Control of medical robotics and neurorobotic prosthetics by non-invasive Brain-Robot Interfaces via EEG and RFID technology

Antoniadou Eleni, *Member, IEEE*

Abstract— **Brain-robot interface (BRI) has been a growing field of innovative research and development in cognitive neuroscience and brain bioimaging processing technologies. In this paper we endeavor to explore how medical robotics and neurorobotic prosthetics can be controlled by Brain-Robot Interfaces and RFID (Radio Frequency Identification) technologies, directly using brain signals obtained non-invasively from the scalp through electroencephalography (EEG) in order to assist disabled patients to ameliorate their everyday lives.**

There is a general consensus that computational visualizations and interfaces are proliferating in every aspect of medical practice, prompted from the current trends in telemedicine. The main focus of the study is on architectures of Brain-robot interfaces for communication and control using one specific modality, namely electroencephalography (EEG), alpha (a) wave-based BRI with an emphasis on biosignal processing aspects.

The main motivation for the application of such scientific methods is the development of an alternative communication and control means for severely disabled people, focusing in replacing total voluntary muscle control using robotic prosthetics. The substantial goal is to demonstrate that an EEG-based brain–robot interface can be used for sophisticated robotic interaction with the environment, involving not only navigation as in previous applications but also manipulation and transport of objects.

Visualization of brain electrical activity and BRI technology, by their intimate connection with the wonder of human thought processes, are a fascinating research field, that has demonstrated the unprecedented ability of direct information transfer from the brain to medical robots or robotic prosthetics. Inclusion of a BRI in a multimodal interface thus results in a net gain of information transfer capability that alters the standards in medical robotics.

Index Terms and Definitions **–Brain Robot Interface (BRI)** is a direct communication pathway between human or animal brain and a robot. **Brain Computer Interface (BCI)**,also called a direct neural interface or a brain-machine interface, is a direct communication pathway between human or animal brain and an external device. **Neurorobotic prosthetics** is an area of neuroscience concerned with neural robotic prosthesis using the artificial devices to replace the function of impaired nervous systems or sensory organs. **RFID** which stands for Radio Frequency Identification is an automatic identification method, relying on storing and remotely retrieving data using devices called RFID tags or transpoders.

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Antoniadou Eleni is with the Department of Biomedical Informatics, University of Central Greece, Lamia, 35100 GREECE (tel: 6974521788, 6949500264; fax: +30 2310862088 ; e-mail: antoniadoueleni@yahoo.com)

Medical robotics is mechanical or virtual artificial agents, automatically controlled, reprogrammable, multipurpose, manipulator programmable in three or more axe, which may be either fixed in place or mobile for use in medical automation applications.

I. Introduction

The synergy between biomedical informatics, neurosciences and medical robotics with common architectural operative elements emerged from evolving applications and systems with specific technical norms. This study illustrates the attainment of notable and substantial advantages of the exciting new partnership that is being forged between medical robotics, Brain-Robot interfaces and RFID technology that allow the direct brain control of devices such as a cursor on a computer screen [1-5] and various prosthetic devices [6–8].

The last decade many types of BRIs have been used, targeting on disabled patients, to realise small tasks such as choosing letters to spell words [9-12], moving a cursor to select from a variety of choices, and mentally directing the motion of a robot, a wheelchair, or a neuroprosthetic limb. Such Brain-Robot Interfaces (BRIs) in collaboration with Radiofrequency Identification technology could potentially lead to sophisticated neural prosthetics and other assistive devices with the aid of Real-Time databases and patient records for paralyzed and disabled patients.

The control of medical robots and especially that of a prosthetic limp have been achieved both using invasive and non-invasive methods depending on the complexity of the desirable task. Specifically , electroencephalography (EEG) recorded from the brain have been used several times in interfaces for cursor control and spelling, however the low bandwidth offered by such non-invasive signals (20–30 bits min−1) makes their use in more complex systems difficult.

By using a dynamic image-based BRI to select between alternatives, and the collaboration of a BRI with RFID chips that can provide information not only from stored databases but also of geometrical distances in the space, the system can seamlessly incorporate newly discovered objects and interaction affordances in the environment.

