The Concept of an Intelligent, Bio-Inspired and Brain Controlled Robotic System

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Abstract— **Between the information transfer rate and the classification accuracy of a brain computer interface (BCI) system a balance occurs. If we want higher correct classification rates the BCI system will consequently become slower. Otherwise, a faster (online) BCI system assumes a lower classification rate. If we analyze the human motor system (HMS) we can view the hierarchical organization (with different control levels that receive specific sensorial information) as a corresponding biological solution to solve the problem of the system complexity versus the real time control. The muscular proprioceptors and the receptors from the vestibular system inform (especially at the low motor control levels) the central nervous system about the locomotor mechanics and the body posture. The tactile, visual and auditory information is mainly used by the high control/command levels of the HMS. HMS requires a training time interval for executing a specific motor program (e.q. walking), followed then by a systematic adaptation to the changing of the human living system parameters and of the environment characteristics. This paper presents the concepts of an intelligent, bio-inspired and with auto-organization robotic system (e.g. a wheelchair), iBiAoRS, that will be capable both: to control the system movement dynamics based on a BCI system and to obey the successive hierarchical subordination principle that characterizes the HMS. An auto-organization robotic system is developed and some preliminary results are presented in order to test one of the main concept of iBiAoRS.**

Index Terms— *BCI, bioinspired systems, human motor system, robot, self-organization*

I. Introduction

In order to develop a BCI system useful in communications and environment control – system dedicated to people with severe motor disabilities (e.g. a simple word processing program, an intelligent wheelchair or a neuroprosthesis) –, at least two issues must be taken into consideration: the online capabilities of the system and the BCI classification performances.

Between the online processing and the classification accuracy a compromise will always be to make. If we want higher correct classification rates the BCI system become slower due to the complexity of the algorithms applied in the features extraction and classification stages.

At this moment, the classification accuracy for a BCI system varies between 70% and 95% [1], [2], [3] and these performances mainly depends on: the number of the EEG channels, the type of the BCI methods, the methods used to remove artifacts, the processing techniques, the complexity and the discrimination power of the classification algorithms, the number and the categories of the mental tasks used etc.

For example, many online BCI systems use continuous motor imagery task in order to obtain a system command from the EEG signals. Even if, major progress were done in the last fifteen years – while in 1998 imagined finger movements could be distinguished from the EEG signals with an accuracy of around 70% [4], right now (in 2009), in average, the accuracy is somewhere between 80% and 86% [2] –, further improvements must be done in order to have an average accuracy of at least 95%.

The classification accuracy strongly depends on the subject brain characteristics and, also, on the existence of special training sessions. The mean classification accuracies in motor imagery tasks are from 75% up to 95% [2], [5] for a subject, but it is also possible to get inferior performances from 60% up to 70% for some subjects [2], [5].

Due to the difficulty of each subject to control his/her own EEG signals, a suitable training protocol, based on a visual feedback and lasting several weeks or months [2], is frequently implemented in many studies [2], [6]. Conventional systems of biofeedback are based on simple visual presentations [2] while other BCI systems use virtual reality as a tool to improve BCI-feedback presentation [6].

In general, the performance of the BCI technologies, measured in information transfer rate (i.e., bit rate), is modest. Actually the bit rate performance is different from system to system. There are BCI systems that achieve an average communication rate of 5.45 bits/min [7] while other systems work around 10 bits/min [2] etc. But, even under the best optimal conditions [8], none of the current existent BCI systems reach more than 25 bits/min. The bit rate is limited by two major factors: the subject ability to interface with a BCI system and the time performances of the algorithms used in the BCI system (processing, feature extraction and classification) – e.g., in motor imagery tasks the subjects must engage in one type of motor imagery brain activity for at least 7–8 s so that mu-rhythm power can be detected accurately [2]. Even if, due to the development of the new algorithms (that are now less time consuming), and

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to the new faster technologies, the human remains the most limiting factor in the desire to get a higher information transfer rate (e.g. in a study about a motor imagery-based BCI system the mean bit rate for all 10 subjects was around 7 bits/min; among them only one subject was able to obtain the higher bit rate, namely, 22 bits/min [2]).

In conclusion, in order to have both, higher information transfer rate and higher mental task classification accuracies, a new BCI system concept must be defined, implemented and tested.

II. BIOLOGICAL CONSIDERATIONS

The HMS has a very complex, hierarchical organization [9], with different control levels, each of them receiving different specific sensorial information needed for their functioning. The proprioceptors from tendons, muscles, joints and ligaments and the receptors from the vestibular system provide information to the brain regarding the adjustment of posture and movement (muscle length and tension, joint angle and the position of the body in space) [10]. This kind of information, of monitoring the details, is necessary especially at the low levels of motor control, while the sensorial information given by the exteroceptors from skin, eyes and ears inform us about the localization of the objects in space and about our relative position to these objects. The sensorial information is used especially at the high movement hierarchical control levels that are involved in the issue of the movement strategies. A key aspect is that these high hierarchical levels do not require a step by step monitoring of the details information.

