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TRILHA ESTUDANTIL

Perspectives and Potential of the Brain-Computer Interface

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***Abstract* — A Brain-Computer Interface (BCI), also known as Brain-Machine Interface, is a system that allows for the interaction between the user and its surroundings using control signals generated by his brain activity. The improvement of the research on BCI correlates mainly with the advances of Neurophisiology and Computer Science. Initial research was dedicated to the development of devices for the communication of individuals who lost voluntary muscle control but had no cognitive impairment. Nowadays, we find applications in the fields of mobility, communication and the treatment of diseases of user who may or may not have movement impairment. Considering the expansion scenario of the BCI applications, this paper presents a pedagogical description of the recent publication on this field of study. Hence, we descrive the basic concepts related to this research area, as well as some of its applications and limitations.**

***Keywords*— BCI, Neural Activity, Robotic Prosthetics, Robotics, Nanotechnology.**

I. Introduction

THe research are call Brain-Computer Interface (BCI) is multidisciplinary, integrating neuroscience, physiology, psychology, engineering, computer science and several other areas related to technical or health studies [29]. The main goal of a BCI is the development of a computer system able to interpret the information coded in the electrical activity of neuron groups associated with a motor process. These signals must be analyzed in real time and translated into commands to control an artificial device [6].

The concept of an interface applied in the detection of brain signals has evolved mainly in the last decade [27. Nowadays there are more than a hundred research groups active worldwide [40]. According to the definition created by Vidal in 1973, until the last decades [apud 40], the main applications of BCI has been related to the creation of new communication and control channels for severely impaired persons [48]. This way, a BCI has been shown as adequate in helping persons with motor limitations interact with the environment in activities such as light and television control, yes/no questions, text processing, wheelchair operation and robotic prosthetics [49]. Among the various applications, we can highlight autonomous vehicles [41], cell phones that perform calls using brain activity [43] and virtual reality games [46].

Considering this expansion scenario, this paper intends to present a short and accurate pedagogic description about the working of BCIs, both to the scientific community and general population. In order to achieve this goal, we approach the basic concepts of this research area, as well as its applications, limitations and the research projects related to it. This text is organized into two main sections: section II present the basic neurological and computational concepts related to the working of a BCI, while section III describes the main applications, limitations and scientific projects related to this topic.

II. Brain-Computer Interface: Basic Concepts

A BCI promotes a new form of communication and new control channels between the user and his muscles without any interference of the peripheral nerves. In order for the interaction between user and BCI to succeed, he must develop a new ability: not his muscle control but the adequate control of the specific electrophysiological signal that corresponds to the user intent [48], [8], [18]. Using electrodes, it is possible to detect activations patterns in the brain that correspond to the user's intention. These signals that indicate the user's brain activity are translated into an output such as cursor or mouse movement or an interaction with any artificial external device [47].

In the next sections we present some basic aspects of the working of a BCI.

A. *Neuroscience and the Brain-Computer Interface*

The progress in BCI research is related to the studies and discoveries on neurophysiology and motor systems made through the last 40 years [27], among other factors.

Some researchers were able to train monkeys to operate and modulate individual neurons in the primary motor cortex [14]. These results inspired the first tests with humans using intra-cranial BCI sensors [20]. Other researchers [16], on the other hand, developed the population vector method, which consists of representing the neurons individually as a vector, which performs a weighted contribution along the axis preferential direction. This method allowed researchers to forecast the direction of the arm movement in three dimensions based on a group of neurons from the motor cortex [16]. This 3D directional coding by the primary motor cortex was expanded by Schwartz and his team [28], in order to include speed, creating a precise forecast of the hand in 3D.

Considering that the main purpose of a BCI is to detect and translate brain state into physical movement, it is essential to understand how the brain communicates with the other body parts before, during and after the movement. The neural code is often compared to a machine code that is the foundation of a computer operational system. Just like the transistors, the neurons work as circuit breakers or logic gates, absorbing and emitting electrochemical impulse called action potentials that remember the basic information units in digital computers [19]. Capturing the neuronal signal depends on the amount and the location of the electrodes. Besides, there are difficulties in understanding the electrical signals so that they can become movement commands [30].

