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A Review: Enhancement of Brain Computer Interface

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Abstract— **An effective brain computer interface (BCI) leverages the separate strengths of both human and machine to create new capabilities and leaps in efficiencies. With B-Alert BCI development tools, developers are provided rapid prototyping tools to fit the right approach to the right task. Within clinical environments, the results are recovery of lost function and accelerated healing. In other applications, BCI's facilitate more efficient interactions between man and machine. The work focus on P300 (Type of EEG signal) signal processing, feature extraction from the processed signals, discovering signal classes, classification and interpretation of unknown signals.**

Index Terms—**BCI, P300, EEG Signal, SOM**

I. Introduction

The work focus on P300 (Type of EEG signal) signal processing, feature extraction from the processed signals, discovering signal classes, classification and interpretation of unknown signals. The research methodology involves following steps:

- EEG Data Sets (Already Collected)
- Signal Preprocessing
- Feature Extraction
- Knowledge Discovery using SOM
- Classification using Classifier Ensemble
- Comparing Accuracy with already work done

a. Signal acquisition

In the BCIs discussed here, the input is EEG recorded from the scalp or the surface of the brain or neuronal activity recorded within the brain. Electrophysiological BCIs can be categorized by whether they use non-invasive (e.g. EEG) or invasive (e.g. intracortical) methodology. They can also be categorized by whether they use evoked or spontaneous inputs. Evoked inputs (e.g. EEG produced by flashing letters) result from stereotyped sensory stimulation provided by the BCI. Spontaneous inputs (e.g. EEG rhythms over sensor motor cortex) do not depend for their generation on such stimulation. There is, presumably, no reason why a BCI could not combine non-invasive and invasive methods or evoked and spontaneous inputs. In the signal-acquisition part of BCI operation, the chosen input is acquired by the recording electrodes, amplified, and digitized[15]

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b. Signal processing-

The goal of signal analysis in a BCI system is to maximize the signal-to-noise ratio (SNR) of the EEG or single-unit features that carry the user's messages and commands. To achieve this goal, consideration of the major sources of noise is essential . Noise has both non neural sources (e.g., eye movements, EMG, 60-Hz line noise) and neural sources (e.g., EEG features other than those used for communication). Noise detection and discrimination problems are greatest when the characteristics of the noise are similar in frequency, time or amplitude to those of the desired signal. For example, eye movements are of greater concern than EMG when a slow cortical potential is the BCI input feature because eye movements and slow potentials have overlapping frequency ranges.

Numerous options are available for BCI signal processing. Ultimately, they need to be compared in on-line experiments that measure speed and accuracy. The new Graz BCI system, based on Matlab and Simulink, supports rapid prototyping of various methods. Different spatial filters and spectral analysis methods can be implemented in Matlab and compared in regard to their online performance. Autoregressive (AR) model parameter estimation is a useful method for describing EEG activity.

Signal processing methods are important in BCI design, but they cannot solve every problem. While they can enhance the signal-to-noise ratio, they cannot directly address the impact of changes in the signal itself. Factors such as motivation, intention, frustration, fatigue, and learning affect the input features that the user provides. Thus, BCI development depends on appropriate management of the adaptive interactions between system and user, as well as on selection of appropriate signal processing methods[14].

c. Feature extraction

The digitized signals are then subjected to one or more of a variety of feature extraction procedures, such as spatial filtering, voltage amplitude measurements, spectral analyses, or single-neuron separation. This analysis extracts the signal features that (hopefully) encode the user's messages or commands. BCIs can use signal features that are in the time domain (e.g. evoked potential amplitudes or neuronal firing rates) or the frequency domain. A BCI could conceivably use both time domain and frequency-domain signal features, and might thereby improve performance [14].

d. The translation algorithm

The first part of signal processing simply extracts specific signal features. The next stage, the translation algorithm, translates these signal features into device commands orders that carry out the user's intent. This algorithm might use linear methods (e.g. classical statistical analyses (Jain et al., 2000) or nonlinear methods (e.g. neural networks). Whatever its nature, each algorithm changes independent variables (i.e. signal features) into dependent variables (i.e. device control commands).

