Electroencephalography (EEG) Based Control in Assistive Mobile Robots: A Review

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Abstract. Recently, EEG based control in assistive robot usage has been gradually increasing in the area of biomedical field for giving quality and stress free life for disabled and elderly people. This study reviews the deployment of EEG based control in assistive robots, especially for those who in need and neurologically disabled. The main objective of this paper is to describe the methods used for (i) EEG data acquisition and signal preprocessing, (ii) feature extraction and (iii) signal classification methods. Besides that, this study presents the specific research challenges in the designing of these control systems and future research directions.

1. Introduction

Robots are with us in everyday life, and do not exist in the industry only, but also increasingly inflowing into human life. In the past few years, due to the advancement of neuroscience has led to a new capability for robots work alongside of humans. Robots can help many kinds of people, such as people who are older, people who are injured and need rehabilitation, people with severe neuromuscular disorders such as amyotrophic lateral sclerosis (ALS), brainstem stroke, cerebral palsy, and spinal cord injury (SCI) even children with autism [1]. According to the US National spinal cord injury statistical center (NSCISC) 2014 annual report, there are 276,000 people in the US who are living with SCI with approximately 12,500 new SCI cases each year [2-4]. In general, assistive robots can perform actions that benefit people with severe physical disabilities, motor diseases, paralyzed, aged or those in need, but there is a big challenge in activating the robots with conventional input methods. To address this challenge, electroencephalography (EEG) based brain controlled robots have been proposed [5, 6]. This system allows users to send comments or instructions to robots or other external devices by using brain signals, which means, the system can bypass conventional channel of communication such as muscles, nerves, speech or others which is also referred as a brain machine interface (BMI) and it creates a new non-muscular channel for relaying a person’s intentions to external devices [7-9]. Apart from that, EEGs are
commonly used in research because the data acquisition method is non-invasive to the research subject and it's capable of sensing changes in electrical activity in the brain on a millisecond-level [10]. EEG based robot system has produced valuable research for a variety of applications and successfully implemented in wide range of disciplines such as biology, computer science, electrical engineering, mathematics, mechanical, medicine, and, physics etc. [11-13].

BMI is an artificial intelligence (AI) system that can identify a certain set of brain signal patterns following by sequential stages which are, signal acquisition, signal preprocessing, feature extraction, signal classification, and the robotic or external device control interface [14] (refer Figure 1).

![Figure 1. Stages of BMI - Artificial Intelligence](image)

In this study, we provide a complete analysis, major techniques, and other issues of brain-controlled mobile robots along with some insights into the research and development of EEG based brain-controlled assistive mobile robots, based on our review of more than 50 related research papers.

This review has threefold; first, we present a comprehensive review of EEG signal acquisition techniques and approaches. Second, we describe and analyze the signal preprocessing, feature extraction and classification methods of brain-controlled assistive mobile robotic systems. Third, we discuss recent challenges and future directions of brain-controlled assistive mobile robot research area.

The remainder of this paper is organized as follows. In Section II, EEG signal acquisition techniques and approaches. In Section III, the signal preprocessing, feature extraction and classification methods are described and analyzed. In Section IV, we conclude this paper with the current challenges and future directions for EEG based brain-controlled assistive mobile robots.

2. Signal acquisition techniques and approaches

Direct neural interface (DNI), also called brain-machine interface (BMI) or brain-computer interface (BCI) to control assistive mobile robot is a communication system that permits direct connection between a human brain and a robot or other external device [15]. Over the past two decades, the Brain Computer Interfaces (BCI) research has developed enormously (refer Figure 2).
BCI research groups, 20 years ago, which was limited to only about three groups and there was a gradual growth after 10 years into six to eight groups.

Recently, now there is a massive growth in the research groups, with over more than 100 groups throughout the world involved in an extensive range of research and development activities, and more towards in the field every month [5] [15, 16].

