UNIVERSITI PUTRA MALAYSIA

ELECTROENCEPHALOGRAM SIGNAL INTERPRETATION SYSTEM FOR MOBILE ROBOT

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By

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In recent years, Brain-Computer Interface (BCI) research has provoked an enormous interest among researchers from different fields since it is an important element in assistive technology. The most popular approach is a non-invasive method, using Electroencephalogram (EEG) analysis which acquires signals from the brain. Currently, the BCI application is to acquire signals from 32 to 64 electrodes' recordings and translate them to a movement using various computing algorithm which can be used in wheelchair navigation, or control robot movements. However, it will be time consuming and an exhausting experience if the single command translation from large number of electrodes is used to help physically disabled and elderly people with their daily tasks or chores. An improved interface needed to be developed to allow BCI to become a user-friendly interface for the targeted groups.

The aim of this project is to develop an algorithm that can choose optimal four electrodes for signal recording, and convert one thought into multiple commands with the chosen electrodes. Using sample datasets, the EEG signal is analyzed to determine the most suitable scalp area for P300 detection, while optimization with genetic algorithm (GA) is developed to select best four channels. Next, a signal interpretation system is designed and developed to translate the signal and send the pre-programmed commands to the robot through the operating computer. Based on the analysis and optimization of the datasets, P300 signals are most clear and robust at the midline and parietal area of the scalp, and can be detected at around 500ms after a stimulus. After 30 GA runs, the optimal four sets of electrodes are chosen based on their coefficient of

determination or r^2 values, where higher values contributes to higher repetition rates. Using signals from the chosen four electrodes to evaluate the signal interpretation system, a success rate of 75-80% is received. With this system, user can expect a more convenient preparation with lesser electrodes used, and faster execution of the robot commands since they are pre-programmed according to user's intention and selected route.

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SISTEM PENTAFSIRAN ISYARAT ELEKTROENSEFALOGRAM UNTUK ROBOT BERGERAK

Oleh

INTAN HELINA HASAN

November 2013

Pengerusi: Abd Rahman Ramli, PhD

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Dalam beberapa tahun kebelakangan ini, penyelidikan dalam Antara Muka Otak-Komputer (BCI) telah menimbulkan minat yang tinggi di kalangan penyelidik dari pelbagai bidang kerana ia adalah elemen penting dalam teknologi bantuan. Pendekatan yang paling popular ialah kaedah bukan-invasif, iaitu dengan menggunakan elektroensefalogram (EEG) untuk memperoleh isyarat dari otak. Pada masa kini, aplikasi BCI adalah untuk memperoleh isyarat daripada 32 hingga 64 elektrod dan menterjemahkan kepada satu pergerakan dengan menggunakan pelbagai algoritma pengkomputeran. Walau bagaimanapun, jika objektif kajian BCI adalah untuk membantu orang kurang upaya dari segi fizikal dan warga tua dengan tugas atau kerja harian mereka, pendekatan ini akan memakan masa yang lama dan memberi satu pengalaman yang meletihkan. Satu antara muka yang lebih baik perlu dibangunkan untuk membolehkan BCI untuk menjadi antara muka yang mesra pengguna bagi kumpulan sasaran.

Tujuan projek ini adalah untuk membangunkan algoritma yang boleh memilih empat elektrod optimum untuk memperoleh isyarat, dan menukar satu pemikiran ke dalam beberapa siri pergerakan dengan elektrod yang dipilih. Dengan menggunakan sampel dataset, isyarat EEG dianalisis untuk menentukan kawasan kulit kepala yang paling sesuai untuk mengesan P300, manakala pengoptimuman dengan algoritma genetik (GA) dibangunkan untuk memilih empat saluran yang terbaik. Seterusnya, sistem tafsiran isyarat direka dan dibangunkan untuk menterjemahkan isyarat dan menghantar arahan yang dipra-programkan untuk robot melalui komputer operasi. Berdasarkan analisis dan

pengoptimuman dataset, isyarat P300 adalah yang paling jelas dan mantap di kawasan garis tengah dan parietal kulit kepala, dan boleh dikesan pada kira-kira 500ms selepas rangsangan . Selepas 30 jalanan GA, empat set elektrod yang optimum dipilih berdasarkan nilai pekali penentuan atau r^2 mereka , di mana nilai yang lebih tinggi menyumbang kepada kadar pengulangan yang lebih tinggi. Menggunakan isyarat daripada empat elektrod yang dipilih untuk menilai sistem tafsiran isyarat, kadar kejayaan 75-80% telah diterima. Dengan sistem ini, pengguna boleh mengharapkan penyediaan yang lebih mudah dengan penggunaan bilangan elektrod yang kurang, dan pelaksanaan arahan robot yang lebih cepat kerana mereka adalah dipra-programkan mengikut niat pengguna dan laluan yang dipilih.