A translation algorithm is a series of computations that transforms the BCI input features derived by the signal processing stage into actual device control commands. Stated in a different way, a translation algorithm takes abstract feature vectors that reflect specific aspects of the current state of the user's EEG or single-unit activity (i.e., aspects that encode the message that the user wants to communicate) and transforms those vectors into application-dependent device commands. Different BCI's use different translation algorithms (e.g., [3]–[9]). Each algorithm can be classified in terms of three key features: transfer function, adaptive capacity, and output. The transfer function can be linear (e.g., linear discriminate analysis, linear equations) or nonlinear (e.g., neural networks). The algorithm can be adaptive or non adaptive. Adaptive algorithms can use simple handcrafted rules or more sophisticated machine-learning algorithms. The output of the algorithm may be discrete (e.g., letter selection) or continuous.[4]

e. The output device

For most current BCIs, the output device is a computer screen and the output is the selection of targets, letters, or icons presented on it. Some BCIs also provide additional, interim output, such as cursor movement toward the item prior to its selection. In addition to being the intended product of BCI operation, this output is the feedback that the brain uses to maintain and improve the accuracy and speed of communication. Initial studies are also exploring BCI control of a neuroprosthesis or thesis that provides hand closure to people with cervical spinal cord. In this prospective BCI application, the output device is the user's own hand.

f. The operating protocol

Each BCI has a protocol that guides its operation. This protocol defines how the system is turned on and off, whether communication is continuous or discontinuous, whether message transmission is triggered by the system (e.g. by the stimulus that evokes a P300) or by the user, the sequence and speed of interactions between user and system, and what feedback is provided to the user. Most

protocols used in BCI research are not completely suitable for BCI applications that serve the needs of people with disabilities. Most laboratory BCIs do not give the user on/off control: the investigator turns the system on and off. Because they need to measure communication speed and accuracy, laboratory BCIs usually tell their users what messages or commands to send. In real life the user picks the message. Such differences in protocol can complicate the transition from research to application.

A standard P300 signal Dataset that has already been collected. The BCI competitions have been used to collect the datasets of P300 signals. These signals will be pre-processed which includes amplification; filtering and then the signals are digitized for further feature extraction and classification purpose. The P300 signals are non-stationary and self-generated signals.

For better interpretation of the EEG signal in time-domain and frequency-domain simultaneously, wavelet Transform (WT) and wavelet Packet Transform (WPT) are good analysis tools. Also, the extensive research has been discussed for feature extraction in P300 based BCI systems using wavelet theory or wavelet packet decomposition. Knowledge Discovery is the process of discovering new patterns from large data sets. Here Self-organizing Feature Map will be used to discover classes from signals. The pre-processed wavelet vectors form 'clusters' on the trained SOM that are related to P300 patterns. Every detected class depicted as a cluster on the map. For the classification of the unknown data samples, various types of classifier exist. A variety of techniques exists for classification purpose like artificial neural network, Back-propagation Neural Network, Hidden Markov Model (HMM) and Bayes Network etc.

Recent work has shown that ensemble learning has employed combining classifiers. This combining classifier approach has solved the problem of reducing variance as unstable classifiers can have universally low bias and high variance. There are various ensemble learning methods, commonly used are Bagging, Boosting, Stacking and Voting. Therefore, classifier ensemble (a recent trend in classifier combination) will be used to obtain a better classification.

II. LITERATURE REVEIW

Anupama.H.S, N.K.Cauvery, Lingaraju.G.M (2012) proposed that A Brain Computer Interface (BCI) provides a communication path between human brain and the computer system. With the advancement in the areas of information technology and neurosciences, there has been a surge of interest in turning fiction into reality. The major goal of BCI research is to develop a system that allows disabled people to communicate with other persons and helps to interact with the external environments. This area includes components like, comparison of invasive and noninvasive technologies to measure brain activity, evaluation of control signals (i.e. patterns of brain activity that can be used for communication), development of algorithms for translation of brain signals into computer commands, and the development of new BCI applications. This Paper provides an insight into the aspects of BCI, its applications, recent developments and open problems in this area of research.

