DEVELOPMENT OF FUNCTIONAL NEAR-INFRARED SPECTROSCOPY-BASED BRAIN-COMPUTER INTERFACE MODEL USING PRINCIPAL COMPONENTS AND LATENT VARIABLES ARTIFICIAL NEURAL NETWORKS

ONG JIA HENG

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Faculty of Electrical and Electronic Engineering
Universiti Tun Hussein Onn Malaysia

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To my beloved parents, thank you.

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ABSTRACT

Functional near-infrared spectroscopy (fNIRS) is a non-invasive brain imaging technology in brain-computer interface (BCI) applications. Poor signal quality and massive irrelevant signals are the shared challenges of fNIRS signal post-processing in real-life. Principal component analysis (PCA) and partial least squares (PLS) extracted principal components (PCs) and latent variables (LVs) are the practical feature extractors in near-infrared chemometric analysis, but both features were rarely studied for fNIRS-BCI application. Thus, this study investigates the feasibility of PCs and LVs as the signal features in fNIRS-BCI model development. First, fNIRS signals were analysed using different signal denoise filters, channel compressions, and feature extraction approaches to produce optimal PCs and LVs features. Next, both features were applied as ANN training inputs to produce PCs-ANN and LVs-ANN in 10-folds cross-validation for fNIRS-BCI applications. The PCs-ANN outperformed benchmark statistical approach literature with average classification accuracy of 71.67% in four class classification. The optimal LVs-ANN outperformed partial least square discriminant (PLS-DA) and traceable best-performed literature of bagging classifiers. The classification accuracies of LVs-ANN, PLS-DA, and the bagging classifier were 84.94%, 77.05%, and 74.00%, respectively, in binary classification. Findings show the PLS is effective in eliminating less relevant training features to improve fNIRS-BCI performance. In conclusion, this study validated the feasibility of PCA and PLS feature extractors by demonstrating reliable performance for fully imagine tasks-based fNIRS-BCI applications, including hand motion imagine and word generation. This demonstrates that both feature extractors were essential to the development of the fNIRS-BCI device for patients with total paralysis.

ABSTRAK

“Functional near-infrared spectroscopy (fNIRS)” merupakan teknologi pemeriksaan aktiviti otak tanpa kerosakan dalam aplikasi *“Brain-computer interface (BCI)”*. Namun, kualiti sinaran *“fNIRS”* adalah sensitif terhadap pergerakan badan pengguna serta memberikan impak yang ketara terhadap ketepatan *“BCI”*. Menurut kajian lepas, isu tersebut dapat diperbaiki melalui pemilihan algoritma ekstrak ciri-ciri sinaran aktiviti otak yang efektif. Manakala, *“Principal components (PCs)”* dan *“Latent variables (LVs)”* merupakan hasil-hasil mampatan *“Principal component analysis (PCA)”* dan *“Partial least squares (PLS)”*, kedua-dua ciri-ciri sinar adalah efektif dalam bidang *“NIRS Chemometric analysis”*. Namun, tiada kajian yang telah menguji-kaji keberkesananya dalam pengunaan *“fNIRS-BCI”* setakat ini. Jadi, kajian ini telah menguji-kaji keberkesanan “*Principal components artificial neural networks* (*PCs-ANN)”* dan “*Latent variables artificial neural networks* (*LVs-ANN)”* dalam tugasan klasifikasi aktiviti-aktiviti sinaran otak. Fasa pertama kajian telah menguji-kaji keberkesanan *“PCs-ANN”* dari segi proses pengurangan kebisingan sinaran, pemampatan saluran sinaran, perahan ciri-ciri sinaran, dan klasfikasi melalui *“ANN”*. Hasilan *“PCs-ANN”* terbaik telah mencatatkan purata ketepatan sebanyak 71.67% dalam tugasan klasifikasi empat kelas. Fasa kedua kajian telah menunjukkan hasilan optimum *“Partial least square discriminant (PLS-DA)”* dan *“LVs-ANN”* mampu mencapai purata ketepatan lebih tinggi pada 77.05% dan 84.94%, berbanding dengan kajian terbaik lepas yang mencapai purata ketepatan sebanyak 74.00% sahaja, dalam tugasan klasifikasi dua kelas. Prestasi *“PLS-DA”* dan *“LVs-ANN”* telah menunjukkan *“PLS”* adalah sesuai sebagai algoritma pemampatan sinaran *“fNIRS”*. Hasilan kajian telah menjadi fakta yang penting dalam proses reka cipta peralatan *“fNIRS-BCI”* bagi kegunaan orang kelainan upaya (OKU). Kesimpulannya, kajian ini telah menunjukkan kebolehan *“PCs”* dan *“LVs”* sebagai ciri-ciri isyarat aktiviti otak alternatif bagi tugasan *“fNIRS-BCI”*.

