



**CLASSIFICATION OF VISION PERCEPTION
USING EEG SIGNALS FOR BRAIN COMPUTER
INTERFACE**

by

**ERIC TIONG KUNG WOO
1330610936**

A thesis submitted
In fulfillment of the requirements for the degree of
Master of Science in Mechatronic Engineering

**School of Mechatronic Engineering
UNIVERSITI MALAYSIA PERLIS**

2016

UNIVERSITI MALAYSIA PERLIS

DECLARATION OF THESIS

Author's full name : **ERIC TIONG KUNG WOO**
Date of birth : **20/11/1988**
Title : **CLASSIFICATION OF VISION PERCEPTION USING EEG SIGNALS FOR BRAIN
COMPUTER INTERFACE**
Academic Session : **2013 - 2016**

I hereby declare that the thesis becomes the property of Universiti Malaysia Perlis (UniMAP) and to be placed at the library of UniMAP. This thesis is classified as:

- CONFIDENTIAL** (Contains confidential information under the Official Secret Act 1972)*
- RESTRICTED** (Contains restricted information as specified by the organization where research was done)*
- OPEN ACCESS** I agree that my thesis is to be made immediately available as hardcopy or on-line open access (full text)

I, the author, give permission to the UniMAP to reproduce this thesis in whole or in part for the purpose of research or academic exchange only (except during a period of _____ years, if so requested above).

Certified by:

SIGNATURE

SIGNATURE OF SUPERVISOR

(NEW IC NO. / PASSPORT NO.)

NAME OF SUPERVISOR

Date: _____

Date : _____

NOTES : * If the thesis is CONFIDENTIAL or RESTRICTED, please attach with the letter from the organization with period and reasons for confidentiality or restriction.

ACKNOWLEDGEMENT

First and foremost, I would like to express my deepest gratitude to my main supervisor, Professor Dr. Abdul Hamid Bin Adom for his constant support throughout the period of this research. Prof Hamid has been very helpful during discussion sessions where motivation, methodologies and result of this study would be discussed. The questions pointed out by Prof. Hamid proved vital in solving the problem statement in relation to this research title.

Moreover, I would like to express my sincere gratitude to my second supervisor Professor Dr. Paulraj M.P. for the continuous support of my M.Sc. study and research, for his patience, persistence, visualization and immense knowledge. In fact, Prof. Paul gave me the inspiration to start this research work. Prof. Paul was very dedicated as a mentor by keeping himself up to date with the latest research progress: from the discussion of research title, the design of experimental protocol, the data recording session, the design of methodologies and the documentation of results.

I would like to express my sincere thanks to the Vice Chancellor of Universiti Malaysia Perlis, Dato' Professor Dr. Zul Azhar Zahid Jamal for his constant encouragement in research and innovation works in providing the facilities at the university for the completion of this research work.

Next, I would like to express gratitude to Kementerian Pengajian Tinggi Malaysia (KPT) for their financial support through the scholarship program: MyBrain15. Without the sponsorship of tuition fee, I would not be able to complete my M. Sc. studies.

I would also like to take this opportunity to give my thanks to my seniors: Dr. Kamalraj Subramaniam and Mr. Sathees Kumar Nataraj for their suggestions and recommendations given during the period of this research work, especially during the

absence of our beloved supervisors. Next, I would also like to thank my dear friends and fellow research partner, Jackie Teh and Tung Kai Xu who we would regularly meet for discussions on the related research topic.

Next, not to forget my, deepest gratitude toward my parents, Tiong Ing Hee and Tang Kiek Ing who supported me financially and giving me constant encouragement to pursue this research work.

Finally, my gratitude towards God Almighty for His blessings.

©This item is protected by original copyright

TABLE OF CONTENTS

THESIS DECLARATION	i
ACKNOWLEDGEMENT	ii
TABLE OF CONTENTS	iv
LIST OF TABLES	ix
LIST OF FIGURES	xii
LIST OF ABBREVIATIONS	xv
LIST OF SYMBOLS	xviii
ABSTRAK	xxi
ABSTRACT	xxii
CHAPTER 1: INTRODUCTION	
1.1 Research Background	1
1.2 Motivation	3
1.3 Problem Statement	4
1.4 Objective	5
1.5 Scope of Research	6
1.6 Thesis Arrangements	7
CHAPTER 2: LITERATURE REVIEW	
2.1 Introduction to BCI Systems	9
2.2 Electroencephalography Used for Brain Computer Interface (BCI)	9
2.3 Understanding Human Visual Perception	11
2.3.1 Photoreceptors	13
2.3.2 Colour Vision	16
2.3.3 Intracortical Signal Flow of Visual Information	17

