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A Review: Analysis of EEG Signal based Brain-Computer Interface

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Abstract: ***In this paper we propose the literature review related to the analysis of EEG Signal based Brain-Computer Interface. One of the main objectives of this survey paper is to find the features extraction used in EEG-based BCI research and to identify their critical properties. Another objective is to provide novel approach in order to help the reader with choosing the most appropriate Classification Algorithms for EEG-based Brain-Computer Interfaces.***

Keywords: Brain Computer interface, Neurosurgical Issues of BCIs, Preprocessing and Feature Selection, classifiers.

1. Introduction

Electroencephalograph (EEG) is an instrument for recording the electrical activity of the brain by suitably placing surface electrodes on scalp. EEG, describing the general function of the brain activity, is the superimposed wave of neuron potentials operating in a non-synchronized manner in the physical sense.

1.1 Brain Computer Interface

A Brain Computer Interface (BCI) is a direct communication pathway between brain and computer. BCI system measures the specific features of brain activity and translates them into device control signals. Electroencephalography (EEG) is an electrical signal recorded from a person's scalp, and is used to monitor the neurological state of the patient. EEG signal analysis and classification is one of the prominent researches in the field of Brain Computer Interface [2]. Electroencephalography (EEG) isthe recording of electrical activity along the scalp produced by the firing of neurons within the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20–40 minutes, as recorded from multiple electrodes placed on the scalp [5].

Brain rhythm Many neurological disorders can be easily identified by brain rhythms which can be easily recognized by visual inspection of the EEG signal. The clinical applications using EEG are to characterize the seizures, to monitor the depth of anesthesia and to locate areas of damage following head injury, stroke, tumor, etc. Indeed, EEG is portable, non-invasive, relatively cheap and provide signals with a high temporal resolution.

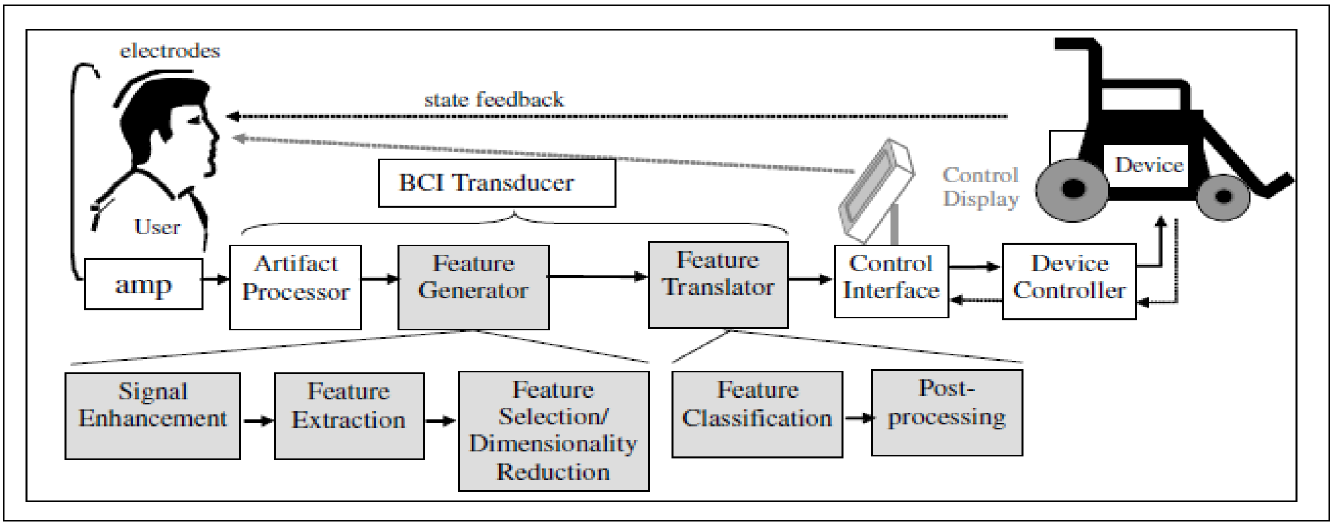

Figure 1: Functional model of a BCI system (Mason and Birch 2003)