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LIST OF SYMBOLS AND ABBREVIATIONS

fNIRS	–	Functional near-infrared spectroscopy
ALS	–	Amyotrophic lateral sclerosis
JKM	–	Department of social welfare Malaysia
PWD	–	Person with disability
BCI	–	Brain-computer interface
EEG	–	Electroencephalogram
ANN	–	Artificial neural networks
PCs-ANN	–	Principal components artificial neural networks
PCs	–	Principal components
LVs-ANN	–	Latent variables artificial neural networks
LVs	–	Latent variables
LMI	–	Left-hand mental imagine
RMI	–	Right-hand mental imagine
MA	–	Mental arithmetic
WG	–	Word generation
PCA	–	Principal component analysis
PLS	–	Partial least squares
ECoG	–	Electrocorticography
SEEG	–	Stereo encephalography
NIR	–	Near-infrared
ΔC	–	Haemoglobin concentration variations
MBLL	–	Modified Beer-Lambert law
I	–	Light intensity
i	–	Channel number
t	–	Time
λ	–	Wavelength

d	–	Optodes
A	–	Attenuation
DPF	–	Differential path-length
μ_a	–	Absorption coefficient
ΔOD	–	Variation of optical density
ε	–	Molar extinction coefficient
ΔC	–	Concentration variations
PET	–	Positron emission tomography
fMRI	–	Functional magnetic resonance imaging
EOG	–	Electrooculogram
ECG	–	Electrocardiogram
DSR	–	Discrimination selection response
sLDA	–	Shrinkage linear discriminant analysis
SVM	–	Support vector machine
LDA	–	Linear discriminant analysis
HMM	–	Hidden Markov model
ICA	–	Independent component analysis
CSP	–	Common spatial pattern
MCSP	–	Modified common spatial pattern
CAR	–	Common average reference
MARA	–	Multiple artefact rejection algorithms
TPR	–	True positive rate
FPR	–	False positive rate
FPS	–	Frame per second
ODT	–	Onset detection time
ITR	–	Information transfer rate
MFCC	–	Mel frequency cepstral coefficients
KNN	–	K-nearest neighbour
RLDA	–	Regularized linear discriminant analysis
SWR-SRS	–	Stepwise regression analysis based on sequential feature selection
DWT	–	Discrete wavelets transform
MSVD	–	Multi-resolution singular value decomposition