**Figure 2.** BCI research groups advancements

**Figure 3.** Components of wireless Brain Machine Interface system
The first stage for BMI is the EEG signal acquisition, and this is the very vital session of this study. In this section contains electrodes (refer Figure 3 & 4 [17]), analog circuit and digital system for neurophysiological signal recording and transmission. The most extensively used electrodes are silver / silver chloride (Ag/AgCl) due to its stability, low contact impedance and most importantly its lower cost. The traditional BMI systems are wired, which is usually complex with a large number of cables between the electrodes and the acquisition parts. During the process of EEG data acquisition, electrodes are placed on the surface of the scalp. In the process fixing Ag/AgCl electrodes requires gel between electrodes and scalp and, this kind of electrodes are called “wet” electrodes. These processes may take longer time to fix electrodes on the scalp and which may end up in discomfort to the users. To overcome these issues, some researchers have been using “dry” electrodes [18-21]. There are few companies such as Emotiv Systems Inc., Neuro Sky Inc. have been introducing the “dry” electrodes method of non-invasive EEG data acquisition systems in the market.
The subsequent significant issue of EEG acquisition is the placement of electrode positions on the scalp. In general, electrodes are placed on the scalp at 10% and 20% of a measured distance from reference sites according to the standard of 10–20 international system, as shown in Figure 5 [22].

Recently, with growing interest, wireless BCI systems have been implemented in biomedical, engineering and entertainment area as well. There are many companies recently developed their wireless EEG BMI / BCI headsets such as Emotiv and Neurosky for mind monitoring and gaming (refer Figure 6).

**Figure 6.** EEG wireless data acquisition system

(a) Emotive EPOC headset [23], (b) NeuroSky Mind Set [24], (c) MyndPlay Brainband [25],
(d) PLX devices XWave headset [26], (e) OCZ Neural Impulse Actuator [27]

Furthermore, the BCI / BMI research groups have practically applied wireless BCI systems for their new research applications and development (as shown in table – 1).

| Product          | Product from | Signal | Channels | Images |
|------------------|--------------|--------|----------|--------|
| eego™mylab [28]  | ANT Neuro    | EEG    | 32 to 256 EEG channels |

In addition, the system’s functionality can be easily extended with EOG, ECG, EMG, real-time data access and physiological sensors for respiration, temperature, skin conductance and acceleration.
3. Signal pre-processing, feature extraction and classification

The objective of BMI or BCI is to translate the EEG signals into actions; such as by mere thinking of writing text or numbers through virtual keyboard is the perfect example of software oriented, and to navigate or monitor a mobile robot is a good example of hardware oriented. To exchange the brain signals into actions, either regression or classification algorithms can be used [32, 33]. After EEG data acquisition, the next process is signal pre-processing and feature extraction. The pre-processing stage is highly dependent on the goal of the application. There are few methods are used very commonly to improve the quality of the EEG signals, such as epoching / segmentation, filtering, artifact detection/rejection, averaging and re-referencing. To get precise data or differentiate the required task from brain signals are apparently called as feature extraction [34] too.
Some of the feature extraction and classification techniques analyzed below the table – 2.

| Author                  | Brain signal types | EEG signal acquisition |
|-------------------------|--------------------|------------------------|
| Azar et al. [35]        | Imaginary signals | EEG signals were recorded using 59 scalp electrodes |
|                         |                    | Non-linear feed-forward neural networks using the standard back-propagation algorithm |
|                         |                    | Move the wheelchair by using simple thoughts such as “go” and “stop” |
| P. Kumari et al. [36]   | Imaginary signals | 14 channels, wireless Emotiv EPOC |
|                         |                    | Wavelet transform to extract EEG signal feature and Learning Vector Quantization (LVQ) Neural Networks for classification |
|                         |                    | The EEG signal generated by visual stimuli for keying in the password |
| Ting Wu et al. [37]     | Imaginary signals | EEG signals were recorded using 6 channel electrodes |
|                         |                    | Probabilistic neural network (PNN) with supervised learning based on Genetic Algorithm |
| Kottaimalai et al. [38] | Imaginary signals | Noninvasive type electro-cap was used for the EEG signal acquisition |
|                         |                    | Principal Component Analysis (PCA) for dimensionality decrease to eliminate the redundant variables in the EEG signals and the Neural Network as a classifier with |