2.3.4 Visual Attention	19
2.4 Visual Evoked Potential as an Event Related Potential	22
2.4.1 Transient VEP	22
2.4.2 Steady State Visual Evoked Potential (SSVEP)	24
2.4.3 Attentional VEP	25
2.5 Feature Extraction and Dimension Reduction	29
2.5.1 Fourier Transform	30
2.5.2 Short-time Fourier Transform	32
2.5.3 Feature Selection Methods	35
2.6 Classification of Stochastic Signal	36
2.6.1 Multi-layered Perceptron	37
2.6.2 Recurrent Neural Networks	39
2.7 Chapter Summary	42
CHAPTER 3: DATA ACQUISITION AND REPROCESSING	
3.1 Introduction to Data Acquisition and Pre-processing	51
3.2 Experimental Design	52
3.2.1 Visual Stimuli Selection and Display Method	54
3.2.2 Subject and Participant Selection	57
3.2.3 Instrumentations	60
3.2.4 Instructions Given to Subjects	64
3.2.5 Protocols and Procedures	65
3.3 Data Pre-Processing	68
3.3.1 Database Construction	68
3.3.2 Data Validation with ANOVA	71
3.3.3 Noise Removal	75

3.3.4 Signal Normalization	79
3.4 Chapter Summary	80
CHAPTER 4: FEATURE EXTRACTION	
4.1 Introduction: Feature Extraction on EEG Signals	81
4.2 Spectral Analysis	82
4.2.1 Fourier Transform	82
4.2.1 Short Time Fourier Transform (STFT)	84
4.2.3 Spectral Energy Features	87
4.2.4 Feature Index on Feature Separability	88
4.3 Principle Component Analysis (PCA)	90
4.3.1 Feature Transformation by Computation of PCA	90
4.3.2 Dimension Reduction with PCA	93
4.4 Chapter Summary	94
CHAPTER 5: CLASSIFICATION	
5.1 Introduction to Artificial Neural Networks	95
5.2 Multi-layered Perceptron	96
5.3 Recurrent Neural Network	101
5.3.1 Elman Recurrent Neural Network	101
5.3.2 Non-linear Autoregressive Exogenous Network Model	103
5.4 Levenberg-Marquardt Learning Algorithm	105
5.5 Analysing Network Performance	109
5.6 Chapter Summary	110
CHAPTER 6: RESULTS AND DISCUSSIONS	
6.1 Introduction	111
6.2 Results of Data Validation	111

6.2.1 Data Validation with Raw EEG Signal	112
6.2.2 Data Validation after Noise Removal	113
6.3 Results on Feature Selection	114
6.3.1 Feature Selection Using DFI	115
6.3.2 Validation of DFI using MLP Classifier	117
6.3.3 Feature Selection Using PCA	115
6.3.4 Validation of PCA using MLP	126
6.3.5 Summary on Feature Selection	128
6.4 Classification Comparison for Location Matching Paradigm	130
6.4.1 Classification of Location Matching Paradigm: MLP	130
6.4.2 Classification of Location Matching Paradigm: Elman RNN	133
6.4.3 Classification of Location Matching Paradigm: NARX	136
6.4.4 Summary on Classification of Location Matching Paradigm	139
6.5 Classification Comparison for Image Recognition Paradigm	140
6.5.1 Classification of Image Recognition Paradigm: MLP	140
6.5.2 Classification of Image Recognition Paradigm: ERNN	142
6.5.3 Classification of Image Recognition Paradigm: NARX	144
6.5.4 Summary on Classification of Image Recognition Paradigm	146
6.6 Chapter Summary	147
CHAPTER 7: CONCLUSION	
7.1 Thesis Summary	148
7.3 Contributions	151
7.4 Future Works	152
REFERENCES	xxiii
APPENDIX A: INFORMATION FORM	xxxvi

APPENDIX B: CONSENT FORM	xxxvii
APPENDIX C: INSTRUCTIONS TO PARTICIPANTS	xxxix
APPENDIX D: DATA VALIDATION OF RAW EEG SIGNALS BY OBTAINING P VALUES FROM ANOVA FOR EACH SUBJECT	xli
APPENDIX E: DATA VALIDATION OF FILTERED EEG SIGNALS BY OBTAINING P VALUES FROM ANOVA FOR EACH SUBJECT	xlvii
PUBLICATIONS	liii