Jonathan R. Wolpawa, Niels Birbaumer, Dennis J. McFarlanda (2002) proposed that For many years people have speculated that electroencephalographic activity or other electrophysiological measures of brain function might provide a new non-muscular channel for sending messages and commands to the external world – a brain–computer interface (BCI). Over the past 15 years, productive BCI research programs have arisen. Encouraged by new understanding of brain function, by the advent of powerful low-cost computer equipment, and by growing recognition of the needs and potentials of people with disabilities, these programs concentrate on developing new augmentative communication and control technology for those with severe neuromuscular disorders, such as amyotrophic lateral sclerosis, brainstem stroke, and spinal cord injury. The immediate goal is to provide these users, who may be completely paralyzed, or 'locked in', with basic communication capabilities so that they can express their wishes to caregivers or even operate word processing programs or neuroprostheses.

Brent J. Lance and Kaleb McDowell(2012) proposed that As the proliferation of technology dramatically infiltrates all aspects of modern life, in many ways the world is becoming so dynamic and complex that technological capabilities are overwhelming human capabilities to optimally interact with and leverage those technologies. Fortunately, these technological advancements have also driven an explosion of neuroscience research over the past several decades, presenting engineers with a remarkable opportunity to design and develop flexible and adaptive brain-based neurotechnologies that integrate with and capitalize on human capabilities and limitations to improve human-system interactions. Major forerunners of this conception are brain-computer interfaces (BCIs), which to this point have been largely focused on improving the quality of life for particular clinical populations and include, for example, applications for advanced communications with paralyzed or "locked-in" patients as well as the direct control of prostheses and wheelchairs.

Luis Fernando Nicolas-Alonso and Jaime Gomez-Gil (2012) proposed that a brain-computer interface (BCI) is a hardware and software communications system that permits cerebral activity alone to control computers or external devices. The immediate goal of BCI research is to provide communications capabilities to severely disabled people who are totally paralyzed or 'locked in' by neurological neuromuscular disorders, such as amyotrophic lateral sclerosis, brain stem stroke, or spinal cord injury. Here, we review the state-of-the-art of BCIs, looking at the different steps that form a standard BCI: signal acquisition, preprocessing or signal enhancement, feature extraction, classification and the control interface.

III. OBJECTIVE

- Investigate the event-related potential (ERP) response for the P300-based brain–computer interface speller.
- A signal preprocessing method integrated coherent average, principal component analysis (PCA) and independent component analysis (ICA) to reduce the dimensions and noise in the raw data.
- The time–frequency analysis will be based on wavelets.

IV. METHODOLOGY

A research methodology provides us the basic concept if other has used techniques or methods similar to the ones we are proposing, which technique is best appropriate for them and what kind of drawbacks they have faced with them. Hence, we will be in better position to select a methodology that is capable of providing a valid answer to all the research questions which constitutes research methodology. At each step of our operation we are provide d with multiple choices either to take this scenario or use any other, which will let us to define and help us to achieve objective. Thus knowledge base of research paper methodology plays an important role.

RESEARCH PLAN

The whole program is divided into 3 phases:

PHASE 1

- load the training dataset
- select the specific channel in which P300 signals are present
- lowpass and highpass butterworth filtering
- coherence averaging
- ICA
- PCA
- wavelet filtering to extract the features to be trained using db4 wavelet
- k means clustering of the obtained features
- SVM training of the clusters obtained after k means

PHASE 2

- load the testing dataset
- select the specific channel in which P300 signals are present
- low pass and high pass butter worth filtering
- coherence averaging
- ICA
- PCA
- wavelet filtering to extract the features to be trained using db4 wavelet
- k means clustering of the obtained features

PHASE 3

Classify using trained clusters from Phase 1 and features from Phase 2

V. FUTURE SCOPE

The discussed study shows that the question about the mechanisms generating the ERP in the human EEG is still far from being answered. It is noteworthy that several studies yielding evidence for phase resetting argue that phase reset may be only one mechanism which is involved in ERP generation, but they also provide evidence for an evoked response. The crucial point, is to quantify the contribution of each mechanism.