Table 2. Brain Controlled Mobile Robots | Signal acquisition & Classification system.
| Authors          | Imaginary signals | Used method                        | Radial basis function neural network (RBFNN) as a classifier tool for rat’s brain signals | The robot was controlled by brain signal mapped into lever actions by RBFNN |
|------------------|-------------------|------------------------------------|------------------------------------------------------------------------------------------|----------------------------------------------------------------------------|
| Mano et al. [39] | Imaginary signals | Used invasive method and the electrodes implanted in the rat’s brain               |                                                                                           |                                                                             |
| Hazrati et al. [40] | Imaginary signals | Used non-invasive method            | Adaptive probabilistic neural network (APNN) for EEG signal classification in an interactive online real-time BCI environment. Eye blink & eye movement signals were collected separately from the right and left earlobe channels. | Interactive online real-time BCI environment. |
| E. Iáñez et al. [41] | Imaginary signals | Used non-invasive method            | Wavelet transform algorithm with DB2 filter has been used for signal discriminator (feature extraction), and multilayer perceptron (MLP) neural network has been used as a classifier | Robotic am controlling |
4. Conclusion
EEG based BMI has increased attention in recent years. This study reviewed recent developments of EEG controlled mobile robots, particularly in data acquisition, feature extraction and classification area. An interesting objective of human-robot collaboration research is to build robots that are intuitive interaction partners for humans. However, more advanced solutions have to be developed for mobile robot’s intelligent support system in the area of biomedical that can be used by disabled people, and thus improve their independence, mobility, and quality of life.

5. References

[1] Wolpaw J R and McFarland D J 2004 Control of a two-dimensional movement signal by a noninvasive brain-computer interface in humans Proceedings of the National Academy of Sciences of the United States of America 101 17849-54
[2] NSCISC 2014 Spinal Cord Injury Model System | 2014 Annual Report Complete Public Version NSCISC National Spinal Cord Injury Statistical Center
[3] Boughner K J and Durfee W K 2014 Preliminary design of an energy storing orthosis for providing gait to people with spinal cord injury. In: Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE, pp 2581-4
[4] Perrin X, Chavarriaga R, Colas F, Siegwart R and Millán J d R 2010 Brain-coupled interaction for semi-autonomous navigation of an assistive robot Robot. Auton. Syst. 58 1246-55
[5] Millán J R, Renkens F, Mourino J and Gerstner W 2004 Noninvasive brain-actuated control of a mobile robot by human EEG Biomedical Engineering, IEEE Transactions on 51 1026-33
[6] Millán J d R 2014 Principles of Tissue Engineering (Fourth Edition), ed R L L Vacanti (Boston: Academic Press) pp 1343-52
[7] Nicolas-Alonso L F and Gomez-Gil J 2012 Brain Computer Interfaces, a Review Sensors (Basel, Switzerland) 12 1211-79
[8] Wolpaw J R, Birbaumer N, McFarland D J, Pfurtscheller G and Vaughan T M 2002 Brain–computer interfaces for communication and control Clinical Neurophysiology 113 767-91
[9] Luna P 2011 Controlling machines with just the power of thought The Lancet Neurology 10 780-1
[10] Plant K A, Ponnappalli P V S and Southall D M 2008 Research and Development in Intelligent Systems XXIV, ed M Bramer, et al.: Springer London) pp 363-8
[11] Millán J d R, Renkens F, Mouriño J and Gerstner W 2004 Brain-actuated interaction Artificial Intelligence 159 241-59
[12] Lebedev M A and Nicolelis M A L 2006 Brain–machine interfaces: past, present and future Trends in Neurosciences 29 536-46
[13] Mussa-Ivaldi F A and Miller L E 2003 Brain–machine interfaces: computational demands and clinical needs meet basic neuroscience Trends in Neurosciences 26 329-34
[14] Khalid M B, Rao N I, Rizwan-i-Haque I, Munir S and Tahir F 2009 Towards a Brain Computer Interface using wavelet transform with averaged and time segmented adapted wavelets. In: Computer, Control and Communication, 2009. IC4 2009. 2nd International Conference on, pp 1-4
[15] Wolpaw J R 2007 Brain–computer interfaces as new brain output pathways The Journal of
Physiology 579 613-9

[16] Murali Krishnan N and Mariappan M 2015 EEG-Based Brain-Machine Interface (BMI) for Controlling Mobile Robots: The Trend of Prior Studies International Journal of Computer Science and Electronics Engineering (IJCSEE) 3

[17] Lin CT K L, Chang MH, Duann JR, Chen JY, Su TP, Jung TP 2010 Review of wireless and wearable electroencephalogram systems and brain-computer interfaces--a mini-review Gerontology 56(1):112-9. doi: 10.1159/000230807. Epub 2009 Jul 25