G-W	–	Gromov–Wasserstein
FG-W	–	Fused Gromov–Wasserstein
TARA	–	Transient artefact reduction algorithm
CNN	–	Convolutional neural networks
ANOVA	–	Analysis of variance
HbO	–	Oxygenated haemoglobin
HbR	–	Deoxygenated haemoglobin
HRF	–	Haemodynamic response function
NMSM	–	Nelder Mead simplex method
IIR	–	Infinite impulse response
FIR	–	Finite impulse response
VLF	–	Very low frequency
LF	–	Low frequency
GLM	–	General linear model
tCCA	–	Temporal canonical correlation analysis
RMSE	–	Root mean square error
CNR	–	Contrast-to-noise ratio
GCCA	–	Generalized canonical correlation analysis
GLRCSP	–	Generalized learning regularizing common spatial patterns
x	–	Response
N	–	Number of samples
μ	–	Mean
σ^2	–	Variance
σ, SD	–	Standard deviation
κ	–	Kurtosis
S	–	Skewness
ΔCBV	–	Variation of cerebral blood volume
ΔCOE	–	Variation of cerebral oxygen exchange
$\lvert L \rvert$	–	Flow vector magnitude
k	–	Vector angle
RCNN	–	Region-based convolutional neural networks
QDA	–	Quadratic discriminant analysis

J	–	Projected vector
V	–	Common projection vector
S_b	–	Scatter metrics between the class
S_w	–	Scatter metrics within the class
m	–	Data group mean
LSTM	–	Long short-term memory
ROC-AUC	–	Area under the curve of receiver operating characteristic
Subj.	–	Subject
mmol/L	–	Millimoles per litre
Min	–	Minimum
Max	–	Maximum
RSD	–	Relative standard deviation
%	–	Percentage
BW	–	Butterworth frequency bandpass filter
SG	–	Savitzky-Golay
SURE	–	Stein's unbiased risk estimator
W	–	Wavelet filter
db	–	Daubechies
$\bar{X}$	–	Mean
NIPALS	–	Nonlinear iterative partial least squares
X	–	Signals
Y	–	Class label
T, U	–	Scores matrix
P, Q	–	Orthogonal loadings matrix
B	–	Regression coefficient of partial least square
SCG	–	Scaled conjugate gradient
AUROC	–	Area under the receiver operating characteristic curve
TP	–	True positive
TN	–	True negative
FP	–	False positive
FN	–	False negative

HMM-CSP	–	Hidden Markov model and common spatial pattern
PCC	–	Pearson correlation coefficients
AUC	–	Area Under the Curve
P	–	Probability
AVG	–	Average
HN	–	Number of hidden neurons
Ref.	–	Reference
i.e.,	–	That is
Acc.	–	Accuracy
Sens.	–	Sensitivity
Spec.	–	Specificity
Prec.	–	Precision
F1.	–	F1- Score

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CHAPTER 1

INTRODUCTION

1.0 Introduction

This chapter described the paralysis issues in Malaysia and the challenges faced. The functional near-infrared spectroscopy brain-machine control interface (fNIRS-BCI) using artificial intelligence was proposed in this study. The research problem statement, objectives, scopes, and the significance of the study were discussed in detail.

1.1 Background of study

Fully control of the body might be a dream for a naturally physically disabled with late Amyotrophic Lateral Sclerosis (ALS) and complete ischemic stroke victim to execute. Based on the statistics reported by the Department of Social Welfare (JKM), Malaysia, in 2017. Four hundred fifty-three thousand two hundred fifty-eight persons reported having personal disabilities. 65.2% of the disabilities potentially left significant effects on the individual working performance in their workspace (Department of Social Welfare, 2018). However, multitasking capability is becoming the main employment criterion in the fast-moving working environment of Malaysia nowadays. Whereby it is not only saving the operation cost in terms of time and money value, but the element of workspace safety can also be secured. Hence, a hand-free neuro activity-based brain-computer interface (BCI) posed high potential which not only enrich the public choice in the multi-tasking and entertainment sections, but its high accessibility characteristic is expected to fit the needs of physical disabled persons for daily welfare enhancement. By integrating non-invasive BCI into wearable gadgets, such as glasses, hairband, and headset; Physical disabled end users may interface with the facilities and perform high informative health status feedbacks to guardians in real-time without the restriction's physical inaccessibility. Hence, it is valuable to focus on the BCI topic, especially in the effort to light weighting the current BCI system for low power embedded system integration without sacrifice the performance.