1.2 Neurosurgical Issues Of BCIs

BCI is framework to evaluate these new systems as they apply to patients.This framework should ask the following six questions. Is the BCI safe? Is the system durable? Will the implant last in the patient for an extended period of time? Is it reliable? Will the BCI perform consistently for the subject? Does the BCI system have sufficiently complex control to be useful? Is the BCI suitable for the given patient population? And, has there been sufficient technical and practical demonstration of the systems efficacy?

In addition to the processing issues that define the requirements of a BCI system, there is a separate and distinct set of factors that a neurosurgeon must consider about a given platform when considering application toward a clinical population. The most fundamental issue is whether a BCI system is safe. First, surgical implementation must have acceptable clinical risk, and then, subsequently over time, the construct must be reliable and durable in its ability to acquire signals. Assessing the risks of initial surgical application is relatively straightforward because this will most likely involve variants of standard surgical practices[6]. Likely equivalent types of technical procedures are the placement of deep brain stimulators, cortical stimulators for pain, and the placement of grid electrodes. What will require closer scrutiny is the construct's likelihood for ongoing function. This can be affected by how the construct is designed (i.e., will the construct break down in a couple years?) and how the patient responds to the construct histologically (i.e., will scar formation prohibit signal acquisition after a period of time?). If the device has a short half-life, this will necessitate removal and reimplantation around areas of eloquent cortex. Because of the inherent risk of reoperation, unnecessarily short time frames for device replacement could potentially increase the risk of injury to those regions. Beyond issues of safety, there are performance-related factors that must be considered for a BCI to have practical application[6]. These issues include complexity of control and levels of speed and accuracy. How complex the control afforded by a given BCI can be assessed by how many degrees of freedom (DOF) of control there are. DOF refer to how many processes can be controlled in parallel. This can also be thought of in terms of dimensions in space [6].

1.3 Preprocessing and Feature Selection

Many different features have been thought up to be extracted from EEG signals. The most frequent transformation used is Fourier analysis to be able to look at specific frequency bands [15]. Firstly, we applied the Common Spatial Patterns (CSP) method (Müller-Gerking, Pfurtscheller and Flyvbjerg (1999) to the raw EEG data. The standard CSP is applicable to two class problems; it transforms the original signal into a new space where the variance of one of the classes is maximised while the variance of the other is minimized.

Good feature selection is the key to the success of a classification algorithm. It is needed to reduce the number of features by selecting the most informative and discarding the irrelevant and redundant features. As EEG data is known to be highly correlated, a feature selection method which exploits this property seems appropriate. We applied a simple, fast and efficient method, called Correlation-Based Feature Section (CFS) (Hall 2000). It searches for the "best" sub-set of features where "best" is defined by a heuristic which takes into consideration 2 criteria: 1) how good the individual features are at predicting the class and 2) how much they correlate with the other features. Good subsets of features contain features that are highly correlated with the class and uncorrelated with each other. The search space is very big for employing a brute-force search algorithm. We used the best first (greedy) search option starting with an empty set of features and adding new features. It is important also to note that the feature selection was done using the training data only[16]. The features properties are as follows:

1.3.1 Band Power (BP)

Band power at each electrode position is estimated by first digitally bandpass filtering the data, squaring each sample and then averaging over several consecutive samples. Before the band power method is used for classification, first the reactive frequency bands must be selected for each subject. This means that data from an initial experiment without feedback are required. Based on these training data, the most relevant frequency components can be determined by using the distinction sensitive learning vector quantization (DSLVQ) algorithm [18], [17]. This method uses a weighted distance function and adjusts the influence of different input features (e.g., frequency components).

