	0.109224	0.129931	0.822564	0.100938	0.130067	0.063707	0.371028	0.030382	0.045664	0.168972	2
18	0.201865	0.529069	0.616304	0.187957	1	0.855444	0.276371	0.143275	0.743314	0.2855	0.398022	0.254329	0.767789	0.279609	0.429441	0.043748	2
19	0.966702	0.221338	0.236366	0.360896	0.935652	0.809688	0.257028	0.075123	0.522614	0.684636	0.319	0.541365	0.904434	0.367195	0.234652	0.121004	2
20	1	0.251424	0.688202	0.79995	0.749349	0.777393	0.569758	0.442459	0.423272	0.606781	0.340303	0.26871	0.950793	0.422681	0.819272	0.398076	2

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2015

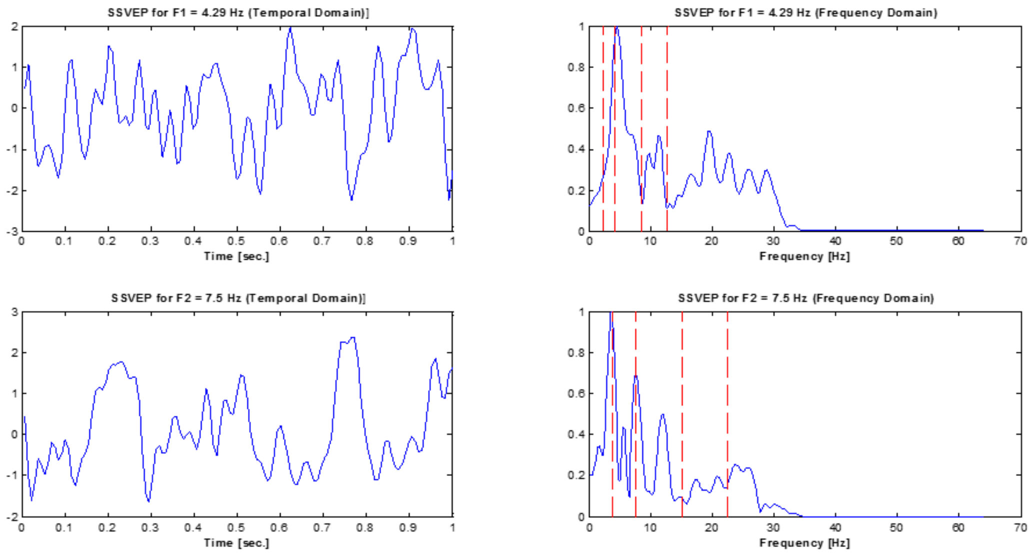
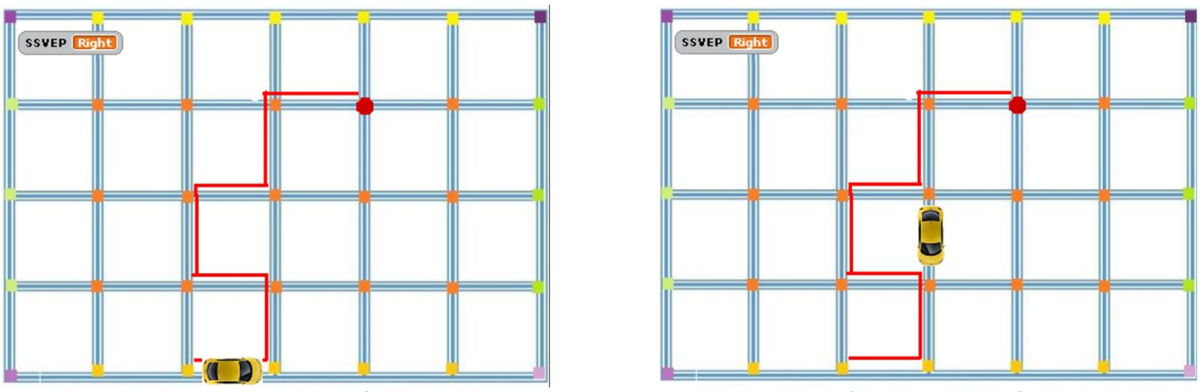


Fig. 9. Averaged EEG signals and their FFT for left and right checkerboards for a user

The obtained feature vectors and their classes are divided into training and test groups using 10-fold cross-validation method. The training samples are used to train a linear classifier and the test samples are used to test the trained classifier. The obtained classification accuracy is 70% (which corresponds to error rate 30%).
The trained classifier is applied in online experiment. Fig. 10 shows snapshots of online experiment in two cases, correct command and wrong command.