The first demonstration of functional near-infrared spectroscopy (fNIRS) technology feasibility in brain-computer interface (BCI) application was back in 2004 by Coyle *et al.*(Coyle *et al.*, 2004). However, the development of fNIRS-BCI remains in the clinical trial stage and struggling toward commercialization (Martini *et al.*, 2020). Numerous studies reported that the classification accuracy of BCI using only fNIRS samples was incomparable with electroencephalogram (EEG) and a combination of both in hybrid mode (Ge *et al.*, 2017), as the quality of fNIRS samples were highly influenced by motion artefacts and scalp intact condition when acquiring signal samples. Besides, direct classification using fNIRS signals from all the sensor channels across the major sections of brain in high-dimensional raw data states can be tedious and inefficient. Conventionally, the raw fNIRS data are pre-processed using signal denoise filters, channel compression, channel selection, and followed by feature extractions. BCI models based on selected or global average channel responses have resulted in relatively lower prediction accuracy when compared to a model trained using all channels (Janani *et al.*, 2018). In all channel scenario, signals acquired from all regions of brain cortexes were included for analysis without additional channel selection. It was vice-versa for regional or selection region average channel.

On the other hand, LVs-ANN and PCs-ANN are the two mature near-infrared spectroscopy (NIRS) signal analysis solution, such as in the chemometric analysis (Mohd Idrus *et al.*, 2019) and hyper-spectral imaging (Uddin *et al.*, 2020), but both solutions were rarely implemented in fNIRS-BCI studies. Hence, the study on both solutions in fNIRS-BCI application are expected to validate their feasibility as an alternative BCI machine learning model without the needs of heavy computing deep learning framework. This topic is crucial in innovating non-invasive BCI system with higher potential for low power embedded system integration. However, a similar approach is rarely found in the fNIRS signal feature extraction process in BCI-related studies. The most recent study applied

PLS superficially for data treatment in the investigation about the relationship between the frontal brain activity and ongoing mental workload level only (Meidenbauer *et al.*, 2021). On the other hand, the viability of principal components (PCs) was confirmed in representing the hand grasping motion feature in EEG-based BCI (Mattar *et al.*, 2017) and four-class BCI problems using fNIRS signals (Ong *et al.*, 2021). Due to the supervised nature of PLS, it is expected to be more effective than PCA in feature extraction (Maitra *et al.*, 2008). This necessitates an evaluation of the viability of PLS in fNIRS for BCI applications.

1.2 Problem statement

Functional near-infrared spectroscopy (fNIRS) probe setups are plug-and-play oriented with a wearable headband or cap appearance. The probe is mounted directly onto the human scalp and temporarily fixed using an elastic band or strap when recording brain activities for brain-computer interface (BCI) application. In real life, fitting influenced light source leakage, high hair density, and natural motion artefacts, such as eye winks and body actions, are the common source of noises found in fNIRS signals. Although the noise contamination is reducible by strict experimental precaution, exploring more dependable denoise filters and feature extractors is more significant in enhancing the BCI model performance.

To date, functional near-infrared-based brain-computer interface (fNIRS-BCI) studies are primarily focusing on the general performance benchmark only, such as the accuracy comparison between different brain imaging modalities (Shin *et al.*, 2018b), pre-processing algorithms (Qureshi *et al.*, 2017), and classifiers variation (Khan *et al.*, 2018; Trakoolwilaiwan *et al.*, 2017) from the superficial perspective with unknown model optimisation status. The usage of ANN on non-binary BCI with non-statistical training features was also rarely reported.