BCI is a complex system due to the fact that the brain works in a complex way. Neurons form a network which must be understood as a whole and must, hence, be studied as a group, not individually. Making an analogy between the Internet and the neuronal information flow, we can see that no isolated computer controls the byte flow throughout the entire network and something similar occurs in the neuronal network, where we can pinpoint no neuron “in charge”. Hence, the advances in scientific knowledge on the brain workings contribute to the advances of neuroscience, and consequently, to the advances of BCI and vice-versa [30].

B. *The working of a Brain-Computer Interface*

A BCI detects activation patterns in the brain that correspond to the person’s desired action. Whenever the user induces a voluntary change in those patterns, a BCI is capable to detect the change and translate those new patterns into an action that corresponds to the user’s will. Recognition of a specific set of patterns in a BCI involves the following steps: signal acquisition, pre-processing, data interpretation and classification [21], [30].

The signal acquisition phase is responsible for capturing the signals that derive from the brain electrical activity, either through invasive methods (intracranial insertion of electrodes into the brain cortex) or non-invasive (electrodes put outside the scalp). Besides acquisition, in this phase we also perform no related information reduction (noise) and the processing of the acquitted signal [21], [30].

Electrocortiography is the invasive method more used in animal studies. It is based on the record of either small or big group of neurons for the acquisition of signals known as electrocortiograms (EcoGs) [25]. Recent studies with mokneys show that ECoG is a stable and robust recording method for BCI applications. Besides, this method has the ability to perform neurophysiologic studies in human beings, rendering it a neuroscience tool useful to study the brain population activity [27].

The acquisition of signals from electrical brain activity with non-invasive methods is normally performed through electrodes put on the person’s scalp. This method is known as Electroencephalography (EEG) and its analysis is complex, given that the amount of information captured by each electrode is quite high. The EEG method has played an important role in the study of brain processes due to the development of more accurate electronic devices and of more efficient signal processing techniques [5];

Non-invasive EEG signals are used in BCI applications because they offer a reasonable signal quality combined with low cost and ease of usage [29]. Besides, they show good time resolution in spite of having less precision when compared to invasive methods [29], [2].

After the signal is obtained, the pre-processing phase prepares the data for its posterior processing [29]. For that, the discriminative characteristics of the recorded signal are identified. This step is called characteristics extraction and its goal is to reduce the dimension of the data vector without loss of the relevant information for a size that does not exceed the number of training samples [29], [45]. This is a crucial step in a BCI system, given that it has a direct influence in the performance of the classifier algorithm that will understand the user intent [1], [45]. Besides, the characteristic selection helps decrease the noise and the redundancy in the data, given that brain signals for a specific action are mixed with other signals that overlap both in time and space [29], [45].

The interpretation of the information resulting from the previous step intends to transform the digitalized signal into a code that represents the desired action. Hence, we use complex algorithms and recording systems [30]. Some examples of the algorithms used in this task are genetic algorithms [7], Kalman filters [23] and Bayesian methods [8], [21], [34], among others. Besides, one of the trends is to use a multiple linear regression algorithm (Wiener filter) [23], which performs the translation of the pure brain activity into digital commands which can be understood by a robotic device. Using this algorithm it is possible to linearly add the electric activity generated by the cortical neurons recorded simultaneously and create precise forecasts of the future position of the person’s member [30].

Finally, the control interface of data output step translates the classified signals into meaningful commands to control a specific device which can be a virtual keyboard, a mouse click, an avatar movement in virtual reality environments or even the control of robotic devices replacing a human member [25]. The schematic version of how a BCI works is presented in Figure 1.

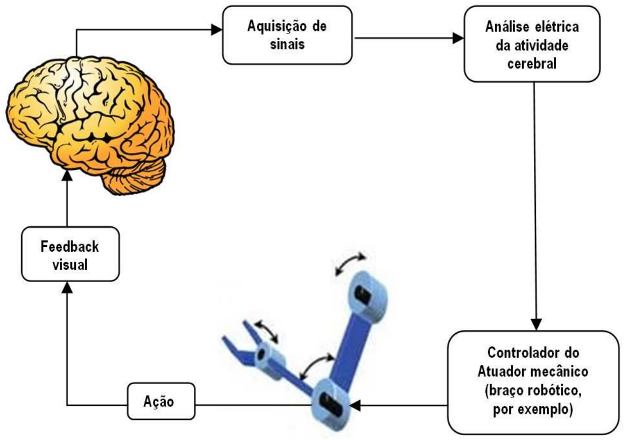

Figure 1: Schematic version of the general organization of a brain-computer interface. Adapted from [30].