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I certify that a Thesis Examination Committee has met on 27 November 2013 to conduct the final examination of Intan Helina binti Hasan on her thesis entitled "**Electroencephalogram Signal Interpretation System for Mobile Robot**" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the Master of Science.

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LIST OF ABBREVIATIONS

BCI	: Brain-Computer Interface
BMI	: Brain-Machine Interface
EEG	: Electroencephalogram
EMG	: Electromyogram
EOG	: Electrooculogram
VEP	: Visual Evoked Potentials
SMR	: Sensorimotor Rhythm
SCP	: Slow Cortical Potentials
ERP	: Event Related Potentials
ALS	: Amyotrophic Lateral Sclerosis
ME	: Micro-Electrode
MEA	: Micro-Electrode Array
LFP	: Local Field Potentials
NMP	: neuromotor prostheses
ECoG	: Electrocorticogram
ER	: Evoked Responses
MEG	: Magnetoencephalogram
fMRI	: Functional Magnetic Resonance Imaging
HRI-JP	: Honda Research Institute Japan Co., Ltd.
ATR	: Advanced Telecommunications Research Institute International

BOLD	: blood oxygenation level dependant
NIRS	: Near-Infrared Spectroscopy
SSVEP	: Steady State Visual Evoked Potential
LED	: Light Emitting Diode
DC	: Direct Current
ERD	: Event Related Desynchronization
ERS	: Event Related Synchronization
ADC	: analog-to-digital converter
PCA	: principal component analysis
ICA	: independent component analysis
CSP	: common spatial pattern
GA	: genetic algorithm
MATLAB	: Matrix Laboratory (programming language)
AR	: autoregressive
FFT	: Fast Fourier transform
GUI	: Graphical User Interface
SSNR	: signal to signal-plus-noise ratio
BLDA	: Bayesian linear discriminant analysis
CNN	: Convolutional Neural Network
SVM	: Support vector machine
EPOC	: name of Emotiv Neuroheadset
SAN	: semi-autonomous navigation

ESIS	: EEG Signal Interpretation System
IDE	: Integrated Development Environment
UDP	: User Datagram Protocol
IP	: Internet Protocol
ISI	: inter stimulus interval
RAM	: Random-access memory
TCP/IP	: Transmission Control Protocol / Internet Protocol
PCM	: Pearson's correlation method
FLD	: Fisher's linear discriminant
SWLDA	: stepwise linear discriminant analysis
LSVM	: linear support vector machine
GSVM	: Gaussian support vector machine

CHAPTER 1

INTRODUCTION

1.1 Overview of Brain-Computer Interface

Brain-Computer Interface (BCI) or Brain-Machine Interface (BMI) is defined as a direct communication pathway between a human brain and a computer or a machine. In near future, it is imagined that human can actually just do the thinking and computers or machines can do the actions needed to execute the human's thoughts. Based on the growing interests in this research area, that future is not too distant as we have anticipated (Lebedev & Nicolelis, 2006). Research laboratories specializing in BCI and its applications have been established in most countries, with the best researchers from different fields; from neuroscientists to communication, computer and electrical engineers collaborating together to produce better results that can contribute to real-life application of BCI.

Figure 1.1 shows the basic BCI system for application in robot or any external devices (Schalk, 2009). Brain signals are recorded using electrodes placed onto or under the human scalp which will then be sent to the computer for processing and analysis for signal features. The signals are then translated to the commands to be sent to external devices using specific algorithm.