©This item is protected by original copyright

LIST OF TABLES

No.		Page
2.1	Bands of different EEG signals and related mental tasks	47
2.2	True positive and true negative conditions in a confusion matrix	50
3.1	Matching/mismatching of expected image with the image being shown	53
3.2	Subjects participated in EEG recording sessions	58
3.3	Trials recorded for each subject	69
3.4	Null-Hypothesis and Hypothesis of ANOVA test	73
3.5	Zeros and poles of the designed low-pass filter to suppress noise component at 50Hz	77
3.6	Zeros and poles of the designed high-pass filter which defines the frequency range of EEG signals	78
4.1	Frequency range for different bands of EEG signals	88
6.1	Maximum and mean of p values in ANOVA of all Subjects for all channels and locational image with raw EEG signal	112
6.2	Maximum and mean of p values in ANOVA of all Subjects for all channels and locational image after noise removal	114
6.3	Feature index by using DFI on SE of EEG signal	116
6.4	Feature significance index(FSI) predicted by DFI	117
6.5	Number of samples used in the classification of Locational Matching Paradigm, represented as features of EEG signals recorded from 10 Subjects	118
6.6	Number of bands selected versus total number of features selected to represent the visual perception of a subject	119
6.7	Network structure and training parameter of MLP used to classify different combinations of SE features	120
6.8	Mean classification accuracy for all 10 Subjects on the combination of one out of six band features (6C_1)	121
6.9	Mean classification accuracy for all 10 Subjects on the combination of two out of six band features (6C_2)	121

6.10	Mean classification accuracy for all 10 Subjects on the combination of three out of six band features (${}_6C_3$)	122
6.11	Mean classification accuracy for all 10 Subjects on the combination of four out of six band features (${}_6C_4$)	123
6.12	Mean classification accuracy for all 10 Subjects on the combination of five out of six and all six band features (${}_6C_5$ and ${}_6C_6$)	123
6.13	Classification accuracy for different number of selected SE band features	124
6.14	Cumulative percentage of variance for different number of selected PCs all five different Images.	126
6.15	Network structure and training parameter of MLP used to classify different number of PCs	127
6.16	Classification accuracy for different number of selected PCs	127
6.17	Network structure and training parameter of MLP used to classify the SE feature of EEG signals pertaining to the Location Matching Paradigm	131
6.18	Mean classification performance of SE band features pertaining to the task of Locational Matching using MLP	132
6.19	Confusion matrix of the trained MLP for the Locational Matching paradigm with highest accuracy	132
6.20	Network structure and training parameter of ERNN used to classify the SE feature of EEG signals pertaining to the Location Matching Paradigm	134
6.21	Mean classification performance of SE band features pertaining to the task of Locational Matching using ERNN	135
6.22	Confusion matrix of the trained ERNN for the Locational Matching paradigm with highest accuracy	135
6.23	Network structure and training parameter of NARX used to classify the SE feature of EEG signals pertaining to the Location Matching Paradigm	137
6.24	Mean classification performance of SE band features pertaining to the task of Locational Matching using NARX	138

6.25	Confusion matrix of the trained NARX for the Locational Matching paradigm with highest accuracy	138
6.26	Network structure and training parameter of MLP used to classify the SE feature of EEG signals pertaining to Image Recognition Paradigm	141
6.27	Mean classification performance of SE band features pertaining to the task of Image Recognition using MLP	141
6.28	Confusion matrix of the trained MLP for the Image Recognition Paradigm with highest accuracy	141
6.29	Network structure and training parameter of ERNN used to classify the SE feature of EEG signals pertaining to Image Recognition Paradigm	143
6.30	Mean classification performance of SE band features pertaining to the task of Image Recognition using ERNN	143
6.31	Confusion matrix of the trained ERNN for the Image Recognition Paradigm with highest accuracy	143
6.32	Network structure and training parameter of NARX used to classify the SE feature of EEG signals pertaining to Image Recognition Paradigm	145
6.33	Mean classification performance of SE band features pertaining to the task of Image Recognition using NARX	145
6.34	Confusion matrix of the NARX for the trained Image Recognition Paradigm with highest accuracy	145