II. METHODS

A. User study Protocol

The decomposition of mental functions provides us with the division of brain activities and set the basis of the design of intelligent machines. While designing learning-algorithms and simulation models adequate for creating intelligence is a very complex process, it is easier to define the basic mental operations and their causes.

Specifically, brains understood as reinforcement learners consist of:

1. Reinforcement values to be increased or decreased - these are the basic motives of behaviour.
2. Algorithms for learning behaviours based on reinforcement values.
3. A simulation model of the world, itself learned from interactions with the world (the reinforcement value for learning the simulation model is accuracy of prediction).
4. A discount rate for balancing future versus current rewards (people who focus on current rewards and ignore the future are generally judged as not very intelligent).

Additionally, the total force exerted by a muscle is the sum of three forces T_A (α, x) + T_P (x) +T_V (x) which depend on the activity of the corresponding motor neuron (α) and on the current elongation of the muscle (x) and which are calculated on the basis of the following equations:

$$T_A = a\left(-\frac{A_{sh} T_{max}(x - R_L)^2}{R_L^2} + T_{max}\right)$$

$$A_{sh} = \frac{R_L^2}{(L_{max} - R_L)^2}$$

$$T_P = T_{max} \frac{\exp\left\{K_{sh} \frac{x - R_L}{L_{max} - R_L}\right\} - 1}{\exp\{K_{sh}\} - 1}$$

$$T_v = b \cdot \dot{x}$$

where L_{max} and R_L are the maximum and the resting length of the muscle, T_{max} is the maximum force that could be generated, K_{sh} is the passive shape factor, b is the viscosity coefficient. In the case of the hand, the positions of the joints are controlled by a limited number of variables (i.e. they are interdependent as in the case of human hands) through a velocity-proportional controller (joint maximum velocity is set to 0.30 rad/second).

The biosignals transmitted from the brain through the electroencephalography (EEG) are conducted to brain-robot interface for processing. Alpha wave-block can be recognized, processed and transmitted to control single option, and design of state selector helps to realize multi-option control.

Tactile neuroscience is concerned with understanding the neural processes that underlie the sense of touch originating from contact between the skin and an object. Traditional studies have focused on characterizing the response of mechanoreceptors in the skin to various stimuli such as vibrating probes or indenting sharp edges. Applications of tactile neuroscience that can be used in medical robots are RFIDs , sensors, biomarkers etc. The medical robot can be provided with RFID chips and tactile sensors distributed over the hand, and of the vision system located on the robot head, to encode the current position of the robotic -DOF of the arm and the hand.

B.. *Brain–robot interface design*

The design of a brain-robot interface is complicated due to the complex processing of biosignals and the variety of parameters that should be taken into consideration.

From a technological standpoint, a brain-robot interface is consisted of a dynamic brain-computer interface that can accommodate a variable number of images by suitably resizing and arranging them in a grid. This allows the interface to incorporate dynamically generated images discovered by the robot and present them as choices to the user.

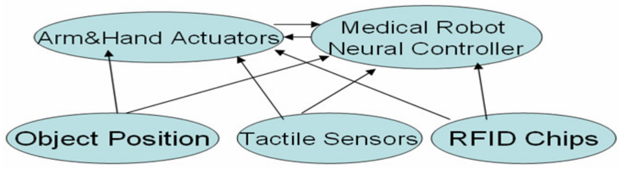

Figure 1 The architecture of medical robot neural controller

As shown in the figure above, different technologies collaborate so as to produce an effective Brain-robot interface. The robot is provided with neural controllers (usually needed 21 sensory neurons, five internal neurons with recurrent connections and 16 motor neurons, for the extended processing of biosignals), hand and arm actuators, depending on the application purpose and RFIDs for radiowave communication with brain-computer interfaces.According to the diagram the object position can be defined and estimated by the arm and hand actuators which are equipped with tactile sensors and RFID chips providing infra red scanning and GPS tracking of the territory and by the medical robot itself, which receives and process all the information from each applied technology.

