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SSVEP AND ANN BASED OPTIMAL SPELLER DESIGN FOR BRAIN COMPUTER INTERFACE

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Abstract. This work put forwards an optimal BCI (Brain Computer Interface) speller design based on Steady State Visual Evoked Potentials (SSVEP) and Artificial Neural Network (ANN) in order to help the people with severe motor impairments. This work is carried out to enhance the accuracy and communication rate of BCI system. To optimize the BCI system, the work has been divided into two steps: First, designing of an encoding technique to choose characters from the speller interface and the second is the development and implementation of feature extraction algorithm to acquire optimal features, which is used to train the BCI system for classification using neural network. Optimization of speller interface is focused on representation of character matrix and its designing parameters. Then again, a lot of deliberations made in order to optimize selection of features and user's time window. Optimized system works nearly the same with the new user and gives character per minute (CPM) of 13 ± 2 with an average accuracy of 94.5% by choosing first two harmonics of power spectral density as the feature vectors and using the 2 second time window for each selection. Optimized BCI performs better with experienced users with an average accuracy of 95.1%. Such a good accuracy has not been reported before in account of fair enough CPM.

Keywords: Brain computer Interface, SSVEP, Neural networks, Mental speller, EEG, Classification

1. Introduction

The ability to communicate with other persons is one of the main factors that making the life of any human being enjoyable. Communication is the basis of human development and it makes possible to convey ideas, desires and opinion. Individual's suffering of motor disorders have restricted possibilities to speak and normally require assistive technologies to complete this primary requirement.The different brain responses, i.e. EEGs (Electroencephalogram) are used to translate different excitation of brain areas. When these responses are used with the proper translation algorithm, it helps us to develop a BCI system. SSVEP provides stronger and relatively easy detectable responses than the other counterparts like P300, Motor imagination. Once the response has been detected and classified, it can be easily converted into computer commands. This kind of BCI system is very helpful for people who are not able to move as it uses only brain responses to drive a system [3, 10]. It has been observed (though not necessary) that people suffering from amyotrophic lateral sclerosis (ALS) are the most suitable candidates for using BCIs on daily basis [3-4]. In Non-Invasive BCI, Brain signals are recorded using Electroencephalography (EEG) from the scalp (Cecotti and Rivet, 2010) whereas in Invasive BCI, it gets recorded from neurons directly within the cortex (Wolpaw et al., 2002).

Even though speller design is not the most common applications in BCI research but recently many attempts have been already made in the development of an SSVEP-based BCI speller system by various methods. Sugiatro I et al.(Sugiarto et al., 2009) used optimization strategy in spelling program application focused on the hardware of speller display, where the decision times were varied according to different group of words and it was slow also. Cecotti H et al. (Cecotti, 2010) worked on self-paced and calibration less SSVEP based speller in which a single character could be selected in 3 steps; this technique was responsible to take more time in the decision. Hwang H J et al. (Hwang et al., 2012) developed Qwerty-style LED keyboard, which provided significant less time in the decision because of designing of speller but chances of error increased and so it provides a poor classification accuracy. Cecotti H et al. (Cecotti and Rivet, 2010) tested frequencies between 20 Hz to 30 Hz for LCD screen and obtained an average accuracy of 89% for the selected frequency.

This paper focuses on the SSVEP based BCI systems to allow communication for people suffering from motor disorder. The BCI module consists of a set of sensors, which was used to receive the signals from the volunteers and an amplifier which is used to amplify the signals received from the sensors for signal processing algorithms. Further, features have been extracted; the feature extraction has been done by choosing the specific frequency components of power spectral density (PSD). These features were used in classification of control signals; the classification strategy was based on neural network. Finally control signals derived from classification of different classes are sent to the output device module. The designing of the speller is done in such a way that it uses two steps for each character selection with a provision of wrong selection delete option.

2. Materials and methods

The experiment was carried out in an ordinary room at normal conditions. The volunteers were seated 60 cm away from the center of the LCD monitor which was used as speller for the volunteer. A snapshot of the experimental setup is shown in Figure 1.