1.3.2 AutoRegressive (AR) modeling

AR modeling is preferred for real-time control of an EEG-based brain–computer interface. Autoregressive (AR) modeling is a commonly used technique for spectral estimation of biosignals because it exhibits several advantages over other spectral estimation techniques in this domain. The AR filter is an all-pole model making it very good at resolving sharp changes in the spectra [20]. Conversely, the fast Fourier transformation (FFT) is a widely used nonparametric approach that is very accurate and efficient but lacks spectral resolution for short data segments. AR modeling has been used successfully for EEG but has not been evaluated extensively for use with ECoG. Because of its superior resolution for short data segments, AR modeling is preferred for real-time control of an EEG-based brain–computer interface (BCI) [19].

1.3.3 Common Spatial Patterns (CSP)

Common spatial pattern (CSP) is very successful in constructing spatial filters for detecting event-related synchronization and event-related desynchronization. In statistics, a CSP filter can optimally separate the motor-imagery-related components. However, for a single trail, the EEG features extracted after a CSP filter still include features not related to motor imagery. In this study, we introduce a linear dynamical system (LDS) approach to motor-imagery-based brain-computer interface (MI-BCI) to reduce the influence of these unrelated EEG features.

2. Classifiers

1.4 Linear Discriminant Analysis (LDA)

In order to classify the extracted features, Linear Discriminant Analysis (LDA) is one of the most popular and efficient classifier for EEG-based BCI. Linear Discriminant Analysis, have a low complexity. They are said stable as small variations in the training set does not affect considerably their performance. The aim of LDA (also known as Fisher's LDA) is to use hyperplanes to separate the data representing the different classes. This technique has a very low computational requirement which makes it suitable for online BCI system. Moreover this classiffer is simple to use and generally provides good results.

1.5 Quadratic Discriminant Analysis (QDA)

Quatratic classiffication aims at assigning to a feature vector the class it belongs to with the highest probability. The Bayes rule is used to compute the so called a posteriori probability that a feature vector has of belonging to a given class [21]. Using the MAP (Maximum A Posteriori) rule and these probabilities, the class of this feature vector can be estimated. Bayes quadratic consists in assuming a different normal distribution of data. This leads to quadratic decision boundaries, which explains the name of the classiffer.

1.6 Gaussian Mixture Model (GMM)

Gaussian classifier to separate the signal into the different classes of mental task. Each class is represented by a number of Gaussian prototypes, typically fewer than four. Training of the classifier starts from an initial model that can be either a previously trained classifier or a new classifier created by estimating the prototype centers with a clustering algorithm.This initial estimate is then improved by stochastic gradient descent to minimize the mean square Error.