As described up to now in this paper, we can see that a BCI requires an underlying computer system to work properly. Hence, more accurate, faster and efficient BCIs are dependent on the increase of the processing capacity of computer and on the improvement of signal analysis techniques and also on the implementation of more robust computational algorithms [22], [34].

In the next sections we describe some of the applications of a BCI.

III. BRAIN-COMPUTER INTERFACE:APPLICATIONS AND LIMITATIONS

BCI was developed as a treatment for patients with different levels of body paralysis, such as paraplegia (loss of sensor and motor functions in the lower limbs) and tetraplegia (loss of those functions also in the arms and body center). Hence, research was focused on the development of communication devices for those who lost voluntary muscle control, but presented no cognitive damage [21], [26], [18]. The main BCI applications are related to mobility, communication and interaction of the users with the persons and objects that surround them.

One of the applications related to mobility consists of using robotic prosthetics or an exoskeleton with brain control (also known as robotic cloth). This is under development in The Walk Again Project, which intends to develop and implement the first BCI able to restore full body mobility to patients with severe paralysis [30].

The Walk Again project is a partnership between institutions from the USA, Switzerland, Germany and Brazil lead by the neuroscientist Miguel Nicolelis and his research team from IINN-ELS (Edmond and Lily Safra International Institute of Neurosciences at Natal) and from the Neuroengineering University Center at Duke (DUCN). At DUCN several pioneer systems were developed to perform different motor functions such as reaching for and grabbing objects, bipedal locomotion and others. Researchers at DUCN were also the first to incorporate artificial somatic sensibility in a BCI [21].

The exoskeleton under development in this Project uses commands extracted from the brain activity to control devices scattered through the joints of the robotic clothing. The neural signals interact with the robotic skeleton in imitation of the functions of the human spinal cord. The interaction between brain and robotic signals will allow for the patient to displace himself at will, adjusting the speed and the movement to the terrain on which he walks [30]. This tool can potentially allow those with muscle paralysis to perform most of their activities, improving their quality of life and giving them greater independence [13].

In spite of the success of those applications, some issues limit the development of neuroprosthetics such as: *(i)* compatibility with the user tissues [21]; *(ii)* improvement of the algorithms used to decode the brain signal [8], [50], given that there is a lot of noise in the data, making it difficult for computational approach and requiring a combination of techniques to improve signal coding; *(iii)* the ability of the prosthetics to control movement with multiple requirements, such as bipedal walking with erect posture and allowing for positional understanding, given that there are a lot of variables involved in those movements [21].

Until the present moment, a BCI for arm movement included a single actuator. This is due to the fact that the process for two actuators needs for different subsets than the single one. Besides, it is important that the positional sense is included, given that a neuroprosthetic must be seen as a natural extension of the used body. The complexity of the spatial position by the brain makes it difficult to create this positional sense. In spite of the theoretical knowledge about this issue be well known [21], its application is full with troubles. There are several uncertainties about the choice of mathematical transformation on the stimulation of angle patterns at the joints, given that the complexity of the cortical processing of the perceived information [21].

Besides movement, BCI also proposes a touch feeling experience. It was possible to establish a bidirectional communication between the brain of two monkeys and a computer in order to explore virtual objects at the computer screen. The animals commanded a digital hand in a screen with three images and when touched, two of those images sent back touch sensations back to the monkeys' brains. The results of this experience bring the possibility to add the ability to feel temperatures and sense the terrain on which we are stepping, making the interaction with the surrounding environment closer to the real one, even with the use of prosthetics [30].