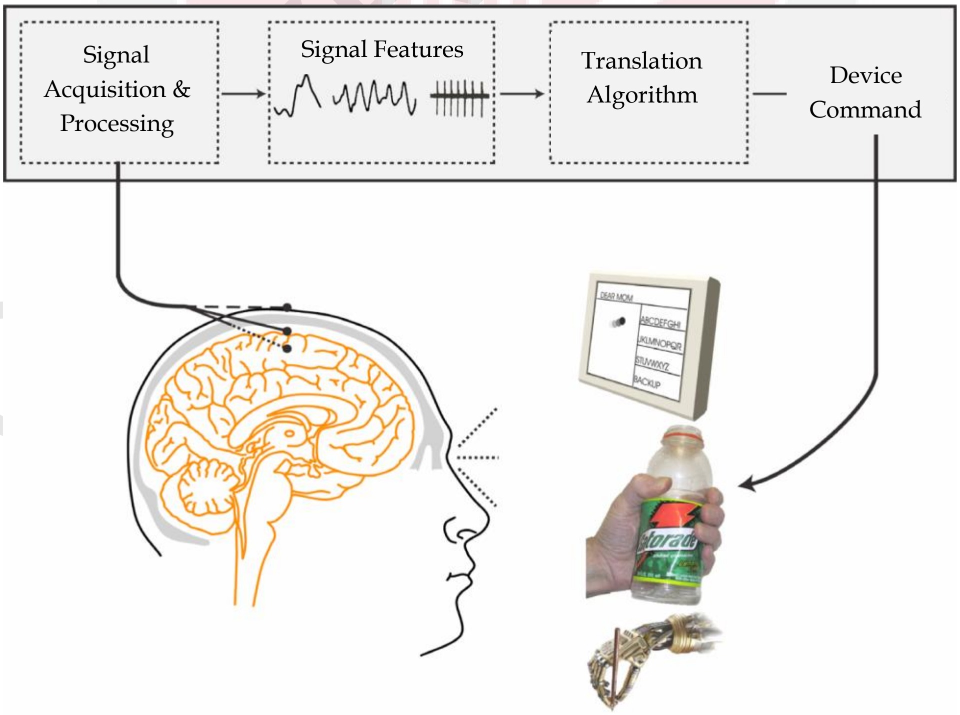

Figure 1.1. A typical BCI system for controlling external devices (e.g. robots, wheelchairs etc.) (Schalk, 2009)

The ideas of thought-controlled devices have long existed in science fictions. However to pursue the research in this field, the biggest question that first needed to be answered was how to actually 'read' human's thought from the brain itself. A human brain normally contains billions of neurons, which connect to each other to form networks. These neurons process and transmit electrical and chemical signals that will then control human muscles and senses. In 1929, Hans Berger, a neuropsychiatric scientist from German published his findings of scalp recordings of a human brain's electrical activity, which later referred to as the Electroencephalogram or EEG (Swartz & Goldensohn, 1998). Since then, EEG is used mainly in neuroscience studies, concentrating on studying the types of signals that can occur in one's brain. It was not until the early 1970s that researchers began to realize that the EEG can also be used to translate human's thoughts or intentions. Vidal (1977) then introduced the term 'Brain-Computer Interface' in his paper to explain the direct communication system between the brain and the computer. The research of BCI field later began to expand vastly around the globe, attracting all kinds of scientists and engineers to pursue this new and exciting idea of BCI.

In general, methods used in extracting signals from the brain are divided into two types: invasive and non-invasive. Invasive methods refer to recordings using electrodes being implanted into the grey matter of the brain through surgery. Non-invasive methods on the other hand refer to recordings made using electrodes that are placed on the skull with no surgery needed. Invasive methods are the most effective way to record firing neurons due to good spatial resolution (0.1mm) and temporal resolution (less than 0.01s). However, there are still few issues need to be solved before the invasive methods can become a clinically useful BCI method in the future. Non-invasive methods, particularly those using EEG device, are considered most convenient for its portability and availability without any surgery needed. However, EEG has its own setbacks, such as limited bandwidth (10 to 40Hz), spatial resolution up to 20mm, and recordings are susceptible to Electromyogram (EMG), Electrooculogram (EOG) and other mechanical artifacts (Schalk, 2009). Nevertheless, researchers prefer to pursue EEG-based BCI for its advantages of non-invasive, convenient and inexpensive. There are four types or features of EEG signals commonly used for BCI: Visual Evoked Potentials (VEP), Sensorimotor Rhythm (SMR), Slow Cortical Potentials (SCP) and Event Related Potentials (ERP). P300 is one of the components in the ERP which is defined as a positive peak that occurs around 300ms after a stimulus is presented to the user. It has robust waveform which makes it popular among EEG-BCI researchers to use it for feature extraction during EEG signal processing and analysis.

1.2 Problem Statement

Although almost everyone can benefit from this interface development, researchers are mainly targeting those with physical disabilities, patients suffering with neuromuscular disorders such as Amyotrophic Lateral Sclerosis (ALS), 'locked-in' syndrome or patients who are totally paralyzed or elderly people to take advantage from BCI to improve their daily lives' tasks (Sellers, 2006; Sirvent Blasco, 2012; Vaughan, 2006). Therefore most researches around the world are dealing with the same research question: How to make BCI a user-friendly system for the targeted groups? To solve this, researchers are pursuing their researches from every angle; from the brain acquisition process to the translation and finally the output or application process.