Sensory neurons are neurons of one sided impulses which transmit information to the brain, where it can be further processed and acted upon. More precisely, these neurons consist of leaky integrators in which the output is calculated on the basis of the following equation (Nolfi and Marocco, 2001):

$$O(t) = \delta \cdot Ac(t) + (1 - \delta) \cdot Act(t - 1)$$

where Act is the activity of the neuron calculated on the basis of the logistic function (with slope coefficient 0.2 for tactile sensors and 1.0 for hand actuators) and δ is a time constant parameter ranging between [0, +1].

C.Structural learning through imitation

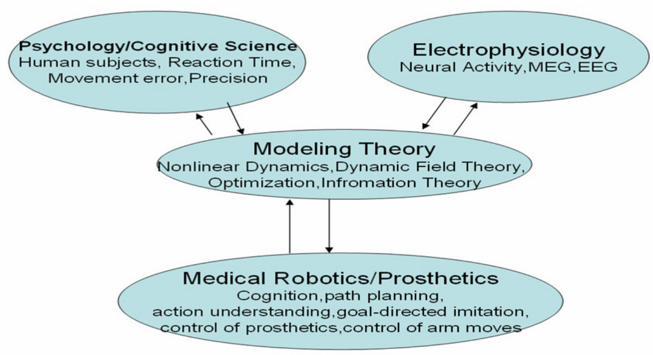

Figure 2 Theoretical approach of structural learning for brain-robot interfaces

Control of medical robotics and prosthetics relies both in the brain-robot interface but to the brain repetitive exercise and movements as well. In the figure above we show the theoretical basis on which experimental practice should be applied in order to achieve an effective coordination of brain stimuli and robot correspondence.

It is of paramount importance to ensure the realization of several steps that concern cognitive science such as to measure the movements that can be executed, to estimate the reaction time, to calculate the movement error and precision of each task.

Furthermore, the usage of electrophysiology and specifically the recording of neural activity of each movement and the brain signals through EEG is part of the systematic experimental task that is necessary to be repeated in order to create a database of biosignals that correspond to a certain movement. In the figure below, are shown the steps of the signal processing. Signal processing module extracts feature of EEG signals, recognizes and transforms them into corresponding control signals. Then computer sends control signals to the next Control interface circuit, and to State selector to remind subject of present state at the same time. Control interface circuit converts control signals and direction signal from State selector into acceptable control commands by service robot.

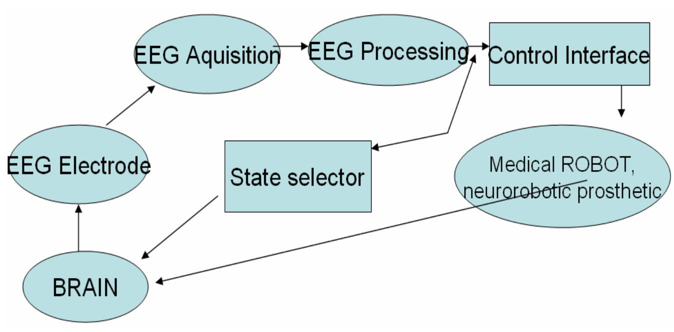

Figure 3 Steps of brain signal processing through the brain-robot interface

Moreover, information and modeling theory are used to provide the mathematical algorithms needed to convert brain signals to movements. A recently proposed spatial projection algorithm [13] that is designed for event-related EEG responses is efficient for brain-robot interfaces.

Briefly, the algorithm considers a multichannel time-series response to an event and projects all the channels to form a *maximally discriminative* single time series. Following the criterion used for optimization, let Ei represent an event-related response to event i, in the form of a C X T matrix (where C is the number of channels and T is the number of time points). Let f be a projection filter and let $xi = f\ T\ Ei$ be the time series of 'features' formed by linearly weighting and combining all channels. We can compute the *within-class* and *between-class* scatter matrices (Sw and Sb respectively) over the set of all xi and maximize the Jacobian J [13]:

$$J = \frac{tr(S_b)}{tr(S_w)}$$

It can be proved that this is equivalent to maximizing the following quantity:

$$J(f) = \frac{f^T S'_b f}{f^T S'_w f}$$

where S'_b, S'_w are calculated directly from the set of Eis [13].