In the field of accessibility, there is a BCI implementation to adapt wheelchairs to the command from signals extracted from the muscles, eye blinking and ocular globe movements or even from images extracted from a camera. This interface uses the record of electrical brain activity from the user, given that the user has full cognitive capacity, even though he may not have the ability to translate these commands into movements [8], [18] e [37].

Besides all those applications on the mobility field, BCI has the potential to insert users into a virtual environment, fostering a direct communication with the monitor, mouse or keyboard without muscle activity. An example of the commercial use of BCI are the EPC – Emotiv® devices [12] anf Neurosky Mindwave [31]. These are tools that use non-invasive EEG signals to capture brain waves and interact with hardware and software resources, computer or mobile devices (cell phones or tablets) [46].

Considering the perspectives of BCI in the area of personal communication, Guenther and Brumberg (2011) presented a device to create speech using a voice synthesizer. The authors used two approaches: an invasive one in a user with difficulties with oral communication and a non invasive one in users with no oral communication impairment. In the first approach, an intracranial electrode was implanted in the speech region with a user with locked in syndrome. In these conditions, the patient loses full body movement, with the exception of his eyes, but his mental faculties remain intact. The neural signals recorded by the implant in those users transmitted the signal to the synthesizer (without wires) allowing for the production of vowels. In the second approach, users with no oral impairment were also able to control the voice synthesizer using only imagined movements which were detected by electroencephalography [17].

Another communication application is the prototype of a BCI to compose written messages proposed by Arboleda et al (2009). This non invasive method allows for written messages to be composed using a matrix of visual stimulation with the letters of the alphabet and other associated symbols. Besides this application, it is also described a non invasive approach for binary communication (yes or no) using classic semantic conditioning [33]. The results presented in these papers are promising and their refinement can be achieved by a better understanding of the neural representation of speech [17].

Other projects under development intend to apply BCIs to cell phone devices, allowing the users to find a number in their contact list and make calls. This method is efficient for persons with motor disabilities [43]. If a BCI based cell phone becomes possible, several other applications in this industry can arise, including wireless technologies. Comparing with the basic or personalized computer platforms, the mobility and processing power of cell phones will make the an important tool for creating mobile BCIs that require data transmission in real time, as well as signal processing in real work environments [43].

The Autonomous Lab from Berlin Freie Universität has several BCI projects, including the BrainDriver one, in which the driver uses a BCI to drive his vehicle [41]. The main goal of this project is to develop a BCI based on EEG using a handheld computer to control a cursor and other hand tool through the brain waves of paraplegic persons. In this case, the user wears a tiara with electrodes and the information is sent to a computer embedded in the car's dashboard [44].

The feedback ability of a BCI allows for several different applications, as presented in Table I. It can be used for selective control over certain areas of the brain, using the neurofeedback in order to modify the person's behavior. The neural feedback from a BCI can improve cognitive performance [3], speech ability [32] and pain management [11], and has also been used to treat mental disturbances such as epilepsy [42], [38], attention deficit disorder [29], [39], schizophrenia [35], depression [36] and others.

It is important to point out that the future importance of BCI applications will depend on its ability, practicality and reliability. Besides, users' acceptance will increase as these substantial advantages go beyond the conventional assistive Technologies [10].

TABLE I
NON EXHAUSTIVE LIST OF BCI APPLICATIONS

Application type	**Improved or replaces function**	**References**
Neuroprosthetics	Movement	[21], [26], [18], [30]
Robotic wheelchairs.	Movement	[8], [18] e [37]
Virtual environments	Communication	[12], [31]
Autonomous car	Movement	[41]
Mental disturbance treatment	Symptoms appeasement	[42], [38], [24], [39], [35], [36]
Voice synthesizer.	Communication	[17]
Message composition	Communication	[33], [4]
Mobile devices	Communication	[43], [46], [12], [31]

IV. CONCLUSION

A BCI can interpret neurophysiologic information from a device with the goal of recovering or improving cognitive and motor functions of a specific person. This paper intended to present a short report on the relevant issues to BCIs, as well as the potential usage, with reference to several papers related to this research topic.