(a) Correct command (b) Wrong command

Fig. 10. Snapshots of online SSVEP experiment

The output of the online experiment is shown in Fig. 11. The blue continuous line shows the desired direction of the car, i.e. the direction that the car should follow to reach the final destination. The red dashed line shows the actual direction of the car obtained from user SSVEPs. Comparing the actual direction with the desired one, one can find that the averaged online error is 36.65%, which is near to the trained error rate (30%).

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2015

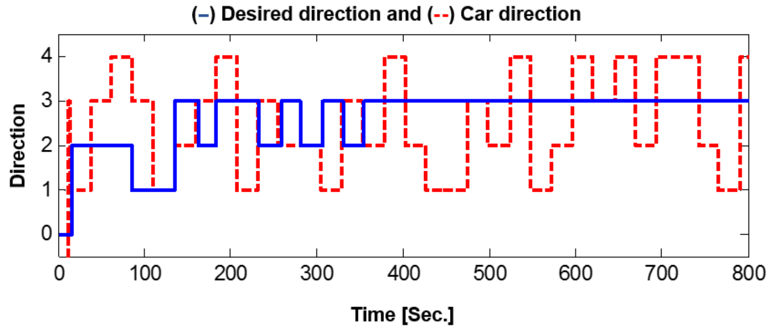
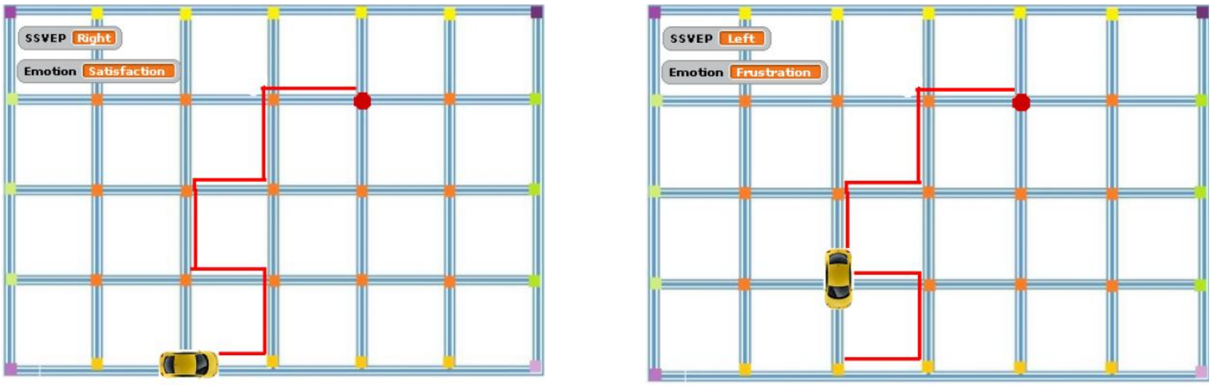


Fig. 11. Output of the online SSVEP experiment

4.2 Emotion Results. Emotional method explained in Subsection 3.2 is applied on four users. Fig. 12 shows snapshots of online experiment in two cases, correct command and wrong command.



(a) Correct command. (b) Wrong command.

Fig. 12. Snapshots of the online Emotional experiment

Fig. 13 shows the error between desired direction and estimated one and the values of arousal and valence. The zeros in the error in direction mean that the car direction confirms with the desired direction.