[18] Sullivan T J, Deiss S R, Tzyy-Ping J and Cauwenberghs G 2008 A brain-machine interface using dry-contact, low-noise EEG sensors. In: Circuits and Systems, 2008. ISCAS 2008. IEEE International Symposium on, pp 1986-9

[19] Seungchan L, Younghak S and Heung-No L 2015 Design of active dry electrodes and its evaluation for EEG acquisition. In: Information and Communication Technology Convergence (ICTC), 2015 International Conference on, pp 560-2

[20] Yeung A, Garudadi H, Van Toen C, Mercier P, Balkan O, Makeig S and Virji-Babul N 2015 Comparison of foam-based and spring-loaded dry EEG electrodes with wet electrodes in resting and moving conditions. In: Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE, pp 7131-4

[21] Kitoko V, Nguyen T N, Nguyen J S, Tran Y and Nguyen H T 2011 Performance of dry electrode with bristle in recording EEG rhythms across brain state changes. In: Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE, pp 59-62

[22] Jaakko Malmivuo R P 1995 Bioelectromagnetism - Principles and Applications of Bioelectric and Biomagnetic Fields: Oxford University Press, 1995)

[23] Emotiv http://emotiv.com/store/hardware/epoc-bci/epoc-neuroheadset/

[24] Neurosky http://www.neurosky.com/Products/MindSet.aspx

[25] MyndPlay Brainband http://myndplay.com/products.php?cat=1

[26] PLX devices XWave headset http://www.plxdevices.com/product_info.php?id=XWAVESONIC

[27] OCZ Neural Impulse Actuator http://www.ocztechnology.com/nia-game-controller.html

[28] eego mylab https://www.ant-neuro.com/products/eggo_mylab

[29] BioRadio https://glneurotech.com/bioradio/physiological-signal-monitoring/wireless-eeg-research-analysis-teaching/

[30] StarLab http://www.starlab.es/neuroscience/

[31] Mindo http://mindo.com.tw/en/goods.php?act=view&no=4

[32] Penny W D, Roberts S J, Curran E A and Stokes M J 2000 EEG-based communication: a pattern recognition approach Rehabilitation Engineering, IEEE Transactions on 8 214-5

[33] McFarland D J and Wolpaw J R 2005 Sensorimotor rhythm-based brain-computer interface (BCI): feature selection by regression improves performance Neural Systems and Rehabilitation Engineering, IEEE Transactions on 13 372-9

[34] Li Y and Zhang S 1996 Apply wavelet transform to analyse EEG signal. In: Engineering in Medicine and Biology Society, 1996. Bridging Disciplines for Biomedicine. Proceedings of the 18th Annual International Conference of the IEEE, pp 1007-8 vol.3

[35] Azar A, Balas V and Olariu T 2014 Advanced Intelligent Computational Technologies and Decision Support Systems, ed B Iantovics and R Kountchev: Springer International Publishing) pp 97-106

[36] Kumari P and Vaish A 2014 Brainwave based user identification system: A pilot study in robotics environment Robotics and Autonomous Systems

[37] Wu T, Yang B and Sun H 2010 Life System Modeling and Intelligent Computing, ed K Li, et al.: Springer Berlin Heidelberg) pp 154-62

[38] Kottaimalai R, Rajasekaran M P, Selvam V and Kannapiran B 2013 EEG signal classification using Principal Component Analysis with Neural Network in Brain Computer Interface applications. In: Emerging Trends in Computing, Communication and Nanotechnology (ICE-CCN), 2013 International Conference on, pp 227-31
[39] Mano M, Capi G, Tanaka N and Kawahara S 2013 An Artificial Neural Network Based Robot Controller that Uses Rat’s Brain Signals Robotics 254-65

[40] Hazrati M K and Erfanian A 2010 An online EEG-based brain–computer interface for controlling hand grasp using an adaptive probabilistic neural network Medical Engineering & Physics 32730-9

[41] Iáñez E, Furió M C, Azorín J, Huizzi J and Fernández E 2009 Bioinspired Applications in Artificial and Natural Computation, ed J Mira, et al.: Springer Berlin Heidelberg) pp353-61

[42] Zhang X 2007 An Approach for Measurement and Recognition of Electroencephalography. In: Electronic Measurement and Instruments, 2007. ICEMI ’07. 8th International Conference on, pp 1-698-1-702