Current research tries to refine the surgical implantation techniques and the analytical algorithms in order to use the most efficient signals coming straight from the human brain [15]. Besides, its usage requires that several areas of the central nervous system, usually involved in the production of motor action, adapt in order to improve the control of the cortical neuron by the user [47]. In spite of the advances of the last decades, there are still challenges to be overcome, from the reception and treatment of the brain signal to the incorporation of brain prosthetics.

REFERENCES

[1] Aydemir, O., Ozturk, M. and T. Kayikcioglu. (2011). Performance evaluation of five classification algorithms in low-dimensional feature vectors extracted from EEG signals. *The Scientific and Technological Research Council of Turkey (TUBITAK)*, pp. 403-407.

[2] Ahmadian, P., Cagnoni, S. and L. Ascari (2013). How capable is non-invasive EEG data of predicting the next movement? A mini review. *Frontiers in Human Neuroscience*, vol. 7, pp. 1-7.

[3] Angelakis, E., S. Stathopoulou, J. Frymiare, D. Green, J. Lubar and J. Kounious (2007). EEG neurofeedback: A brief overview and an example of peak alpha frequency training for cognitive enhancement in the elderly. *Clinical Neuropsychology*, **21**, pp. 119-129.

[4] Arboleda, C., Arboleda, C., García, E., Posada, A., Torres R. (2009). Diseño y construcssión de um protótipo de interfaz cérebro-computador para facilitar la comunicación de personas com discapacidad motora. *Revista EIA*, No. 11, pp. 105-115.

[5] Azevedo, A. P. (2005). Estudo do sinal eletroencefalográfico (EEG) aplicado à interface cérebro computador com uma abordagem de reconhecimento de padrões. *Dissertação de Mestrado em Engenharia Elétrica*, 110 p.

[6] Barbosa, A. F., B. C. Souza, A. Pereira e A. A. D. Medeiros (2009). Implementação de classificador de tarefas mentais baseado em EEG. *Anais do IX Congresso Brasileiro de Redes Neurais / Inteligência Computacional (IX CBRN)*, Ouro Preto, MG, Brasil.

[7] Battapady, H., Lin, P., Fei, D., Huang, D. and O. Bai (2009). Single trial detection of human movement intention from SAM-Filtered MEG signals for a high performance two-dimensional BCI. *31st Annual International Conference of the IEEE EMBS*, Minneapolis, Minnesota, USA.

[8] Benevides, A. B., M. Sarcinelli-Filho and T. F. B. Filho (2011). Design of a general brain-computer interface. *Controle & Automação*, vol. 22, No.6, pp. 638-646.

[9] Cincotti, F., D. Mattia, F. Aloise, S. Bufalari, G. Schalk, G. Oriolo, A. Cherubini, M. G. Marciani and F. Babiloni (2008). Non-invasive brain-computer interface system: towards its application as assistive technology. *Brain Research Bulletin*, **75**, pp. 796-803.

[10] Daly, J. J. and J. R. Wolpaw (2008). Brain-computer interfaces in neurological rehabilitation. *Lancet Neural*, **7**, pp. 1032-1043.

[11] deCharms, R. C., F. Maeda, G. H. Glover, D. Ludlow, J. M. Pauly, D. Soneji, J. D. E. Gabrieli and S. C. Makey (2005). Control over brain activation and pain learned by using real-time functional MRI. *Proceedings of the National Academy of Sciences USA*, **102**, pp. 18626-18631.

[12] EPOC Features. (2014). Access date: March, 02, 2014. Available http://emotiv.com/epoc/

[13] Fazel-Rezai, R. (2011). *Recent advances in brain-computer interface systems*. pp. 01-08, 1rd ed, InTech, India.

[14] Fetz, E.E. and D. V. Finocchio (1971). Operant conditioning of specific patterns of neural and muscular activity. *Science*, **174**(7), pp. 431-435.

[15] Friehs, G. M., V. A. Zerris, C. L. Ojakangas, M. R. Fellows and J. P. Donoghue (2004). Brain-machine and brain-computer interfaces. *Stroke: Journal of The American Heart Association*, **35** (suppl. I), pp. 2702-2705.

[16] Georgopoulos, A. P., A. B. Schwartz and R. E. Kettner (1986). Neuronal population coding of movement direction. *Science*, **233**(4771), pp. 1416-1419.