The most common brain signal acquisition method used is EEG which is non-invasive since no surgery needed prior to using the EEG equipment. Out of the four EEG features mentioned, the P300 component of ERP is the most widely used feature for BCI operation due to its high-amplitude waveform which makes it easier for classification. In order to obtain good information and better accuracy of P300 signals, the recordings are usually made by placing from 32 to 64 electrodes or sensors on the scalp, depending on the recording device's recording channel capacity. This is however can be inconvenient to operators and users since the process of placing a lot of electrodes will take a lot of preparation time, and it will make the users feel discomfort with the setup and eventually reject the idea of putting sensors on the scalp (Mak, 2011). Reducing the number of electrodes for EEG recordings is possible; previous literatures showed promising results using four midline electrodes (Serby et al., 2005; Sellers and Donchin, 2006; Piccione et al., 2006). Hoffman et al. (2008) experimented with nine subjects with minimum four electrodes and have produced good results. However the recordings' quality and signal accuracy may deteriorate if wrong configuration is used to place the electrodes, and since human's EEG signals are quite similar to fingerprints which have unique pattern for every person, the mentioned electrode configuration might not be the optimal combination for other subjects. Therefore a suitable method or algorithm needs to be studied and developed to be able to automatically select the optimal number of electrodes for P300 recording. It is hoped that even with minimum electrodes used, the P300 accuracy can still be acquired to control the mobile robot navigation according to the user's intention.

A number of researchers have succeeded in translating human thoughts to action, such as controlling a robot arm, a wheelchair, or even a spelling device. The next problem that needs to be tackled is how to make BCI a user-friendly device for the targeted groups, for example patients with physical disabilities or the elderly. Current approach is to directly translate the brain signals to movements using computing algorithms, which is focusing more on the accuracy of the translation but consumes a lot of time and energy to complete one task. The main problem is to figure out how to translate brain signals into chains of commands without exhausting the user in terms of preparation and operation. To solve this problem, a more reliable algorithm or system needs to be developed, such as introducing a system that can be integrated with pre-programmed robot software or simulator. It is expected that this system can be applied as a medium to relieve the user from the exhaustion of having to operate the BCI movement by movement, thus can shorten the time needed to operate the system by issuing only one command for mobile robot to navigate from home position to the goal desired by the user.

1.3 Research Objectives

To tackle the problems discussed above, this project aims to develop an algorithm to perform optimization of EEG channel selection to help translate one instruction to multiple commands for robot navigation with minimum number of electrodes used for recording. For example, if the user imagines 'drink', the brain signal evoked will be captured, processed and analyzed. Then, after P300 signal is detected, channel selection optimization is done to find the best four combinations of channels for the specific signal recordings. Once the channels are determined, signals from the selected channels will be translated to sequences of commands that will allow the robot to do specific movements which are initially programmed into the device, such as move to the place where the drink is located, then return back to pass the drink to the user.

Research objectives are:

1. To investigate and analyze the P300 signal strength and automatically select four optimal locations of electrodes.
2. To develop a translation algorithm for the acquired P300 signals and send commands to the external device to perform tasks with the above minimum electrode configuration.

1.4 Scope of the Project

Although this project aims to develop a system that can help patients with physical disabilities and elderly people, due to ethical reasons, only sample datasets will be used in data processing, analysis and system evaluation. The sample datasets which are available from the BCI2000 website (for more details please refer to Chapter Three: Methodology) will be used. The interpretation system built in this project will be solely developed to communicate with mobile robots (in robot simulation programs) that can be pre-programmed. A robot simulator called RobotBASIC is used in this project. Therefore all system evaluation and BCI verification will be using the environment that is suited with the simulator's movement capability.

1.5 Contribution

The contributions of this project are an improved channel selection algorithm that utilizes Genetic Algorithm (GA) to choose optimal subsets of electrodes with minimum numbers possible; and development of new EEG Signal Interpretation System to control mobile robot or any external device. GA is used in the channel selection algorithm because of its behavior that mimics the natural evolution of human population based on genes' mutation, cross-over, and elitism, among others. The stochastic approach is considered useful to optimize the best combination of electrode configurations. As for the signal interpretation system, instead of focusing on how to improve the accuracy of signal translation using computing algorithm, the new EEG Signal Interpretation System is developed using a new technique of combining a simple signal translation with pre-programmed mobile robot navigation, which is more user-friendly, low cost in maintenance since it does not involve any extra tools such as visual camera software, and higher value of commercialization since it is a standalone system which can be used with any mobile robot available in the market, regardless of the programming language used by the robot.

Looking at the current advances and commercialization development concerning BCI technology, this innovation is designed with aim to be used by human regardless of their movement capability. Healthy users can use this system to help them in daily chores in terms of multi-tasking, while physically disabled users can use this system to help ease the burden of moving around or simply to fetch drinks or food. Elderly users can also benefit from this system as it can be their 'helper' to do simple chores or task in a short amount of time that if to be done by them, can be extremely time consuming and exhausting. It is also can be more appealing if the system can be operated with minimum number of electrodes possible without compromising the signals' accuracy, therefore can reduce the discomfort of having to wear too many sensors on the scalp to operate a robot.

1.6 Thesis Organization

The body of this thesis is divided into several chapters. Chapter One includes the introduction, problem statement, research objectives, scope of the project and contribution to the society. Chapter Two consists of the literature review of the project, where past related researches are analyzed and discussed to relate to the problem statement. Chapter Three describes the materials and equipments used in the project, and methods used to achieve the objectives. Chapter Four includes the results obtained, and discussion of the results. Finally, Chapter Five contains the summary and conclusions of the thesis, and some recommendations for future research that can help other researchers in the same field.