LIST OF FIGURES

No.		Page
2.1	Visual pathway of human's visual system	12
2.2	Structure of Human Eyeball	13
2.3	Distribution of the light-sensitive photo receptors (rods and cones) across the retina of human eye in relation to the vertex of the retina, indicated by the region called fovea	14
2.4	Response of different types of light sensitive colour receptors towards visible light of different wave length	15
2.5	Distribution of different cone receptors across the retina of human eye in relation to the vertex retina	16
2.6	Structure of human brain	18
2.7	Regions in the human brain involved in visual perception and visual imagery. PFC: pre-frontal cortex; IOG: inferioroccipital gyrus; SPL: superior parietal lobule	21
2.8	VEP responses (a) POVEP response and its components: N1, P1, N2 and P2 (b) Inattentive SSVEP to a static image at relaxation state	26
3.1	Block diagram of BCI: DAQ and Pre-processing	51
3.2	Images of five locations in a house, being used as visual stimuli: (Image 1) toilet, (Image 2) living room, (Image 3) kitchen, (Image 4) children bedroom and (Image 5) bedroom	55
3.3	Positioning of the subjects and their FOV against a 24" LCD screen area	56
3.4	Video playback to display 5 locational images in sequential order	57
3.5	Protocol A (Subject selection protocol)	59
3.6	Electrode sites for the 10-20 electrode placement system	61
3.7	Equipment used to record EEG signal	62
3.8	Protocol B (Equipment inspection protocol)	63
3.9	Protocol C (Instructions given to the subjects prior EEG recording sessions)	64

3.10	Protocol of Location Matching Paradigm	66
3.11	Protocol D: Flowchart of EEG recording session	67
3.12	Distribution pattern seen in an EEG signal of 6s length for electrode channel O1	72
3.13	Component of power line noise in EEG signals, elicited at 50Hz	76
3.14	Frequency response of filter of type Elliptic, Butterworth and Chebychev	76
3.15	50Hz power line noise filtered with a 10-th order Elliptic filter	78
3.16	Spectrogram of the filtered EEG signal	79
4.1	Block diagram of BCI: Feature Extraction/Selection Block	81
4.2	Periodogram of a one second segment of EEG signal	83
4.3	Hamming window function	85
4.4	Segmentation of EEG signal while performing STFT at 1 second (256 sample points) for each window with overlap of 50%	86
4.5	Spectrogram of EEG signal	86
4.6	Histogram of two class discriminable features	89
5.1	Basic structure of a 2 layered MLP neural network model	96
5.2	Log-sigmoid activation function's transfer function	99
5.3	Structure of arrangement of MLP network models of locational perception paradigm	100
5.4	Structure of arrangement of MLP network model of image recognition paradigm	100
5.5	A single layered single input single output (SISO) RNN structure	101
5.6	Partially recurrent network structure, with additional context layer	102
5.7	Basic structure of a NARX neural network model	104
5.8	Comparison between 2 different learning rates for several iterations of training across the contour error gradient	105
5.9	Flow chart of LM's training algorithm	108

5.10	Decrease of MSE of training, validation and testing sets over epochs of training	109
6.1	Mean classification accuracy for different number of selected band features selected	125
6.2	Classification accuracy vs. percentage of cumulative variance of the number of selected PCs	128
6.3	Classification accuracy vs. features for the two feature sets: SE and PCA	129
7.1	BCI system with the Image Recognition and Locational Matching Paradigm	150

©This item is protected by original copyright

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	Discrete 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°}	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-linear 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

©This item is protected by original copyright

LIST OF SYMBOLS

<i>Database</i> _{subject}	Vector containing trails of 17 channel of EEG signals recorded from a particular subject
<i>EEG</i> _{trial}	Particular trial of EEG signals recorded on 17 different channels
<i>eeg</i> _{channel}	EEG signal of a particular channel
<i>Expectation</i> (<i>trial</i>)	The expected image by the subject for that particular trial
v_t	Potential difference values as a time function
t	Time component
H_0	Null hypothesis
H_1	Hypothesis
μ	Average
X	Element in a population
\bar{X}	Mean
$\bar{\bar{X}}$	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
$ee\mathbf{g}_{energy}$	Spectral energy feature of the EEG signal
f_1	Lower frequency limit
f_2	Upper frequency limit
<i>Index</i>	Devijver's Feature Index
C	Covariance matrix
$cov(\mathbf{feature}_i, \mathbf{feature}_j)$	Covariance between 2 features
I	Identity matrix
λ	Eigen values
V	Eigen Vector
PC	Principle coponents
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
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

©This item is protected by original copyright

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 untuk 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 hasil 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 , β_1 , β_2 , β_3 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 , β_1 , β_2 , β_3 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