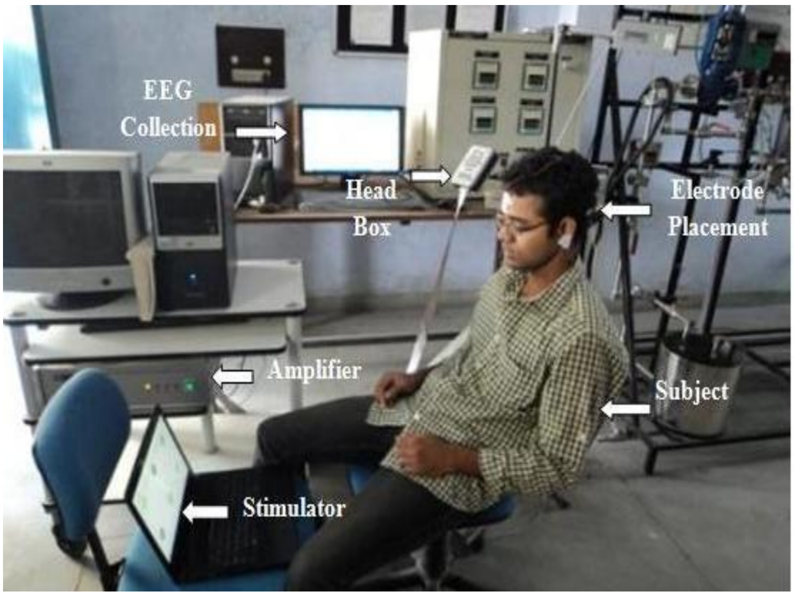

Figure 1. **Experimental setup for EEG acquisition**

2.1 System overview

As shown in Figure 2, the spelling interface helps the BCI module and user to retrieve the information of exact time instants in which the acquired signal should be recorded and classified by providing visual feedback. The BCI module mainly consists of four stages: filtering of EEGs, feature extraction, classification and conversion into control signals as shown in Figure 3.

