



INVESTIGATION OF UNSUPERVISED PROCESSING METHODS FOR BRAIN-COMPUTER INTERFACE

By

Ola Aboul Fotouh Mohamed Ali Sarhan

A Thesis Submitted to the
Faculty of Engineering at Cairo University
in Partial Fulfillment of the
Requirements for the Degree of
MASTER OF SCIENCE
in
Biomedical Engineering and Systems

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Title of Thesis:

Investigation of Unsupervised Processing Methods for Brain-Computer Interface.

Key Words:

Brain computer interface; Motor imagery; P300; Signal processing; Unsupervised;
Online Classification.

Summary:

In this thesis we study a new technique for BCI data that requires no earlier training. The new approach is applied to experimental data for motor imagery and P300-based BCI for both healthy and disabled subjects and compared to the classification output results of the same data utilizing the conventional processing techniques requiring earlier training. Regarding P300 based-BCI, The fundamental rule of this new class of unsupervised methodologies is that the trial with true activation signal inside every block must be distinctive from whatever remains of the trials inside that block. Consequently, a measure that is delicate to this difference can be utilized to settle on a choice taking into account a single block with no earlier training. As well, we tend to study different algorithms of aggregating info from many trials to extend communication speed and bit rate. Such aggregation strategies include simple average, PCA and PPCA. The results by averaging, from the sample individual cases show that the proposed technique supported SVD provided the most effective performance reaches 98.61%. Regarding the motor imagery part, we tend to used different classification methodologies as in time and frequency domain. And then we found that wavelet transform get best performance reaches 82.14%. So, these promising results recommend that this approach can reach accuracies not extremely far from those got with training while keeping up robust performance in practice.

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Dedication

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Nomenclature

ALS	Amyotrophic Lateral Sclerosis
BCI	Brain Computer Interface
BLDA	Bayesian Linear Discriminant Analysis
CNV	Contingent Negative Variety
EEG	Electroencephalography
EMG	Electromyography
ER	Error Rate
ERD	Event Related Desynchronization
ERP	Event Related Potential
ERS	Event Related Synchronization
FFT	Fast Fourier Transform
ISI	Inter-Stimulus Interval
MEG	Magnetoencephalography
MI	Mutual Information
MRI	Magnetic Resonance Imaging
MRPs	Motor-Related Potentials
PCA	Principal Component Analysis
PET	Positron Emission Tomography
PPCA	Probabilistic Principal Component Analysis
SNR	Signal to Noise Ration
SS	Spectral Subtraction
SSVEPs	Steady-State Visual Evoked Potentials
SVD	Singular Value Decomposition

SVM	Support Vector Machine
VEP	Visual Evoked Potential

Abstract

Brain-Computer Interface (BCI) is man-machine communication system that allows subjects to send commands to computers by using solely their brain activity while not using any peripheral system or muscles. The significant objective of BCI research is to develop systems that let incapacitated users to communicate with different persons, to manage artificial limbs, or communicate with their surroundings.

BCI system comprised of three main parts; preprocessing, feature extraction and classification. The most important stages are feature extraction and preprocessing. In this contribution, the main target is to study the effect of different processing techniques on the accuracy of ERP especially P300 based and motor imagery BCI experiments.

One of the major problems in BCI's application is the difficulty to find response from a single trial. Hence, several trials are performed for each element in order to decrease the error in prediction. This led to longer time before accurately predicting the user intent and need intensive training to the user or the operator who work on that device.

In this thesis we study a new technique for BCI data that requires no earlier training. The new approach is applied to experimental dataset used for "Graz" motor imagery and Hoffmann dataset of P300-based BCI for both healthy and disabled subjects and compared to the classification output results of the same data utilizing the conventional processing techniques requiring earlier training. Regarding P300 based-BCI, The fundamental rule of this new class of unsupervised methodologies is that the trial with true activation signal inside every block must be distinctive from whatever remains of the trials inside that block. Consequently, a measure that is delicate to this difference can be utilized to settle on a choice taking into account a single block with no earlier training. As well, we tend to study different algorithms of aggregating info from many trials to extend communication speed and bit rate. Such aggregation strategies include simple average, PCA and PPCA. The results by averaging, from the sample individual cases show that the proposed technique supported SVD provided the most effective performance reaches 98.61%. Regarding the motor imagery part, we tend to used different classification methodologies as in time and frequency domain. And then we found that wavelet transform get best performance reaches 82.14%. So, these promising results recommend that this approach can reach accuracies not extremely far from those got with training while keeping up robust performance in practice.