Within the motor system, the spinal cord performs a triple function: the reflex integration, the reflex coordination (movement command) and the conductive function. The ***spinal reflexes*** (SR – ***rapid***, ***involuntary motor responses to a stimulus***) are somatic reflexes mediated by the spinal cord. Reflexes are quick because they involve few neurons that ***trigger the response without waiting for brain analysis***. The sensory stimuli for SRs arise from receptors in muscles, joints and skin and ***the neural circuitry responsible for the motor response is entirely contained within the spinal cord***. In these spinal networks the interneurons are key elements that: (1) mediate influences of sensory input upon motoneurons and (2) constitute the networks generating complicated patterns (reverberating network, rhythm generator etc.). Also, the spinal reflex circuits provide the higher centers with a set of elementary patterns of coordination, from relatively simple combinations, like reciprocal innervation at a single joint, to more complex spatial patterns of movement, such as flexion reflex, and temporal patterns, as in the scratch reflex.

Beside the reflex function the spinal cord has also a coordination function. Though reflex behaviors are automatic, the processing centers in brain can facilitate or inhibit reflex motor patterns based in spinal cord [11]. The spinal cord is a major component of the reflex acts adjustment process where it contributes at: the assessment of the chronological time evolutions, the control of the intensity of the responses, the rhythm and the rhythm modulation [12]. Thus, ***the spinal cord is responsible for the coordination of different motor patterns such as: walking, swimming, chewing, running etc***.

The reflex movements are involuntary, quick and stereotyped. However, the same command centers also participates to the realization of the conditioned reflexes and of the voluntary acts; this is because they receive – from the superior encephalic centers – commands that are further passed on to the execution systems. As one can remark, at human at least, each medullary reflex has a double integration. ***This double integration is drawn from the principle of the hierarchical subordination of the movement dynamics control levels***.

In humans ***the general command of the movement is issued by the superior cerebral centers while the execution's details of each movement are under the control of the sub-cortical and cerebellar areas*** [13]. The SRs are integrated with centrally generated motor commands to produce adaptive movements by adjusting the motor output during an evolving movement and by compensating the intrinsic variability of motor output.

According to the complexity and the voluntary control, the movements issued by the human motor system can be classified in three classes: voluntary movements, reflex responses and rhythmic motor patterns. Among these classes of movements the voluntary movements are the more complex, they have a certain aim, can be learned and improved in time. ***In the movement patterns only their initiation and finishing are voluntary processes and these are combining the characteristics of both, the reflex and the voluntary acts.*** Moreover, it was found that the spinal circuitry in humans has the capability of generating locomotor-like activity (e.g. the stepping pattern) even when isolated from brain control and peripheral afferent feedback [14]. These spinal central pattern generators (CPGs) proved to play a major role in the organization of the locomotion activity by producing coordinated motor output. Under normal conditions, CPGs are under brain control, and sensory peripheral inputs can modulate their activity.

III. THE IBIAORS CONCEPTS

Having in mind the biological solution presented above, the fundamental concept of iBiAoRS consists in building up a bio-inspired, self – organized intelligent robotic system (a) able to have a dynamical movement control similar with the HMS. Hence, the proposed system will respect the hierarchical subordination principle. The system will consist in three control levels, feed-back loops, for dynamical movement (DM). Every component of the system will receive differentiate and specific information, according to their needs. In this way, it will obtain different internal representations for the continual changing external world. In accordance with these representations, every control hierarchical level will react in order to meet a global objective imposed by a human subject.

The three levels of the iBiAoRS' control hierarchical structure (see Fig. 2) are as follows:

1. On the first DM control level, the revolutions speed of

each of the two engines will be adjusted using two loops. Every loop is composed by a PI type controller. The first controller will adjust the current through engine and the second one will adjust its revolution speed. This engines-control level is equivalent with the reflex paths (from spine) from the living human systems. In human living systems this control level is equivalent with the equilibrium mentioning reflexes or muscle length mentioning reflexes.

2. The second DM control level is composed of an adaptive system that allows the iBiAoRS to avoid the obstacles from the immediate proximity; this adaptive process, that is continuous self-organizing, uses only the local representation of the external world, obtained from the sensors. This level could be implemented using, for example, a neural network (or a fuzzy system, genetic algorithm etc.) that has as objective to minimize the error given by the amount of the relative distances derived from the sensors' outputs, $E = \sum_i (\Delta d_i)^2$. In previous equation, Δd_i is the gradient of the distance information from the sensor i. In this way, in a first stage, iBiAoRS will behave like a human being that learns first to walk by a continuous learning process. The second control level of DM is equivalent with the sub-cortical and cerebellar areas that control the execution's details of each movement.