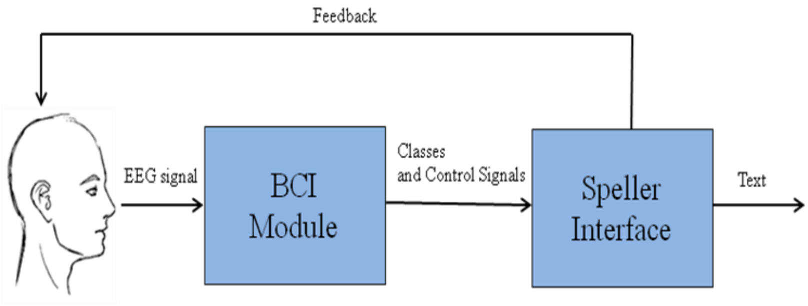

Figure 2. **Block diagram of the system.**

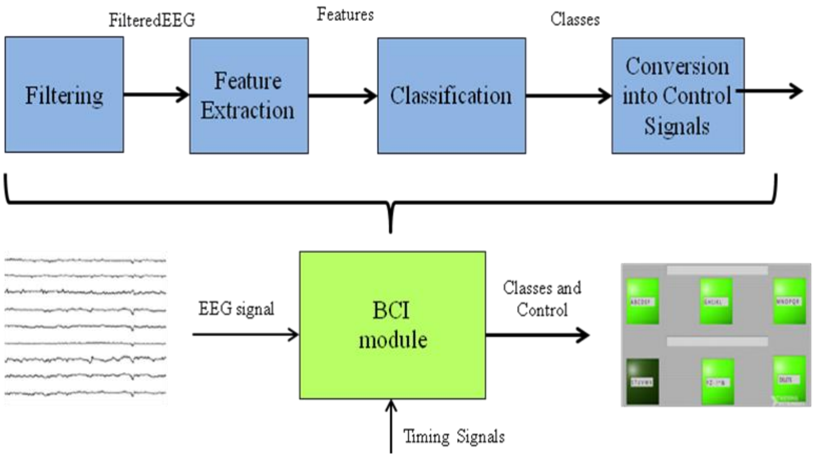

Figure 3. **Block diagram BCI module.**

The speller interface used to present choices of the alphabetical letter and symbols to the volunteers and apply the control signal received in actual target selections. The visual stimulation consists of 6 flickering targets; each of them produces different responses over the visual cortex as they are flickering at different frequencies. These SSVEP responses are analyzed and converted into 6 command signals to select anyone flickering targets. Five of them flickering targets will expand into 6 new expanded targets, whereas DELETE target will not expand. Speller interface simply shows the chosen word by the user as its output.

2.2 Signal acquisition

An array of Ag/AgCl electrodes was placed over the scalp according to the international 10–20 standard system (Homan et al., 1987). Reference electrode was used at Linkedearlobes. EEG recordings were done with the help of RMS-32 module. The set configured parameters of RMS-32 module were: sampling frequency 256 Hz, hardware filter between 2 Hz and 55 Hz, and a 50 Hz notch filter to avoid the line frequency interference. The electrode impedances kept below 5 kΩ for proper recording of EEG. These EEG signals were analyzed, stored and processed with the self-developed program in MATLAB. The recording electrodes Fp1, Fp2, A1, A2, C4, Cz, C3, T4, T5, P3, Pz, P4, O1, Oz, O2, GND, REF were distributed according to 10-20 electrode system, on the head surface. O1, O2, and Oz usually have strong SSVEP waveforms. Electrode Oz was used to develop the power spectral density based frequency recognition (speller) as it has the best response.

Fifteen healthy right-handed volunteers were participated in this experiment. The vision correction was not required as all volunteers had a normal vision. Average ages of volunteers were 23.65 years and were ranged from 21 years to 28 years. None of the volunteers has a history of epileptic seizure. They don't have any prior experience of SSVEP-based BCI equipment and paradigm. In the experiment, six stimuli (targets) were coded with six frequencies (7 Hz, 9 Hz, 11 Hz, 13 Hz, 15 Hz, and 17 Hz) in such a way that when the user looks at any of the targets the associated frequency gets generated at the visual cortex. The chosen time durations for frequency recognition were 1.5 seconds, 2 seconds and 3 seconds. Each time, the experiment runs two sessions. Each session had ten trials for each of the six targets. This results into total sixty trials per session. Each trial lasted for 3 seconds, 4 seconds and 6 seconds as we are using time duration of 1.5 seconds, 2 seconds and 3 seconds. After each trail there was a rest time of 2 seconds for the volunteer. The flickering sequence of the six targets was arbitrary, but the presentation order of flickering was steady between different volunteers and condition. By the help of visual indication the volunteers were asked to gaze at already defined flickering objects. Instruction about the next target which is going to be gazed by volunteer was appearing in the middle of the screen.

As external visual stimulation appears to human eyes the brains visual cortex start producing SSVEPs which are synchronized with the frequency of visual stimulation. SSVEPs, having a main frequency and its harmonics can be easily detected using PSD within the frequency band of 4 to 60 Hz (Pastor et al., 2003). SSVEP has been chosen to drive the BCI system because of its response can easily detect with a high degree of accuracy as compared to other neurophysiological phenomena. For this kind of the BCI system, a very little amount of training is required. All it needs a good gazing control of the volunteers (Ding et al., 2006).

2.3 Signal processing and feature extraction

The EEG signal is recorded from the scalp then it is amplified and sampled before feature extraction. The recorded signal is pre-processed in order to improve the spatial resolution and to eliminate artifacts.

Power spectral density (PSD) is a powerful tool to analyze SSVEPs and the same has been used in this work. Figure 4 represents the PSD of fixed length window time.