REFERENCES

[1] Jonathan R. Wolpaw, Niels Birbaumer, William J. Heetderks," Brain–Computer Interface Technology: A Review of the First International Meeting" IEEE TRANSACTIONS ON REHABILITATION ENGINEERING, VOL. 8, NO. 2, JUNE 2000
[2] Lance, B.J.; Kerick, S.E.; Ries, A.J.; Oie, K.S.; McDowell, "Brain–Computer Interface Technologies in the Coming Decades,"

Proceedings of the IEEE, vol.100, no. Special Centennial Issue, pp.1585-1599, May 13 2012.
[3] J. R. Wolpawet al., "Brain–computer interface research at the Wadsworth Center," IEEE Trans. Rehab. Eng., vol. 8, pp. 222–226, June 2000.
[4] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," Clin. Neurophysiol. vol. 113, Jun. 2002, pp. 767–791,Doi:10.1016/S1388-2457(02)00057-3.
[5] F. Nijboer et al., "A P300-based brain–computer interface for people with amyotrophic lateral sclerosis," Clin. Neurophysiol vol. 119, Aug. 2008, pp. 1909–1916, doi:10.1016/j.clin ph.2008.03.034.
[6] R. T. Lauer *et al.*, "Applications of cortical signals to neuroprosthetic control: A critical review," *IEEE Trans. Rehab. Eng.*, vol. 8, pp. 205–208, June 2000.
[7] P. J. Rousche and R. A. Normann, "Chronic recording capability of the Utah intracortical electrode array in cat sensory cortex," *J. Neurosci. Math.*, vol. 82, pp. 1–15, 1998.
[8] A. Kostov and M. Polak, "Parallel man-machine training in development of eeg-based cursorcontrol," IEEE Trans. on Neural Systems and Rehabilitation Engineering, pp. 203–205, 2000.
[9] Y. Wang and T. P. Jung, BA collaborative brain-computer interface for improving human performance, PLoS ONE, vol. 6, no. 5, e20422, 2011.
[10] E. Donchin, K. Spencer, and R.Wijesinghe, "The mental prosthesis: assessing the speed of a P300-based brain-computer interface," IEEE Transactions on Rehabilitation Engineering, vol. 8, no. 2, pp. 174–179, 2000.
[11] U. Hoffmann, J.-M. Vesin, T. Ebrahimi, and K. Diserens, "An efficient p300-based brain-computer interface for disabled subjects," Journal of Neuroscience Methods, vol. 167, no. 1, pp. 115–125, 2008.
[12] H. Serby, E. Yom-Tov, and G. Inbar, "An improved P300-based brain-computer interface," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 13, no. 1, pp. 89–98, 2005.
[13] F. Nijboer, E.W. Sellers, J. Mellinger, M.A. Jordan, T. Matuz, A. Furdea, S. Halder, U. Mochty, D.J. Krusienski, T.M. Vaughan, J.R. Wolpaw, N. Birbaumer, A. Kübler, "A P300-based brain–computer interface for people with amyotrophic lateral sclerosis", Clinical Neurophysiology 119 (8) (2008) 1909–1916.
[14] Dong Minga,b, Xingwei Ana, Youyuan Xia,Yong Hub ∗, Baikun Wana, Hongzhi Qia, Longlong Chenga, Zhaojun Xue,"Time locked and phase locked features of ERPs for BCI speller",Bio medical signal processing and control 5 (2010) 243-251.
[15] Sarah N. Abdulkader *, Ayman Atia, Mostafa-Sami M. Mostafa, "Brain computer interfacing: Applications and challenges", Egyptian Informatics Journal (2015) 16, 213–230.