REFERENCES / BIBLIOGRAPHY

Allison, B. Z., McFarland, D. J., Schalk, G., Zheng, S. D., Jackson, M. M., & Wolpaw, J. R. (2008). Towards an independent brain–computer interface using steady state visual evoked potentials. *Clinical Neurophysiology*, 119(2), 399-408.

Barbosa, A. O. G., Achanccaray, D. R., & Meggiolaro, M. A. (2010). Activation of a mobile robot through a brain computer interface. *2010 IEEE International Conference on Robotics and Automation (ICRA)*, 4815-4821.

Bell, C. J., Shenoy, P., Chalodhorn, R., & Rao, R. P. N. (2008). Control of a humanoid robot by a noninvasive brain-computer interface in humans. *Journal of Neural Engineering*, 5(2), 214-220.

Beverina, F., Palmas, G., Silvoni, S., Piccione, F., & Giove, S. (2003). User adaptive BCIs: SSVEP and P300 based interfaces. *PsychNology Journal*, 1(4), 331-354.

Birbaumer, N., Kubler, A., Ghanayim, N., Hinterberger, T., Perelmouter, J., Kaiser, J., Flor, H. (2000). The thought translation device (TTD) for completely paralyzed patients. *IEEE Transactions on Rehabilitation Engineering,* 8(2), 190-193.

Blankenship, J., & Mishal, S. (2012). Robotbasic. Retrieved January, 2012, from http://www.robotbasic.org/index.html

Blankertz, B., Sannelli, C., Halder, S., Hammer, E. M., Kübler, A., Müller, K., Dickhaus, T. (2010). Neurophysiological predictor of SMR-based BCI performance. *Neuroimage*, 51(4), 1303-1309.

Bostanov, V. (2004). BCI competition 2003-data sets Ib and IIb: Feature extraction from event-related brain potentials with the continuous wavelet transform and the t-value scalogram. *IEEE Transactions on Biomedical Engineering*, 51, 1057–1061.

Boye, A.T.; Kristiansen, U.Q.; Billinger, M.; do Nascimento, O.F.; Farina, D. (2008). Identification of movement-related cortical potentials with optimized spatial filtering and principal component analysis. *Biomedical Signal Processing Control,* 3, 300–304.

Buch, E., Weber, C., Cohen, L. G., Braun, C., Dimyan, M. A., Ard, T., Birbaumer, N. (2008). Think to move: A neuromagnetic brain-computer interface (BCI) system for chronic stroke. *Stroke*, 39(3), 910-917.

Castellanos, N.P.; Makarov, V.A. (2006). Recovering EEG brain signals: Artifact suppression with wavelet enhanced independent component analysis. *Journal of Neuroscience Methods*, 158, 300–312.

Cecotti, H., Rivet, B., Congedo, M., Jutten, C., Bertrand, O., Maby, E., Mattout, J. (2011). A robust sensor-selection method for P300 brain-computer interfaces. *Journal of Neural Engineering,* 8(1), art. no. 016001.

Chapin, J. K., Moxon, K. A., Markowitz, R. S., & Nicolelis, M. A. L. (1999). Real-time control of a robot arm using simultaneously recorded neurons in the motor cortex. *Nature Neuroscience*, 2(7), 664-670.

Cherubini, A., Oriolo, G., MacRí, F., Aloise, F., Cincotti, F., & Mattia, D. (2008). A multimode navigation system for an assistive robotics project. *Autonomous Robots*, 25(4), 383-404.

Coles, M. G. H., & Rugg, M. G. (1996). Event-related brain potentials: An introduction. *Electrophysiology of Mind, Oxford Scholarship Online Monographs*, 1-27.

Czernochowski, D., Mecklinger, A., & Johansson, M. (2009). Age-related changes in the control of episodic retrieval: An ERP study of recognition memory in children and adults. *Developmental Science*, 12(6), 1026-1040.

Dal Seno, B., Matteucci, M., Mainardi, L. (2008). A genetic algorithm for automatic feature extraction in P300 detection. *Proceedings of the International Joint Conference on Neural Networks,* art. no. 4634243, pp. 3145-3152.

Escolano, C., Antelis, J. M., & Minguez, J. (2011). A telepresence mobile robot controlled with a noninvasive Brain–Computer interface. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, PP(99), 1-12.

Fabiani, G. E., McFarland, D. J., Wolpaw, J. R., & Pfurtscheller, G. (2004). Conversion of EEG activity into cursor movement by a brain-computer interface (BCI). *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 12(3), 331-338.