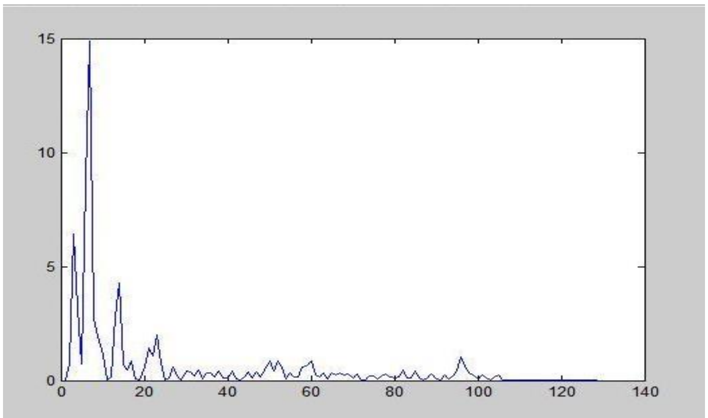

Figure 4. **Peaks corresponding to flickering frequency and its harmonics.**

The PSD has been computed for different time intervals. It has been observed that the flickering frequency that the user is looking at, produces the highest PSD peak. If the user is gazing at a square which is flickering at 7 Hz then in frequency domain, we get a peak at 7 Hz, 14 Hz (first harmonic) & 21 Hz (second harmonic). The PSD peaks of the harmonics of these frequencies kept on decreasing as the order increases. These PSD peaks have been used as feature vectors of our BCI system.

2.4 Classification into control signals

After features have been extracted and selected, the next step is the classification. There are many types of classification procedures that can be used in BCI systems. The classifiers can be categorized as linear and non-linear. Examples of linear classifiers are Bayesian Classifiers, LDA (Linear discriminant analysis) and FLD (Fisher Linear Discriminant). Examples of non-linear classifiers are neural networks and SVM. The extracted features use in BCI systems provides better/worse separability to the classes used for control. Two classification schemes have been used in the experiment:

2.4.1 Thresholding method

In order to classify the gaze of user, a threshold value has been assigned. The average peak power of EEG for all the frequencies (that the user gazed) is called threshold. Now if the power value corresponding to any frequency and its harmonic is more than this threshold then the user was looking at the object flickering at the same frequency. This gives us an output classified result corresponding to each selection, which can be converted into command signals easily.

2.4.2 Neural network method

Artificial neural networks (ANNs) are used for the classification and pattern recognition. ANNs have the capability of generalization, noise immunity, robustness, and fault tolerance. It has to be configured such that the application of a set of inputs produces the required set of outputs. One way is to set the weights with a prior knowledge. Another way is to train the neural network by providing it learning patterns and letting it modify its weights according to various learning inputs. Here we used the later method to train the neural network. PSD of EEG works as the input matrix to neural networks after preprocessing. Output matrix has been created as per the gazing instructions given to volunteers during trail sessions. Neural Network toolbox of MATLAB has been used to train a simple feed forward neural network with these input-output matrices.

2.5 Development of optimized speller interface

The efficiency of final system directly depends on the design of speller interface. Speller interface was designed in such a way that wrong selection of character by the user or wrong classification should not affect the further correct selection.

2.5.1 Symbols and functions

The considered sets of symbols consist of standard 26 English alphabets and 4 symbols - ! & *. All alphabets were taken as the uppercase. As shown in Figure 5, 26 Alphabetical letters have been used along with these four characters - ! & *. They were divided into six groups of equal lengths. There was a provision of one special character DELETE, which is sixth flickering square in the front panel. It can be used to delete the last selection of users when they choose something by mistake/ by system mistake.

