CLASSIFICATION OF VISION PERCEPTION USING EEG SIGNALS FOR BRAIN COMPUTER INTERFACE

by

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LIST OF ABBREVIATION

ALS	Amyotrophic Lateral Sclerosis
ANOVA	Analysis of Variance
AEP	Auditory Evoked Potential
BPTT	Back-propagation Through Time
BCI	Brain Computer Interface
DAQ	Data Acquisition
DFT	Descrete Fourier Transform
DFI	Devijver's Feature Index
DE	Differentially Enabled
ECG	Electrocardiogram
ECoG	Electrocorticography
EEG	Electroencephalograph
ERNN	Elman Recurrent Neural Network
EBP	Error Back-propagation
ERP	Event Related Potential
FFT	Fast Fourier Transform
FSI	Feature Significance Index
FOV	Field of Vision
$FOV_{20^{\circ}}$	FOV, covering 20 degrees from the centroid
FT	Fourier Transform
fMRI	Functional Magnetic Resonance Image
ICA	Independent Component Analysis

IRR	Infinite Impulse Response
LEP	Laser Evoked Potential
LGN	Lateral Geniculate Nucleus
LOC	Lateral Occipital Cortex
LM	Levenberg-Marquadt
MRI	Magnetic Resonance Image
MSE	Mean Squared Error
MND	Motor Neuron Disease
MLP	Multi-layered Perceptron
NARX	Non-liner Autoregressive Exogenous Network Model
POVEP	Pattern-Onset Visual Evoked Potential
PET	Positron Emission Tomography
PSD	Power Spectral Density
PSE	Power Spectral Energy
PC	Principle Component
PCA	Principle Component Analysis
RNN	Recurrent Neural Network
SEE	Shanon's Energy Entropy
STFT	Short-time Fourier Transform
SNR	Signal to Noise Ratio
SSEP	Somatosensory Evoked Potential
SE	Spectral Energy Feature
SSR	Steady State Response
SSVEP	Steady State Visual Evoked Potential
SVM	Support Vector Machine

VEP	Visual Evoked Potential
WT	Wavelet Transform

LIST OF SYMBOLS

$\boldsymbol{Database}_{subject}$	Vector containing trails of 17 channel of EEG signals recorded from a particular subject
$\boldsymbol{EEG}_{trial}$	Particular trial of EEG signals recorded on 17 different channels
$\boldsymbol{eeg}_{channel}$	EEG signal of a particular channel
Expectation*(trial)*	The expected image by the subject for that particular trial
v_t	Potential difference values as a time function
t	Time component
$\boldsymbol{H_0}$	Null hypothesis
$\boldsymbol{H_1}$	Hypothesis
μ	Average
X	Element in a population
$\overline{X}$	Mean
$\overline{\overline{X}}$	Grand Mean
C	Number of Population
i	Element index / Input neuron indexing
j	Group index / Hidden neuron indexing
R	Number of elements in a group
C	Number of Groups
$b(n)$	Zeros
$a(n)$	Poles
N	Signal length in discrete form
ω	Continuous spectral component

n	Discrete time component
k	Discrete frequency component / Output neuron indexing
ψ	Window function
$\boldsymbol{eeg}_{energy}$	Spectral energy feature of the EEG signal
f_1	Lower frequency limit
f_2	Upper frequency limit
Index	Devijver's Feature Index
$\boldsymbol{C}$	Covariance matrix
$cov(\boldsymbol{feature}_i, \boldsymbol{feature}_j)$	Covariance between 2 features
I	Identity matrix
λ	Eigen values
V	Eigen Vector
$\boldsymbol{PC}$	Principle coponents
$\boldsymbol{S}$	Samples containing all the input vector
x_i	Element of the input vector
y_k	Element of the output vector
X_i	Input neuron
Z_j	Hidden neuron
Y_k	Output neuron
$y(t)$	System output
$u(t)$	System input
d	Delay units
$\boldsymbol{J}$	Jacobian Matrix
$w(new)$	New update of weight connection

w(old)	Old weight in previous iteration
μ_0	Initial damping factor
μ_+	Increased damping factor for every iteration
μ_-	Increased damping factor for every iteration
e	Error
$t_{p,o}$	Target for *p*-th pattern and *o*-th output
$y_{p,o}$	Output for *p*-th pattern and *o*-th output

KLASIFIKASI PERSEPSI PENGLIHATAN DENGAN MENGGUNAKAN ISYARAT EEG UNTUK ANTARA MUKA OTAK-KOMPUTER (BCI)