Farwell, L. A., & Donchin, E. (1988). Talking off the top of your head: Toward a mental prosthesis utilizing event-related brain potentials. *Electroencephalography and Clinical Neurophysiology*, 70(6), 510-523.

Fetz, E. E. (1969). Operant conditioning of cortical unit activity. *Science*, 163(3870), 955-958.

Fetz, E. E., & Finocchio, D. V. (1971). Operant conditioning of specific patterns of neural and muscular activity. *Science*, 174(4007), 431-435.

Galán, F., Nuttin, M., Lew, E., Ferrez, P. W., Vanacker, G., Philips, J., & Millán, J. d. R. (2008). A brain-actuated wheelchair: Asynchronous and non-invasive Brain–computer interfaces for continuous control of robots. *Clinical Neurophysiology*, 119(9), 2159-2169.

Gerven, M. V., Farquhar, J., Schaefer, R., Vlek, R., Geuze, J., Nijholt, A., . . . Desain, P. (2009). The brain-computer interface cycle. *Journal of Neural Engineering*, 6(4), article no. 041001

Griffiths, D., Peters, J., Robinson, A., Spaar, J. & Vilnai, Y. (2003). The modular EEG design. Retrieved February, 2012, from http://openeeg.sourceforge.net/doc/modeeg/modeeg_design.html

Grosse-Wentrup, M.; Buss, M. (2008). Multiclass common spatial patterns and information theoretic feature extraction. *IEEE Transactions on Biomedical Engineering*, 55, 1991–2000.

Guo, C., Yang, X. (2011). A programming of genetic algorithm. *Modern Applied Science*, 5 (1), 230-235.

Hinterberger, T., Schmidt, S., Neumann, N., Mellinger, J., Blankertz, B., Curio, G., & Birbaumer, N. (2004). Brain-computer communication and slow cortical potentials. *IEEE Transactions on Biomedical Engineering*, 51(6), 1011-1018.

Hochberg, L. R., Serruya, M. D., Friehs, G. M., Mukand, J. A., Saleh, M., Caplan, A. H., Donoghue, J. P. (2006). Neuronal ensemble control of prosthetic devices by a human with tetraplegia. *Nature*, 442(7099), 164-171.

Hoffmann, U., Vesin, J., Ebrahimi, T., & Diserens, K. (2008). An efficient P300-based brain–computer interface for disabled subjects. *Journal of Neuroscience Methods*, 167(1), 115-125.

Honda, W. (2009). Honda, ATR and Shimadzu Jointly Develop Brain-Machine Interface Technology Enabling Control of a Robot by Human Thought Alone. Retrieved 26 September 2012, from http://world.honda.com/news/2009/c090331Brain-Machine-Interface-Technology/

Huppert, T. J., Diamond, S. G., Franceschini, M. A., & Boas, D. A. (2009). HomER: A review of time-series analysis methods for near-infrared spectroscopy of the brain. *Applied Optics*, 48(10), D280-D298

Hwang, H. -., Lim, J. -., Jung, Y. -., Choi, H., Lee, S. W., & Im, C. -. (2012). Development of an SSVEP-based BCI spelling system adopting a QWERTY-style LED keyboard. *Journal of Neuroscience Methods*, 208(1), 59-65.

Iturrate, I., Antelis, J. M., Kubler, A., & Minguez, J. (2009). A noninvasive brain-actuated wheelchair based on a P300 neurophysiological protocol and automated navigation. *IEEE Transactions on Robotics*, 25(3), 614-627.

Iversen, I. H., Ghanayim, N., Kübler, A., Neumann, N., Birbaumer, N., & J. Kaiser. (2008). A brain–computer interface tool to assess cognitive functions in completely paralyzed patients with amyotrophic lateral sclerosis. *Clinical Neurophysiology*, 119(10), 2214-2223.

Jinyin Zhang, Sudre, G., Xin Li, Wei Wang, Weber, D. J., & Bagic, A. (2011). Clustering linear discriminant analysis for MEG-based brain computer interfaces. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 19(3), 221-231.

Kamitani, Y., & Tong, F. (2005). Decoding the visual and subjective contents of the human brain. *Nature Neuroscience*, 8(5), 679-685.

Kaper, M.; Meinicke, P.; Grossekathoefer, U.; Lingner, T.; Ritter, H. (2004). BCI competition 2003-data set IIb: Support vector machines for the P300 speller paradigm. *IEEE Transactions on Biomedical Engineering*, 51, 1073–1076.

Kun, L.; Sankar, R.; Arbel, Y.; Donchin, E. (2009). Single trial independent component analysis for P300 BCI system. *In Proceedings of the 31th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBCS'09), Minneapolis, MN, USA,* pp. 4035–4038.