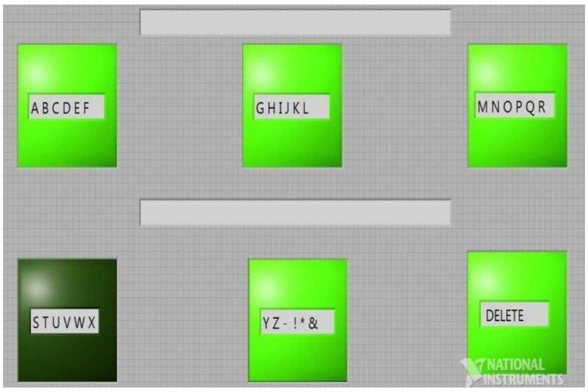

Figure 5. **Speller interface used for stimulus.**

2.5.2 Symbol selection strategy

The existing BCI speller applications are suffering from a large set of alphabets and symbols need to be mapped to a very restricted set of control states. The direct selection of alphabets or symbols can never be a good approach, although it can reduce the selection time but it will introduce high degree of complexity and inaccuracy in system. There are two symbol selection strategies that can be applied, one of them is direct and another one is encoding technique.

Encoding method has been chosen over direct method because of less accuracy and high error rate of direct method. As shown in Figure 6, encoding method constructs the grouping of characters in hierarchical tree targets and the final character is chosen through recursive targets expansions. Each character is encoded in the sequence of targets which is going to be expanded for its selection.

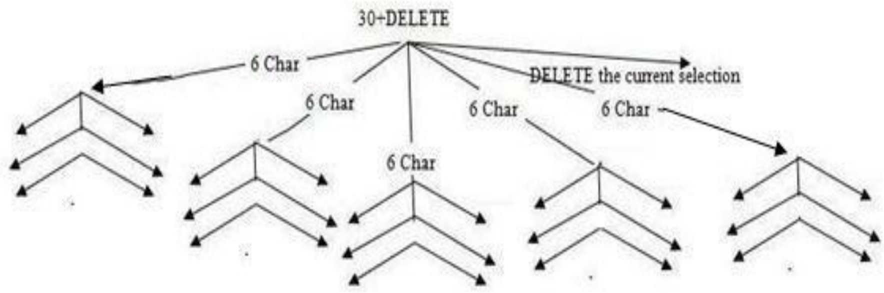

Figure 6. **Strategy of character selection.**

3. Results

15 healthy right handed male (volunteers) participated in the experiment. 10 volunteers were used for optimization of speller as well as for train, whereas 5 volunteers were used to test the optimized SSVEP based speller. Different electrodes placements were tested and finally it was concluded that Oz with REF, A1, A2 and ground electrodes can provide satisfactory results when minimum number of electrodes need to be used. After the electrodes selection, further experiment has been performed using this set of electrodes only.

3.1 Variation in accuracy with harmonics

As shown in Figure 7, Experimental results demonstrated that the use of two harmonics in the classification provided the best result. This is because, after second harmonic the signal strength goes down around the noise level of system and noise starts to interfere the classification accuracy. So, only two harmonics were used to construct the final train signals for neural network training.

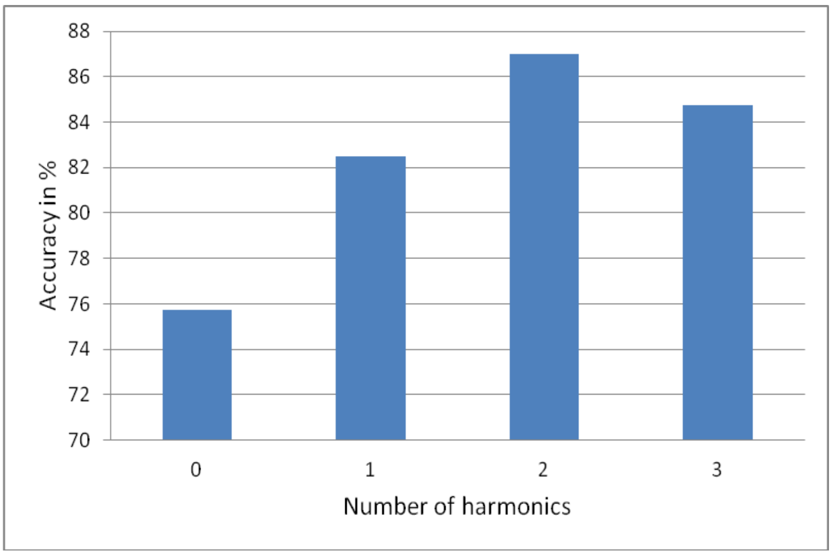

Figure 7. **Relationship between the recognition accuracy and the number of harmonics.**

3.2 The effect of classification

In this study, two classification methods have been explored. So, comparison between classification methods has been done and results reflect a clear edge of neural network over the threshold method. It can be seen from results given in Table 1 that the best result is obtained for 1000 samples training. Even though, only after 500 samples training the accuracy reached about a saturation point and beyond that the improvement is negligible.