ABSTRAK

Pengidap penyakit *Neuron Motor Disorder* (MND) dan separa lumpuh kebiasaannya akan menghadapi masalah umtuk bergerak sekiranya tiada bantuan daripada orang lain. Oleh itu, kajian ini dijalankan untuk menunjukkan bahawa persepsi visual boleh digunakan untuk membantu pesakit bagi mengawal pergerakan menggunakan kerusi roda. Ini boleh tercapai dengan mengintegrasikan hasilan kawalan tersebut ke pengawal kerusi roda automatik. Sistem *Brain-Computer Interface* (BCI) memerlukan signal Electroencephalography (EEG) diekstrak daripada subjek menggunakan *Mindset24 EEG Amplifier*. Selepas itu, nisbah isyarat-kepada-hingar dianalisa dengan kaedah Analisa Varians (ANOVA) bagi mendapatkan isyarat dengan kandungan hingar yang tinggi dapat dihasilkan daripada sampel. Kemudian, tenaga spektrum daripada jalur isyarat EEG (θ, α, β1, β2, β3 dan γ) yang berkaitan dengan persepsi visual individu diekstrak. Kemudiannya, pengurangan dimensi dibuat untuk memastikan pengasingan ciri-ciri dengan menggunakan *Devijver's Feature Index* (DFI) dan *Principle Component Analysis* (PCA). Akhir sekali, model rangkaian neural seperti *multi-layer perceptron* (MLP), *Elman Recurrent Neural Network* (ERNN) dan *nonliner autoregressive exogenous model* (NARX) telah digunakan untuk menentukan persepsi visual subjek, dengan mencapai ketepatan purata yang melebihi 90%. Pengkelas ERNN telah menunjukkan pencapaian ketepatan tertinggi di dalam kedua-dua paradigma *Locational Matching* dan *Image Recognition* dengan masing-masing mencapai tahap 98.96% dan 97.81%. Oleh itu, pengkelas ERNN adalah yang paling sesuai untuk digunakan bagi aplikasi menggunakan persepsi visual bagi membantu pesakit MND bergerak menggunakan kerusi roda automatik.

CLASSIFICATION OF VISION PERCEPTION USING EEG SIGNALS FOR BRAIN-COMPUTER INTERFACE (BCI)

ABSTRACT

Patients suffering from Motor Neuron Disease (MND) and semi-paralysis have trouble to maneuver a conventional wheelchair independently. As a response, this research was conducted whereby an individual's visual perception can associate to movement controls. The designed system could later on be integrated into an autonomous wheelchair. The Brain Computer Interface (BCI) system would require the Electroencephalography (EEG) signal to be recorded from the subject using Mindset24 EEG amplifier. Subsequently, the signals' noise content was been analysed with analysis of variance (ANOVA) whereby signal with high noise content was removed from the samples. Then, spectral energy of different bands of EEG signal (θ, α, $\beta1$, $\beta2$, $\beta3$ and γ) pertaining to an individual's visual perception were extracted. Next, dimension reduction was performed to select band features based on feature separability using Devijver's Feature Index (DFI) and Principle Component Analysis (PCA). Finally, neural network models, namely, multi-layered perceptron (MLP), Elman Recurrent Neural Network (ERNN) and nonlinear exogenous autoregressive model (NARX) have been designed to as classifiers to determine the subject's visual perception, with an average accuracy of over 90%. Among the trained classifier, ERNN was chosen for it yielded a relatively higher performance in the both the Locational Matching and Image Recognition Paradigm in terms of classification accuracies (97.75% and 97.81% respectively). Therefore ERNN is the most suitable classifier to be used for application of visual perception to help MND patient navigate in a wheelchair.

CHAPTER 1

INTRODUCTION

1.1 Research Background

The recent advances in neuroscience enable the design of revolutionary ways for humans to communicate with a machine using Brain Computer Interfaces (BCI). A BCI system let humans interact with the physical world without depending on muscular movements (Wolpaw et al., 2000; Cheng et al., 2002; Allison, 2012). Such a technology proved invaluable for those suffering from motor neuron impairments (Leigh et al., 1994), or otherwise, known as a group of disease called Motor Neuron Disease (MND). Patients with MND, including those suffering from Cerebral Palsy or Amyotrophic Lateral Sclerosis (ALS) are known as lock-in patients, where they can still be fully aware of their surroundings but are unable to respond physically like normal humans do (Patterson et al., 1986).

ALS is defined as a devastating and fatal neurological disorder due to selective degeneration of neurons responsible for voluntary movements. Therefore, patients suffering from ALS will gradually have trouble to perform physical movements. Moreover, these patients can experience weakness and paralysis, while in some cases, might even be fatal (Ilzecka, 2003). This genetic abnormality is affecting one in every 24,000 individuals around the world (Fehr et al., 2000). The idea that the disease is hereditary was rejected by most researchers as only a small proportion of ALS patients being identified (10%) having a history of family background related to the disease (ALS Association). More plausible causes that lead to the disease were studied by medical researchers which include gene mutation, chemical imbalance and disorganised immune response (Mayo Clinic). To worsen the situation, no known cure for ALS was being identified. Henceforth, with the only option left, most researchers involved in the study had shifted their attention in search of effective ways of treatment instead. The main goal and motivation of those studies and development projects are to at least improve the every-day-living of MND patients (Clark et al., 2005).

Therefore, BCI provides an alternative solution to improve or overcome the limitations faced by MND patients. BCI enables lock-in patients to communicate with the physical world, thus compensating their physical constraints (Anupama et al., 2012), (Hema et al., 2006), (Yuksel et al., 2011). Attempts to design intelligent wheelchairs with automated control system thus far have been promising. The main aim is to provide navigational aid for this group of patients (Montesano, 2010), (Iturrate et al., 2009), (Mandel et al., 2009). Eventually, the integration of BCI in robotic technologies can potentially improve the lifestyles of the differentially enabled (DE) communities (Jackson, 1993).

Robotic wheelchairs can be categorised under rehabilitation and assistive technology. It aids those with disabilities, diseases, injury or ageing problems to restore the loss of ability to perform voluntary movements (Bourke, 2001). In relation to the subject, a survey was done among clinicians where 91% of them are confident that robotic wheelchair with automated navigational system might be useful for at least 40% of the patients (Neuper, 2003). Hence, it was explicitly stated that a wheelchair with high level of autonomy helps to aid the differentially enabled (DE) communities with their day-to-day tasks.