Krusienski, D. J., Sellers, E. W., Cabestaing, F., Bayoudh, S., McFarland, D. J., Vaughan, T. M., & Wolpaw, J. R. (2006). A comparison of classification techniques for the P300 speller. *Journal of Neural Engineering*, 3(4), article no. 007

Krusienski, D. J., Sellers, E. W., McFarland, D. J., Vaughan, T. M., & Wolpaw, J. R. (2008). Toward enhanced P300 speller performance. *Journal of Neuroscience Methods*, 167(1), 15-21.

Lebedev, M. A., & Nicolelis, M. A. L. (2006). Brain–machine interfaces: Past, present and future. *Trends in Neurosciences*, 29(9), 536-546.

Lee, J., Ryu, J., Jolesz, F. A., Cho, Z., & Yoo, S. (2009). Brain–machine interface via real-time fMRI: Preliminary study on thought-controlled robotic arm. *Neuroscience Letters*, 450(1), 1-6.

Leuthardt, E. C., Schalk, G., Wolpaw, J. R., Ojemann, J. G., & Moran, D. W. (2004). A brain-computer interface using electrocorticographic signals in humans. *Journal of Neural Engineering*, 1(2), 63-71.

Li, R., Keil, A., & Principe, J. C. (2009). Single-trial P300 estimation with a spatiotemporal filtering method. Journal of Neuroscience Methods, 177, 488-496.

Lotte, F., Congedo, M., Lécuyer, A., Lamarche, & F., Arnaldi, B. (2007). A review of classification algorithms for EEG-based brain-computer interfaces. *Journal of Neural Engineering,* 4 (2), 1-13.

Mak, J.N., Arbel, Y., Minett, J.W., McCane, L.M., Yuksel, B., Ryan, D., Thompson, D., Bianchi, L., Erdogmus, D. (2011). Optimizing the P300-based brain-computer interface: Current status, limitations and future directions. *Journal of Neural Engineering,* 8 (2), art. no. 025003

Matteucci, M., Carabalona, R., Casella, M., Di Fabrizio, E., Gramatica, F., Di Rienzo, M., Sancrotti, M. (2007). Micropatterned dry electrodes for brain–computer interface. *Microelectronic Engineering*, 84(5-8), 1737-1740.

Mellinger, J., Schalk, G., Braun, C., Preissl, H., Rosenstiel, W., Birbaumer, N., & Kübler, A. (2007). An MEG-based brain–computer interface (BCI). *Neuroimage*, 36(3), 581-593.

Millan, J. R., Renkens, F., Mourino, J., & Gerstner, W. (2004). Noninvasive brain-actuated control of a mobile robot by human EEG. *IEEE Transactions on Biomedical Engineering*, 51(6), 1026-1033.

Mousavi, E.A.; Maller, J.J.; Fitzgerald, P.B.; Lithgow, B.J. (2011). Wavelet common spatial pattern in asynchronous offline brain computer interfaces. *Biomedical Signal Processing Control,* 6, 121–128.

Nagaoka, T., Sakatani, K., Awano, T., Yokose, N., Hoshino, T., Murata, Y., Eda, H. (2010). Development of a new rehabilitation system based on a brain-computer interface using near-infrared spectroscopy. In Takahashi E., Bruley D. F.(Eds.), *Oxygen Transport to Tissue XXXI, Advances in Experimental Medicine and Biology*, 662 (pp. 497-503) Springer US.

Nicolas-Alonso, L.F., Gomez-Gil, J. (2012). Brain computer interfaces, a review. *Sensors,* 12 (2), pp. 1211-1279.

Perrin, X., Chavarriaga, R., Colas, F., Siegwart, R., & Millán, J. d. R. (2010). Brain-coupled interaction for semi-autonomous navigation of an assistive robot. *Robotics and Autonomous Systems*, 58(12), 1246-1255.

Pfurtscheller, G., Neuper, C., Muller, G. R., Obermaier, B., Krausz, G., Schlogl, A., Schrank, C. (2003). Graz-BCI: State of the art and clinical applications. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 11(2), 1-4.

Piccione, F., Giorgi, F., Tonin, P., Priftis, K., Giove, S., Silvoni, S., Palmas, G., Beverina, F. (2006). P300-based brain-computer interface: Reliability and performance in healthy and paralysed participants. *Clinical Neurophysiology*, 117 (3), 531-537.

Polich, J. (2007). Updating P300: An integrative theory of P3a and P3b. *Clinical Neurophysiology*, 118(10), 2128-2148.

Popescu, F., Fazli, S., Badower, Y., Blankertz, B., & Müller, K. R. (2007). Single trial classification of motor imagination using 6 dry EEG electrodes. *Plos One*, 2(7)

Rebsamen, B., Burdet, E., Guan, C., Zhang, H., Teo, C. L., Zeng, Q., Ang Jr., M. H. (2007). Controlling a wheelchair indoors using thought. *IEEE Intelligent Systems,* 22(2), 18-24.