Table 1. Effect of classification method

Method	Average recognition accuracy
Simple Threshold	87.00
Neural Network for 200 Sample training	89.50
Neural Network for 500 Sample training	95.50
Neural Network for 1000 Sample training	95.75

3.3 The effect of data length on performance

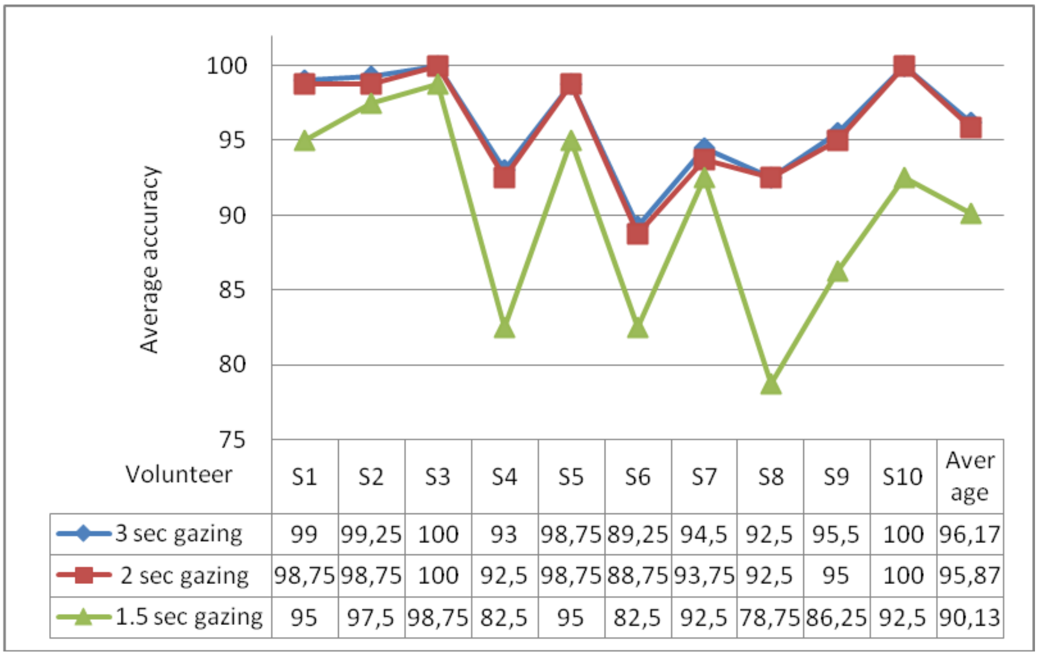

Figure 8. **The effect of data length on performance.**

The EEG signals have been recorded and PSD was computed for 1.5 seconds, 2 seconds and 3 seconds to find the optimal time slot. The results in Figure 8 confirmed that 3 seconds duration for each frequency has a better performance than the 2 seconds and 1.5 seconds time duration. Even though, the performance of 3 seconds and 2 seconds time window is providing almost same accuracy and so the choice of 2 seconds is more optimal.

3.4 The effect of user's experience on target recognition

The experiment consists of two major sessions, and the overall accuracy of both sessions is listed in the Figure 9. It can be clearly seen from the Figure 9 that all the volunteers are performing well in session 2 as compared to session 1. So we can conclude that experience of BCI system improves the performance of individual's accuracy.