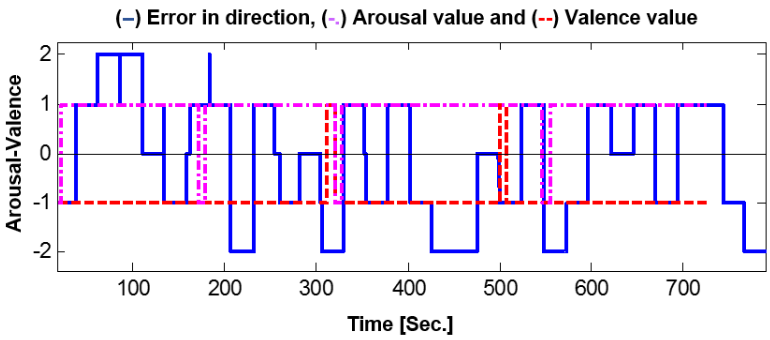


Fig. 13. Output of the online Emotional experiment

From Fig. 13, we can notice that the zero errors correspond to change in arousal and valence values. The arousal value decreases while the valence value increases and this corresponds to satisfaction emotion according to bi-dimension arousal-valence emotion model shown in Fig. 4. On the other hand, the nonzero errors correspond to increase in arousal values and decrease in valence values which also correspond to frustration emotion according to bi-dimension arousal-valence emotion model shown in Fig. 4. This means that the emotion unit estimates correctly the

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 12, December 2015

user's emotion. Therefore, the performance of the combined SSVEP Emotional units is only limited by the performance of the SSVEP unit. It should be noted that the combined system, the SSVEP and the Emotional systems, are not tested in real-time. However, it is expected that adding emotional feedback will reduce the errors committed in steering the car.

V. CONCLUSION AND FUTURE WORK

In this work, we have proposed a combined BCI experiment where two BCI units are run in the same experiment. The first unit is an SSVEP unit that permits the user to select a steering command by looking at the appropriate visual flickering checkerboard. The second unit is an emotional system that permits to estimate the user's emotion using bi-dimension arousal-valence emotion model.

Each unit was tested separately in a real-time experiment and the error rates were evaluated. We found that the SSVEP unit estimates correctly 63.35% of the desired directions and the Emotional unit estimates the emotion correctly. The error rate of the SSVEP unit affects the error rate of the overall system; therefore, SSVEP unit needs to be improved by considering other features or/and classification algorithms.

It should also be noted that the emotion unit needs heavy processing. Therefore, a parallel implementation of emotional unit will be considered in future works. It could also be better to increase the number of commands (flickers) in the SSVEP unit and the number of estimated emotions in the Emotional unit.