Schalk, G., McFarland, D. J., Hinterberger, T., Birbaumer, N., & Wolpaw, J. R. (2004). BCI 2000: A general-purpose brain-computer interface(BCI) system. *IEEE Transactions on Biomedical Engineering,* 51(6), 1034-1043.

Schalk, G., Miller, K. J., Anderson, N. R., Wilson, J. A., Smyth, M. D., Ojemann, J. G., Leuthardt, E. C. (2008). Two-dimensional movement control using electrocorticographic signals in humans. *Journal of Neural Engineering*, 5(1), 75-84.

Schalk, G. (2009). Sensor modalities for brain-computer interfacing. In J. Jacko (Ed.), *Human-computer interaction. novel interaction methods and techniques* (pp. 616-622) Springer Berlin / Heidelberg.

Sellers, E.W., Donchin, E. (2006). A P300-based brain-computer interface: Initial tests by ALS patients. *Clinical Neurophysiology,* 117 (3), 538-548.

Sellers, E. W., Turner, P., Sarnacki, W. A., McManus, T., Vaughan, T. M., & Matthews, R. (2009). A novel dry electrode for brain-computer interface. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 5611 LNCS (PART 2), 623-631

Sharbrough, F., Chatrian, G. E., Lesser, R. P., Luders, H., Nuwer, M., & Picton, T. W. (1991). American electroencephalographic society guidelines for standard electrode position nomenclature. *Journal of Clinical Neurophysiology*, 8(2), 200-202.

Serby, H., Yom-Tov, E., Inbar, G. (2005). An improved P300-based brain-computer interface. *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* 13 (1), 89-98.

Sirvent Blasco, J.L., Iáñez, E., Úbeda, A., Azorín, J.M. (2012). Visual evoked potential-based brain-machine interface applications to assist disabled people. *Expert Systems with Applications,* 39 (9), pp. 7908-7918.

Sitaram, R., Zhang, H., Guan, C., Thulasidas, M., Hoshi, Y., Ishikawa, A., Birbaumer, N. (2007). Temporal classification of multichannel near-infrared spectroscopy signals of motor imagery for developing a brain–computer interface. *Neuroimage*, 34(4), 1416-1427.

Strehl, U., Trevorrow, T., Veit, R., Hinterberger, T., Kotchoubey, B., Erb, M., & Birbaumer, N. (2006). Deactivation of brain areas during self-regulation of slow cortical potentials in seizure patients. *Applied Psychophysiology Biofeedback*, 31(1), 85-94.

Swartz, B. E., & Goldensohn, E. S. (1998). Timeline of the history of EEG and associated fields. *Electroencephalography and Clinical Neurophysiology*, 106(2), 173-176.

Tonin, L., Menegatti, E., Cavinato, M., D'Avanzo, C., Pirini, M., Merico, A., Piccione, F. (2009). Evaluation of a robot as embodied interface for brain computer interface systems. *International Journal of Bioelectromagnetism*, 11(2), 99-104.

Vaughan, T.M., McFarland, D.J., Schalk, G., Sarnacki, W.A., Krusienski, D.J., Sellers, E.W., Wolpaw, J.R. (2006). The wadsworth BCI research and development program: At home with BCI. *IEEE Transactions on Neural Systems and Rehabilitation Engineering,* 14 (2), 229-233.

Vialatte, F., Maurice, M., Dauwels, J., & Cichocki, A. (2010). Steady-state visually evoked potentials: Focus on essential paradigms and future perspectives. *Progress in Neurobiology*, 90(4), 418-438.

Vidal, J. J. (1973). Toward direct brain-computer communication. *Annual Review of Biophysics and Bioengineering*, 2, 157-180.

Vidal, J. J. (1977). Real-time detection of brain events in EEG. *Proceedings of the IEEE*, 65; 65(5), 633-641.

Weiskopf, N., Mathiak, K., Bock, S. W., Scharnowski, F., Veit, R., Grodd, W., Birbaumer, N. (2004). Principles of a brain-computer interface (BCI) based on real-time functional magnetic resonance imaging (fMRI). *IEEE Transactions on Biomedical Engineering*, 51(6), 966-970.

Wolpaw, J. R., McFarland, D. J., Neat, G. W., & Forneris, C. A. (1991). An EEG-based brain-computer interface for cursor control. *Electroencephalography and Clinical Neurophysiology*, 78(3), 252-259.

Wolpaw, J. R., McFarland, D. J., & Vaughan, T. M. (2000). Brain-computer interface research at the wadsworth center. *IEEE Transactions on Rehabilitation Engineering*, 8(2), 222-226.

Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., & Vaughan, T. M. (2002). Brain-computer interfaces for communication and control. *Clinical Neurophysiology*, 113(6), 767-791.