Figure 9.**The effect of user's experience on target recognition.**

3.5 Introduction of new user for testing

In this phase of the experiment, we test our optimized speller on 5 new right handed male volunteers, having no prior experience of SSVEP-based BCI. They have been told to gaze on the screen as per the instructions. This time only Oz, REF, A1, A2 and ground electrodes were used for recording.

Table 2. Accuracy testing on 5 new volunteers

Volunteers	Average Accuracy	
	Session 1	Session 2
S11	92.50	92.75
S12	94.25	95.00
S13	89.75	91.00
S14	98.50	98.75
S15	97.50	98.00
Overall Average accuracy	94.50	95.10

The average accuracy of these new volunteers for both sessions are listed in Table 2, quite good accuracy can be seen without any calibration and training of volunteers.

4. Discussion

By assuming the threshold classification method and gazing time of 2 seconds, we started to evaluate and found two harmonics should be included in the train signals for neural network training. Higher gazing times were increasing a little amount of accuracy but cost a large amount of time in decision making; thus reducing the CPM drastically. Whereas, more number of harmonics were increasing the error rate in the system recognition and reduce the accuracy. So, two harmonics and 2 second time window are used as an optimal choice in this experiment. Now assuming all other parameters same except classification method technique, more accuracy can be obtained by training ANN using more samples but very little improvement in accuracy was found on the cost of large training sample/training time. It was the reason to choose 500 samples for training over 1000. The CPM of the simulated tests for the three conditions was obtained 8, 13 and 18 for 3 second, 2 second & 1.5 second time window respectively. It has been observed that the average variation in CPM in ANN classifier was ± 2 char/min during two second time window due to human error in choosing the letter/ classification error. As the results show that increment of time window from 2 second to 3 second, the accuracy was increased from 95.87% to 96.17% but it has no significance as compared to the decreasing the speed of speller (13 CPM to 8 CPM). A tradeoff has been achieved between accuracy and communication speed of proposed BCI system. So, the optimal choice of time window was 2 second. It has also been found that the user who are familiar with the paradigm of SSVEP based BCI can perform better. The experience gain in session 1 was helpful for the volunteers in session 2.

5. Conclusion

An optimal BCI speller for disable person has been proposed in this work. Different strategies for the speller interface have been considered. Finally it was decided to divide the 31 targets into six groups which lead to two selections for each character except single section of 'DELETE'. Intelligent design of speller interface helped to obtain good communication rate, reduce the wrong selection of the characters which provided accuracy of 13 ± 2 CPM and restricted the use of different frequency up to six. Optimized BCI speller has been realized by considering 2 harmonics in PSD, data window length of 2 second, 500 samples were trained for classification with the help of neural network in order to maintain good accuracy with little amount of training. BCI classification performance was evaluated and designed on 15 different volunteers by training and testing 10 and 5 volunteers respectively. Experimental results showed optimized BCI speller provides considerable improvements in accuracy as compared to non-optimized BCI spellers reported previously. In the first session approximately 94.5% accuracy with optimized BCI module has been achieved, where as in second session results were improved with 95.1% accuracy.

Though with some volunteers, we get lower classification accuracies and handling of the BCI speller become difficult for them. That is the problem of inter subject variability and it is one of the most challenging issues in BCI research these days. To enhance the generalization capabilities better feature extraction methods (wavelet transforms (Ansari et al., 2014), SVD (Ansari and Millie, 2015) etc.) and better classifiers (Surya and Irshad, 2015) along with ANN need to be used in future work. This will help us to deal with inter subject variability and improves the accuracy also.

References

Ansari, I.A., Millie P. (2015). SVD Watermarking: Particle Swarm Optimization of Scaling Factors to Increase the Quality of Watermark, In Springer Proceedings of Fourth International Conference on Soft Computing for Problem Solving, pp. 205-214.

Ansari, I.A., Millie P., Ferrante N. (2014) Analysis of gray scale watermark in RGB host using SVD and PSO. In IEEE Symposium on Computational Intelligence for Multimedia, Signal and Vision Processing (CIMSIVP), pp. 1-7.