3. Literature Review

Sr. No.	*Name of Author*	*Paper Title/Reference*	*publication*	*Appraoch & Concept about Work*	*Advantages*	*Limitations of Works*
1	Anderson C W and Sijercic Z	Classification of EEG signals from four subjects during five mental tasks Solving Engineering Problems with Neural Networks [3].	Proc. Int. Conf. on Engineering Applications of Neural Networks (EANN'96)	In his work, he divided the classification algorithms are used to design BCI systems into different categories: linear classifiers, neural networks, nonlinear Bayesian classifiers, nearest neighbor classifiers and combinations of classifiers.	It is necessary to extract features from EEG Signals.	Transfer function performance is the lowest.
2	F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi	A review of classification algorithms for EEG-based brain-computer Interfaces [7].	Journalof Neural Engineering, 4:R1–R13, 2007.	This paper proposed Band power (BP) features are known to be efficient for motor imagery classification	A strong real-time constraints that are imposed when using a BCI online prevent the use of non-linear inverse solutions as they are computationally demanding.	In the off-line scenario can evaluate the performance of a number of classifiers using a benchmark dataset.
3	Ali Bashashati, Mehrdad Fatourechi, Rabab K Ward and Gary E Birch	A survey of signal processing algorithms in brain–computer interfaces based on electrical brain signals[12].	J. Neural Eng. **4** (2007) R32–R57.	This work presents the comprehensive survey of all BCI designs using electrical signal recordings published prior to January 2006.	This survey is valuable for newcomers to the field, as they can now find out which signal processing methods have been used for a certain type of a BCI system.	The proposed taxonomy and classes defined represent a proposed set of subcategories, not a final one, and need to revise or expand upon this initial set.
4	C. Guger, H. Ramoser, and G. Pfurtscheller	Real-Time EEG Analysis with Subject-Specific Spatial Patterns for a Brain–Computer Interface (BCI)[13].	IEEE TRANSACTIONS ON REHABILITATION ENGINEERING, VOL. 8, NO. 4, DECEMBER 2000	This paper demonstrates that the method of common spatial patterns can be used to analyze the EEG in real time in order to give feedback to the subject. The method was utilized to give fast, continuous, and accurate feedback during left- and right-hand movement imagination.	spatial patterns is a promising method for an EEG-based brain–computer interface.	For practical applications, the training time must be minimized to increase the acceptance of the system and motivation of the BCI operator.
5	YI Fang, LI Hao and JIN Xiaojie	Improved Classification Methods for Brain Computer Interface System[14].	*I.J. Computer Network and Information Security*, 2012, 2, 15-21	For the EEG signals of left and right hand motor imagery, the event-related desynchronization (ERD) and event-related synchronization (ERS) are used as classification features in this paper.	A good BCI real-time system not only requires a low misclassification rate, but also requires balance of the two kinds of misclassifications. A balance of the two kinds of misclassifications means the system's performance is more stable.	Nonstationarity of EEG leads to a decline of accuracy over time. So a further improvement was raised. With a feedback adjustment.

4. Need for the study

A Brain Computer Interface creates many mentals tasks or generating neurophysiological signal is being measured and processed by the system. Current BCI systems have a relatively low information transfer rate that is the rate is equal to or lower than 20 bits/min [10]. This means that the user needs arelatively long period of time in order to send only a small number of commands. In order to increase the information transfer rates of current BCI systems and to design interpretable BCI, improvements can be brought at all processing levels: at the preprocessing level, at the feature extraction level and at the classification level. To improve the information transfer rate at the feature extraction level, we could design more robust and efficient features [8]. Consequently, an ideal feature extraction algorithm for BCI should be trainable in the sense that it should be able to learn and use subject-specific features. Moreover, it is particularly important to design feature extraction methods that can be trained on multiclass data [11].

5. Future work

It is necessary that there should be some computing statistics applied to the observation of group, session or condition measure differences in order to estimate the reliability of these differences across conditions or groups. So the future work is to perform classical parametric tests like paired t test, unpaired t test, Analysis of variance (ANOVA) on ERPs, power spectra, ERSPs, and ITCs measured from the epoched imagery data.

6. Conclusion

Brain-computer interface (BCI) is an cornerstone research is only beginning to crack the electrical information encoding the information in a human subject's thought . It is especially appealing to severely paralyzed patients, since motor ability is no longer a prerequisite for this communication. It has not only introduced new dimensions in machine control but the researchers round the globe are still exploring the possible uses of such applications.

The main moto of analysis of EEG Siganl based brain–computer interface (BCI) is to allow an individual with severe motor disabilities to have effective control over devices such as computers, speech synthesizers, assistive appliances and neural prostheses. Such an interface would increase an individual's independence,leading to an improved quality of life and reduced social costs.Numerous studies haves hown that, using EEG, healthy and motor impaired individuals can control devices without using muscles.

References

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan. Braincomputer interfaces for communication and control. Clinical Neurophysiology, 113(6):767{791, 2002.

[2] American electroencephalographic society: Guidelines for standard electrode position nomenclature. J Clin Neurophysiol., 8(2):200–202, 1991.