[17] Guenther, F. H. and Brumberg, J. S. (2011). Brain-Machine Interfaces for real-time speech synthesis. *33rd Annual International Conference of the IEEE EMBS*. Boston, Massachusetts USA, pp. 5360-5363.

[18] Halder, S., Varkuti, B., Bogdan., Kübler, A., Rosenstiel, W., Sitaram, R. and Birbaumer, N. (2013). Prediction of brain-computer interface aptitude from individual brain structure. *Frontiers in Human Neuroscience*, vol. 7, pp. 1-9.

[19] Horgan, J. (2004, October), The mith of mind control. *Discover*, pp. 40-46.

[20] Kennedy, P. R. and R. A. Bakay (1998). Restoration of neural output from a paralyzed patient by a direct brain connection. *Neuroreport*, **9**(8), pp. 1707-1711.

[21] Lebedev, M. A., A. J. Tate, T. L. Hanson, Z. Li, J. E. O'Doherty, J. A. Winans, P. J. Ifft, K. Z. Zhuang, N. A. Fitzsimmons, D. A. Schwarz, A. M. Fuller, J. H. An and M. A. L. Nicolelis (2011). Future developments in brain-machine interface research. *Clinics*, **66**(S1), pp. 25-32.

[22] Leuthardt, E. C., G. Schalk, Roland, J., Rouse, A., and Moran, D. W. (2009). Evolution of brain-computer interfaces: going beyond classic motor physiology. *Neurosurg Focus*, **27**(1), pp. 1-21.

[23] Li, Z., O'Doherty, J.E., Hanson, T.L., Lebedev, M.A., Henriquez, C.S. and Nicolelis, M.A.L (2009). Unscented kalman filter for Brain-Machine Interfaces. *PLos ONE*, **4**(7), pp. 1-18.

[24] Lim, C. G., Lee, T. S., Guan, C., Fung, D. S. S., Zhao, Y., Teng, S. S. W., Zhang, H. and Krishnan, K. R.R. (2012). A brain-computer interface based attention training program for treating attention deficit hyperactivity disorder. *PLoS ONE*, **7**(10) , pp. 1-8.

[25] Machado, S., M. Cunha, B. Velasques, D. Minc, V. H. Bastos, H. Budde, M. Cagy, R. Piedade e P. Ribeiro (2009). *Interface cérebro-computador: novas perspectivas para a reabilitação.* Relatório de Pesquisa, Instituto Brasileiro de Biociências Neurais (IBBN), Rio de Janeiro, RJ.

[26] Mak, J. N., Y. Arbel, J. W. Minett, L. M. McCane, B. Yuksel, D. Ryan, D. Thompson, L. Bianchi and D. Erdogmus (2011). Optimizing the P300-based brain-computer interface: current status, limitations and future directions. *Journal of Neural Engineering*, **8**, pp. 1-7.

[27] Moran, D, (2010). Evolution of brain-computer interface: Action potentials, local field potentials and electrocorticograms. *Current Opinion of Neurobiology*, **20**(6), pp. 741-745.

[28] Moran, D. W. and A. B. Schawartz (1999). Motor cortical representation of speed and direction during reaching. *Journal Neurophysiol*, **82**(5), pp. 2676-2692.

[29] Nicolas-Alonso, L. F. and J. Gomez-Gil (2012). Brain computer interfaces, a Review. *Sensors*, **12**, pp. 1211-1279.

[30] Nicolelis, M. (2011). *Muito além do nosso eu: a nova neurociência que une cérebro e máquinas e como ela pode mudar nossas vidas*. 534 p., 1rd ed. Companhia das Letras, São Paulo.

[31] NeuroSky – Body and Mind. Quantified. (2014). Access date: March, 02, 2014. Available http://store.neurosky.com/products/mindwave-1

[32] Rota, G., R. Sitaram, R. Veit, M. Erb, N. Weiskopf, G. Dogil and N. Birbaumer (2009). Self-regulation of regional cortical activity using real-time fMRI: The right inferior frontal gyrus and linguistic processing. *Human Brain Mapping*, **30**, pp. 1605-1614.