Cecotti H. (2010). A self-paced and calibration-less SSVEP-based brain–computer interface speller, IEEE Trans Neural SystRehabilEng 18: 127.

Cecotti H., Rivet B. (2010). A solution to solve the dilemma of high frequencies and LCD screen for SSVEP responses, IntJbioelectromag 11.

Ding J., Sperling G., Srinivasan R. (2006). Attentional modulation of SSVEP power depends on the network tagged by the flicker frequency, Cereb Cortex 16: 1016.

Homan R.W, Herman J., Purdy P. (1987). Cerebral location of international 10–20 system electrode placement, ElectroencephalogrClinNeurophysiol 66: 376.

Hwang H.J., Lim J.H., Jung Y.J. (2012). Development of an SSVEP-based BCI spelling system adopting a QWERTY-style LED keyboard, J neurosci meth 208: 59.

Pastor M.A., Artieda J., Arbizu J. (2003). Human cerebral activation during steady-state visual-evoked responses, JNeurosci 23: 11621.

Sugiarto I., Allison B., Graser A. (2009). Optimization strategy for SSVEP-based BCI in spelling program application, International Conference on Computer Engineering and Technology, Singapore, pp. 223-226.

Surya K., Irshad A.A. (2015). An improved K means clustering with Atkinson index to classify liver patient dataset Int J Syst Assur Eng Manag, 10.1007/s13198-015-0365-3

Wolpaw J.R., Birbaumer N., McFarland D.J. (2002). Brain–computer interfaces for communication and control, Clinneurophysiol 113: 767.

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PUSIAUSVYRINIAIS VIZUALIAI AKTYVUOJAMAIS POTENCIALAIS IR DIRBTINIU NEURONINIU TINKLU GRINDŽIAMAS OPTIMALAUS SKIEMENUOKLIO SMEGENŲ IR KOMPIUTERIO SĄSAJAI PROJEKTAVIMAS

Irshad Ahmad Ansari, Rajesh Singla and Munendra Singh

S a n t r a u k a

Šiame darbe projektuojamas optimalus pusiausvyriniais vizualiai aktyvuojamais potencialais ir dirbtiniu neuroniniu tinklu grindžiamas skiemenuoklis smegenų ir kompiuterio sąsajai (*angl.* Brain Computer Interface, BCI) siekiant padėti sunkių motorikos sutrikimų turientiems žmonėms. Atliekant šį darbą buvo siekiama pagerinti smegenų ir kompiuterio sąsajos tikslumą ir komunikacinį dažnį. Sistemos optimizavimas buvo atliekamas dviem etapais. Pirma buvo atliekamas kodavimo technikos projektavimas siekiant parinkti simbolius iš skiemenuoklio sąsajos. Antra buvo kuriamas ir programuojamas požymių išskyrimo algoritmas siekiant išgauti optimalias savybes, naudojamas smegenų ir kompiuterio sąsajos mokymui klasifikuoti objektus panaudojant dirbtinį neuroninį tinklą. Skiemenuoklio sąsajos optimizavimas sutelktas į simbolių matricos atvaizdavimą ir jos parametrų parinkimą. Atlikti tyrimai siekiant parinkti optimalias savybes ir taip vadinamą vartotojo laiko langą (*angl.* user's time window). Optimizuota sistema su nauju vartotoju veikia beveik taip pat gerai kaip su jau žinomu, išduodama 13 ± 2 simbolių per minutę (CMP) su vidutiniu 94,5% tikslumu, kai savybių vektoriumi yra pasirinktos dvi pirmosios spektrinio tankio galios harmonikos ir naudojamas 2 sekundžių laiko langas kiekvienam išrinkimui. Optimizuota smegenų ir kompiuterio sąsajos sistema su jau žinomais naudotojais veikia vidutiniu 95.1% tikslumu.

Pagrindiniai žodžiai: smegenų ir kompiuterio sąsaja, SSVEP, dirbtinis neuroninis tinklas, mentalinis skiemenuoklis, EEG, klasifikavimas.