Besides, conventional NIRS chemometric analysis methodologies, such as principal components artificial neural networks (PCs-ANN) and latent variables artificial neural networks (LVs-ANN), are not studied in fNIRS-BCI-related studies. Although, the previous study proved that LVs were effective in enhancing machine learning model performance and simplifying optimal network structure in NIRS chemometric analysis

(Mohd Idrus *et al.*, 2019). No traceable study has examined the extraction efficiency of PCs and LVs features in fNIRS-BCI applications, especially when coupled with ANN classifier. Thus, there is a need to investigate the feasibility of PCs-ANN and LVs-ANN modelling in fNIRS signals for BCI applications, along with the support of quantitative performance measures.

1.3 Research objectives

i. To investigate the feasibility of principal components (PCs) in representing functional near-infrared spectroscopy (fNIRS) signal features as training inputs in developing principal components artificial neural networks (PCs-ANN) for brain-computer interface (BCI) application.
ii. To investigate the feasibility of principal components (LVs) in representing functional near-infrared spectroscopy (fNIRS) signal features as training inputs in developing latent variables artificial neural networks (LVs-ANN) for brain-computer interface (BCI) application.
iii. To evaluate the classification accuracy of developed artificial neural networks (ANN) for brain activities classification using cross-validation.

1.4 Research scope

This study was primarily targeted as the algorithmic methodology justification of functional near-infrared spectroscopy (fNIRS) signals in the brain-computer interface (BCI). Due to the concern sample's homogeneity, all the fNIRS signals analysed in this study were recorded from healthy subjects only, which are free from any psychiatric, neurological, and other neurological-related diseases. This setting was implemented to minimize the effect of subject-influenced uncertainties on the validity of study outcomes.

The usage of public access datasets enhanced the study's transparency and improved research outcomes' reliability when benchmarked with relevant literature. On the other hand, the fNIRS signal analysed in this study was partially extracted from two open-access datasets (Shin *et al.*, 2017b, 2018d). A total of 240 and 1560 brain activities samples were analysed in principal components artificial neural networks (PCs-ANN) and

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APPENDIX A

The list of publication is as follows:

1. J. H. Ong and K. S. Chia, "Principal Components-Artificial Neural Network in Functional Near-Infrared Spectroscopy (fNIRS) for Brain Control Interface," *2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT)*, 2021, pp. 714-719.
   Status: Published.
2. J. H. Ong and K. S. Chia, "Supervised Feature Extraction in Functional Near-infrared Spectroscopy-based Brain-Computer Interface Model using Partial Least Square: A Comparative Study" *SN Computer Science.*
   Status: In peer-review.
3. J. H. Ong and K. S. Chia, " Developing an Optimal Brain Computer Interface Model using Functional Near Infrared Spectroscopy: A Review" *Engineering Journal (Eng. J.)*.
   Status: In peer-review.

APPENDIX B

VITA

The author was born on June 12, 1996, in Johor, Malaysia. He went to SMK Sri Kukup, Pontian, Johor, Malaysia for his secondary school study and attended to Pusat Tingkatan Enam Seri Bandar Pontian, Johor, Malaysia, for his Malaysian Higher School Certificate (STPM). He was awarded with Bachelor's Degree of Mechanical Engineering with Honours from Universiti Tun Hussein Onn Malaysia, Batu Pahat, Johor, Malaysia in 2020. During the Bachelor's Degree study, he was appointed as the team leader of Robotic Club UTHM and managed the team to participate in ROBOCON MALAYSIA Competition 2018 and 2019. In 2020, he was admitted into Faculty of Electrical and Electronic Engineering in Universiti Tun Hussein Onn Malaysia, Batu Pahat, Johor, Malaysia for the Master's Degree program by full research in Electrical Engineering program. During the time, he was focused on the research related to the advancement of signal processing and machine learning model advancement for functional near-infrared spectroscopy (fNIRS) signal classification in brain computer interface application (BCI). In 2021, he was participated in the 2021 International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies (3ICT) that held virtually by University of Bahrain, Zallaq, Bahrain and presented the study findings about the implementation of principal components artificial neural networks (PCs-ANN) model in fNIRS-BCI application.