[33] Ruf, C. A., Massari, D., Furdea, A., Matuz, T., Fioravanti, C., Heiden, L., Halder, S. and Birbaumer, N. (2013). Semantic classical conditioning and brain-computer interface control: encoding of affirmative and negative thinking. *Frontiers in Neuroscience*, vol. 7. pp. 1-13.

[34] Shanechi, M. M., Williams, Z. M., Wornell, G. W., Hu, R. C., Powers, M. and Brown, E. N. (2013). A real-time brain-machine interface combining motor target and trajectory intent using an optimal feedback control design. *PLoS ONE*, 8(4), pp. 1-15.

[35] Scheneider, F., B. Rockstroh, H. Heimann, W. Lutzenberger, R. Mattes, T. Elbert, N. Birbaumer and M. Bartels (1992a). Self-regulation of slow cortical potentials in psychiatric patients: Schizophrenia. *Applied Psychophysiology and Biofeedback*, **17**, pp. 277-292.

[36] Scheneider, F., H. Heimann, R. Mattes, W. Lutzenberger and N. Birbaumer (1992b). Self-regulation of slow cortical potentials in psychiatric patients: Depression. *Applied Psychophysiology and Biofeedback*, **17**, pp. 203-214.

[37] Silva, V. A. S. (2005). Implementação de um protótipo de uma interface para um controlador de cadeiras de rodas guiado pela direção do olhar. Projeto de implementação, Universidade Católica Dom Bosco, Campo Grande, MS, Brasil.

[38] Sterman, M. and T. Egner (2006). Foundation and practice of neurofeedback for the treatment of epilepsy. *Applied Psychophysiology and Biofeedback*, **31**, pp. 21-35.

[39] Strehl, U., U. Leins, G. Goth, C. Klinger, T. Hinterberger and N. Birbaumer (2006). Self-regulation of slow cortical potentials: A new treatment for children with attention-deficit/hyperactivity disorder. *Pediatrics*, **118**, pp. 1530-1540.

[40] Vaughan, T. M. and J. R. Wolpaw (2006). The third international meeting on brain-computer interface technology: making a difference. *IEEE Transactions Neural Systems and Rehabilitation Engineering*, **14**(2), pp. 126-127.

[41] Waibel, M. (2011). *BrainDriver: A mind controlled car*. New York. [On-line]. Access date: August 29, 2012. Available http://spectrum.ieee.org/automaton/robotics/robotics-software/braindriver-a-mind-controlled-car

[42] Walker, J. E. and G. P. Kozlowski (2005). Neurofeedback treatment of epilepsy. *Child & Adolescent Psychiatric Clinics of North America*, **14,** pp. 163-176.

[43] Wang, Y., W. Wang and T. Jung (2011). A cell-phone-based brain-computer interface for communication in daily life. *Journal of Neural Engineering*, No. 08, pp. 01-05).

[44] Wang. S., Heinrich, S., Wang. M. and R. Rojas (2012). Shader-based sensor simulation for autonomous car testing. *15th International IEEE*

Conference on Intelligent Transportation Systems. Anchorage, Alaska, USA.

[45] Wang, S., Li, D., Song, X., Wei, Y. and H. Li (2011). A feature selection method based on improved fisher's discriminant ratio for text sentiment classification. *Elsevier: Expert Systems with Applications*, **38**(2011), pp. 8696-8702.

[46] Waters, D. (2008). *Brain control headset for gamers*. San Francisco. [On-line]. Access date: May 15, 2012. Available http://news.bbc.co.uk/2/hi/technology/7254078.stm

[47] Wolpaw, J. R. (2007). Brain-computer interfaces as new brain output pathways. *The Physiological Society*, **579**(3), pp. 613-619.

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

[49] Zander, T. O. and C. Kothe (2011). Towards passive brain-computer interfaces: applying brain-computer interface technology to human-machine systems in general. *Journal of Neural Engineering*, **8**, pp. 1-5.

[50] Zhang. Y., Zhou, G., Zhao, Q., Jin, J., Wang, X. and Cichocki, A. (2013). Spatial-temporal discriminant analysis for ERP-based brain-computer interface. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 21, No. 2, pp. 233-243.