Finally, medical robotics and prosthetics must serve a goal-directed imitation through a visual environmental software so as to omit pointless movements and increase the precision.

III. DISCUSSION AND CONCLUSIONS

The non-invasive brain signals can be used to command a sophisticated mobile device such as a humanoid medical robot or a neurorobotic prosthetic to perform a useful task such as navigating to a desired location and fetching a desired object. In principle, the robot could execute a wider range of actions, and arbitrary commands could be presented to the user as choices using images describing available actions.

A BRI system such as the one explored in this paper could potentially be used, for instance, in medical helper robots for paralyzed and disabled patients. Such robots would possess the ability to move about in a home, perform different manipulative actions on objects and provide visual feedback to the patient for monitoring progress and for subsequent action selection. Such robots could potentially act as surrogate bodies for the paralyzed that are remotely commanded at the cognitive level by a brain-robot interface.

Invasive BCIs such as cortical implants and RFIDs would allow control at finer temporal granularity, albeit with the risks associated with invasive devices. Our conclusions suggest that the advent of adaptive, autonomous robotic devices could help pave the way for a new generation of non-invasive brain–machine interfaces that allow direct closed-loop interaction with the physical world.

Though in its infancy, brain-robot interfaces , medical robotics and neurorobotic prosthetics are gaining recognition, accelerating the scientific evolution from the

Information Age to the Computational Robotics Age in a way that extends the perceptions of our knowledge and senses.

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 *Proc. Natl Acad. Sci.* **101** 17849–54

[2] Pfurtscheller G *et al* 2000 Current trends in Graz brain computer interface (BCI) research *IEEE Trans. Rehabil. Eng.* **8** 216–9

[3] Kubler A *et al* 1999 The thought translation device: a neurophysiological approach to communication in total motor paralysis *Exp. Brain Res.* **124** 223–32

[4] Serruya M D, Hatsopoulos N G, Paminski L, Fellows M R and Donoghue J P 2002 Brain-machine interface: instant neural control of a movement signal *Nature* **416** 141–2

[5] Musallam S, Corneil B D, Greger B, Scherberger H and Andersen R A 2004 Cognitive control signals for neural prosthetics *Science* **305** 258–62

[6] Wessberg J *et al* 2000 Real-time prediction of hand trajectory by ensembles of cortical neurons in primates *Nature* **408** 361–5

[7] Taylor D M, Tillery S I and Schwartz A B 2002 Direct cortical control of 3D neuroprosthetic devices *Science* **296** 1829–32

[8] Hochberg L R, Serruya M D, Friehs G M, Mukand J A, Saleh M, Caplan A H, Branner A, Chen D, Penn R D and Donoghue J P 2006 Neuronal ensemble control of prosthetic devices by a human with tetraplegia *Nature* **442** 164–71

[9] J. R.Wolpaw, N. Birbaumer,D. J. McFarland, G. Pfurtscheller, and T. M Vaughan, "Brain–computer interface for communication and control,"*Clinical Neurophysiol.*, vol. 113, pp. 767–791, 2002.

[10] N. Birbaumer, N. Ghanayim, T. Hinterberger, I. Iversen, B. Kotchoubey,A. Kübler, J. Perelmouter, E. Taub, and H. Flor, "A s pelling device for the paralyzed," *Nature*, vol. 398, pp. 297–298, 1999.

[11] J. Kaiser, A. Kübler, T. Hinterberger, N. Neumann, and N. Birbaumer,"A noninvasive communication device for the paralyzed," *Minimally InvasiveNeurosurgery*, vol. 45, pp. 19–23, 2002.

[12] P. R. Kennedy, R. A. E. Bakay, M. M. Moore, K. Adams, and J. Goldthwaite, "Direct control of a computer from the human central nervous system," *IEEE Trans. Rehab. Eng.*, vol. 8, pp. 198–202, June 2000.

[13] Hoffmann U, Vesin J-M and Ebrahimi T 2006 Spatial filters for the classification of event-related potentials *Proc. ESANN* pp 47–52