REFERENCES

1. Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., and Vaughan, T. M., "Brain–Computer Interfaces for Communication and Control", Clinical Neurophysiology, Vol.113, pp767-791, 2002.
2. Wolpaw, J. R., "Brain–Computer Interfaces as New Brain Output Pathways", The Journal of Physiology, Vol.579, pp.613-619, 2007.
3. Christoph, G., Allison, B. Z., and Edlinger, G., "Brain-Computer Interface Research: A State-of-the-Art Summary", Springer, 2013.
4. Van Erp, J. B., Lotte, F., and Tangermann, M., "Brain-Computer Interfaces: Beyond Medical Applications", Computer, Vol.4, pp.26-34, 2012.
5. Nijholt, A., Tan, D., Allison, B., Milan, J. d. R., and Graimann, B., "Brain-computer Interfaces for HCI and Games", in CHI'08 Extended Abstracts on Human Factors in Computing Systems, ACM, pp.3925-3928, 2008.
6. Babiloni, F., Cichocki, A. and Gao, S., "Brain-Computer Interfaces: Towards Practical Implementations and Potential Applications", Computational Intelligence and Neuroscience, Vol.2007, 2007.
7. Dornhege, G., "Toward Brain-Computer Interfacing", MIT Press, 2007.
8. Bashashati, A., Fatourechi, M., Ward, R.K. and Birch, G.E., "A Survey of Signal Processing Algorithms in Brain–Computer Interfaces based on Electrical Brain Signals," Journal of Neural Engineering, Vol.4, 2007.
9. Pfurtscheller, G., and Neuper, C., "Future Prospects of ERD/ERS in the Context of Brain–Computer Interface (BCI) Developments," Progress in Brain Research, Vol.159, pp.433-437, 2006.
10. Kachenoura, A., Albera, L., Senhadji, L., and Comon, P., "ICA: A Potential Tool for BCI Systems," IEEE Signal Processing Magazine, Vol.25, pp.57-68, 2008.
11. Schlogl, A., Kronegg, J., Huggins, J. E., and Mason, S. G., "19 Evaluation Criteria for BCI Research", Toward Brain-Computer Interfacing, 2007.
12. Boss, D. P. O., Gorki, H., Van de Lair, B., Nimbler, F., and Nichols, A., "User Experience Evaluation in BCI: Mind the Gap!", International Journal of Bio electromagnetism, Vol.13, pp.48-49, 2011.
13. Wang, Y., Gao, X., Hong, B., Jian, C., and Gao, S., "Brain-Computer Interfaces Based on Visual Evoked Potentials", IEEE Engineering in Medicine and Biology Magazine, Vol.27, pp.64-71, 2008.
14. Zhu, D., Bieger, J., Molina, G. G., and Aarts, R. M., "A Survey of Stimulation Methods used in SSVEP-Based BCIs," Computational Intelligence and Neuroscience, Vol.2010, 2010.
15. Rached, T. S., and Perkusich, A., "Emotion Recognition Based on Brain-Computer Interface Systems", Brain-Computer Interface Systems - Recent Progress and Future Prospects, 2013.
16. Adolphs, R., "Recognizing Emotion from Facial Expressions: Psychological and Neurological Mechanisms", Behavioral and Cognitive Neuroscience Reviews, Vol.1, pp.21-62, 2002.
17. Sourina, O., and Liu, Y., "A Fractal-Based Algorithm of Emotion Recognition from EEG using Arousal-Valence Model", BIOSIGNALS, pp.209-214, 2011.
18. Garcia-Molina, G., Tsoneva, T., and Nijholt, A., "Emotional Brain–Computer Interfaces", International Journal of Autonomous and Adaptive Communications Systems, Vol.6, pp.9-25, 2013.
19. Makeig, S., Leslie, G., Mullen, T., Sarma, D., Bigdely-Shamlo, N., and Kothe, C., "First Demonstration of an EEG-Based Emotion BCI", ACII 2011, Part II, LNCS 6975, pp.487–496, 2011.
20. Sitaram, R., Lee, S., Ruiz, S., Rana, M., Veit, R., and Birbaumer, N., "Real-Time Support Vector Classification and Feedback of Multiple Emotional Brain States", Neuroimage, Vol.56, pp.753-765, 2011.
21. Fattouh, A., Horn, O., and Bourhis, G., "Emotional BCI Control of a Smart Wheelchair", International Journal of Computer Science Issues, Vol.10, pp. 32-36, 2013.
22. Vuilleumier, P., and Driver, J., "Modulation of Visual Processing by Attention and Emotion: Windows on Causal Interactions between Human Brain Regions", Philosophical Transactions of the Royal Society B: Biological Sciences, Vol.362, pp.837-855, 2007.

23. Bakardjian, H., Tanaka, T., and Cichocki, A., "Emotional Faces Boost up Steady-State Visual Responses for Brain–Computer Interface", Neuroreport, Vol.22, pp.121-125, 2011.
24. Bekhtereva, V., and Müller, M. M., "Affective Facilitation of Early Visual Cortex during Rapid Picture Presentation at 6 and 15Hz", Social Cognitive and Affective Neuroscience, Vol.10, pp.1623-33, 2015.

BIOGRAPHY

Hadi Mohsen M. Oqaibi is a Teaching Assistant in the Faculty of Computing and Information Technology, King Abdulaziz University.Mr. Oqaibireceived his Master in Computer Science from King Abdulaziz University in Jeddah, Saudi Arabia.

Anas M. Ali Fattouh is Associate Professor of Automatic Control. Dr. Fattouh received his Ph.D. from the Grenoble Institute of Technology (INPG) in France, completed Post-Doctoral research at Grenoble University, and taught at the University of Aleppo in Syria before going to King Abdulaziz University in Jeddah, Saudi Arabia.