[3] Duda R O, Hart P E and Stork D G 2001 Pattern Recognition 2nd edn (New York: Wiley-Interscience).

[4] Anderson C W and Sijercic Z 1996 Classification of EEG signals from four subjects during five mental tasks Solving Engineering Problems with Neural Networks: Proc. Int. Conf. on Engineering Applications of Neural Networks (EANN'96).

[5] Statsny, J. *Analysis of states in EEG signals*. M. Sc. Thesis. Prague: Czech Technical University, 2001. (In Czech).

[6] Eric C. Leuthardt, Gerwin Schalk, Daniel Moran and Jeffrey G. Ojemann, *Neurosurgery 59:1-14, 2006* DOI: 10.1227/01.NEU.0000221506.06947.AC www.neurosurgery-online.com

[7] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi. A review of classification algorithms for EEG-based brain-computer interfaces. Journalof Neural Engineering, 4:R1–R13, 2007.

[8] S. Mason, J. Kronegg, J. Huggins, M. Fatourechi, and A. Schloegl.Evaluating the performance of self-paced BCI technology. Technical report, Neil Squire Society, 2006.

[9] Rabiner L R 1989 A tutorial on hidden Markov models and selected applications in speech recognition Proc. IEEE.

[10] Hiraiwa A, Shimohara K and Tokunaga Y 1990 EEG topography recognition by neural networks IEEE Eng. Med.Biol. Mag.

[11] B.Z. Allison, E.W.Wolpaw, and J.R.Wolpaw. Brain-computer interface systems: progress and prospects. Expert Review of Medical Devices, pp: 463– 474, 2007.

[12] Ali Bashashati, Mehrdad Fatourechi, Rabab K Ward and Gary E Birch. A survey of signal processing algorithms in brain–computer interfaces based on electrical brain signals: J. Neural Eng. **4** (2007) R32–R57.

[13] C. Guger, H. Ramoser, and G. Pfurtscheller. Real-Time EEG Analysis with Subject-Specific Spatial Patterns for a Brain–Computer Interface (BCI): IEEE TRANSACTIONS ON REHABILITATION ENGINEERING, VOL. 8, NO. 4, DECEMBER 2000

[14] YI Fang, LI Hao and JIN Xiaojie. Improved Classification Methods for Brain Computer Interface System: *I. J. Computer Network and Information Security*, 2012, 2, 15-21.Published Online March 2012 in MECS (http://www.mecs-press.org/).

[15] B. D. Storey. Computing fourier series and power spectrum with matlab, 2002. Lecture notes.

[16] Omar AlZoubi , Irena Koprinska and Rafael A. Calvo. Classification of Brain-Computer Interface Data: The Australasian Data Mining Conference: AusDM 2008.

[17] M. Pregenzer and G. Pfurtscheller, "Frequency component selection for an EEG-based brain computer interface (BCI)," *IEEE Trans. Rehab. Eng.*, vol. 7, pp. 413– 419, Dec. 1999.

[18] M. Pregenzer, G. Pfurtscheller, and D. Flotzinger, "Automated feature selection with a distinction sensitive learning vector quantizer," *Neurocomp.*, vol. 11, pp. 19–29, 1996.

[19] J. R. Wolpaw and N. Birbaumer, “Brain-computer interfaces for communication and control,” in *Textbook of Neural Repair and Rehabilitation; Neural Repair and Plasticity*, M. E. Selzer, S. Clarke, L. G. Cohen, P. Duncan, F. H. Gage, Eds. Cambridge: Cambridge Univ. Press, 2006, pp. 602–614.
[20] S. L. Marple, *Digital Spectral Analysis With Applications*. Englewood Cliffs, NJ: Prentice-Hall, 1987.
[21] K. Fukunaga. Statistical Pattern Recognition, seconde edition. ACADEMIC PRESS, INC, 1990.

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