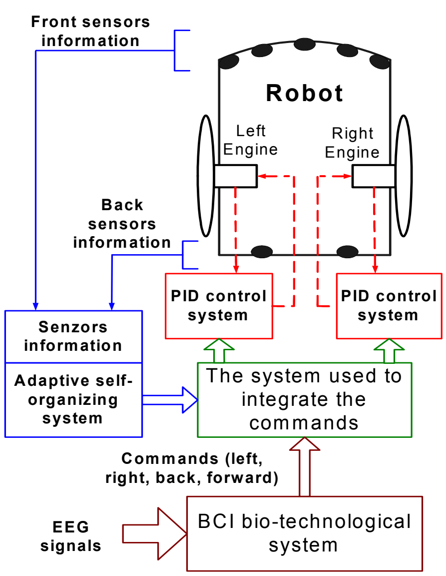

Fig. 1. The bio-inspired robotic system

3. The last level of DM control, namely the BCI system, consists, as in the HMS, in a voluntary motor command issued at the cortical level of a human subject. In this case, the motion dynamics of the iBiAoRS will be given by the cerebral activity of the subject that visually evaluates the trajectory which the robot must to follow and, then, gives a global command (ahead, back, left, right) by means of the BCI system. Due to its local autonomy, the iBiAoRS will execute this global command with no need of extra detail commands to avoid the local obstacles. But to do this the iBiAoRS makes a double integration: that of the global command and that of the local control of the motion dynamics. Thus, the local autonomy relieves the BCI system of the motion details–related commands, giving it the possibility to increase its performances.

Even if the information transfer rate obtained by the BCI system is low, due to the local autonomy of the iBiAoRS (which does not receive a motion-details type command), the time between two movement commands delivered by the BCI system increases; thus, the global real-time movement dynamic behavior improves. More, the classification accuracy can be increased (through complex time consuming algorithms) without any side effects to the real time operation of the system.

IV. The Intelligent Self-Organizing Controller

In order to develop the global iBiAoRS one of the first step was to implement and test each level of the DM control presented above.

In this part of the paper we present the intelligent self-organizing controller. This second level of DM control has to learn (in an adaptive manner, through an ongoing auto-organizing process) to move by avoiding the obstacles and by using for this only the local environment representation provided by the sensors.

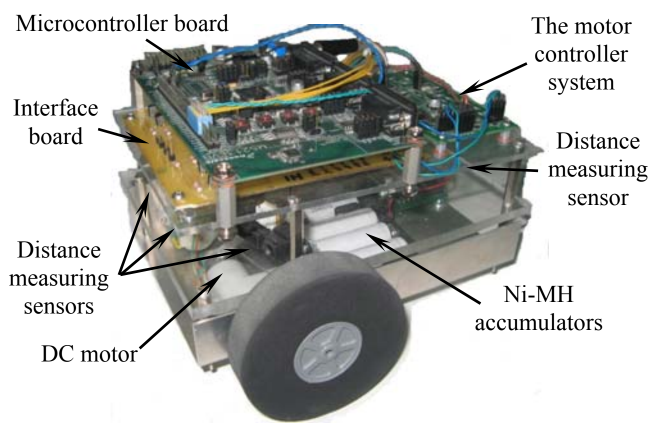

Fig. 2. The intelligent self-organizing robotic system

The implementation of the concepts for this level of DM was done based on a small robotic system that had a number of distance sensors and that had to learn, in an adaptive manner, to minimize the value of the error proposed above.

The intelligent self-organizing robotic system (ISoRSy) was constructed based on the MCF5213 development board that run the algorithm. This microcontroller is a highly integrated implementation of the ColdFire™ family of reduced instruction set computing (RISC) microcontrollers, produced by Freescale™ Company. The MCF5213 represents a family of highly-integrated 32-bit microcontrollers, featuring up to 32 Kbytes of internal SRAM and 256 Kbytes of Flash memory, eight PWM channels, four 32-bit timers with DMA request capability, eight channels ADC, 3 UARTs etc. The robot has four distance measuring sensors (GP2D120XJ00F), 3 of them placed in front and one placed in back position, Fig. 2. Each DC engine is controlled by the microcontroller through a PWM channel based on an H-bridge.

The intelligent self-organizing algorithm used to control the robot was a multilayer perceptron (MLP) neural network with two hidden layers. On the first hidden neural layer the MLP had 5 neurons, while the second hidden layer had 3 neurons. The MLP network had 4 inputs (the normalized values obtained from the distance sensors) and two outputs (that supplied the command to the engines). Each output could take values in the interval [-1, 1], with the following connotations: 1 forward full power engine, -1 back full power engine and 0 stop the engine. The MLP network was trained based on the backpropagation algorithm. The error term used was:

$$err = \frac{1}{4}\sum_{i=1}^{4}\left(s_i[n] - s_i[n-1]\right)^2 \qquad (1)$$

where s_i is the value of sensor i and n is the time moment. Between n and n-1 moments there exists a time delay of 0.4 seconds. This time delay is necessary for the intelligent robotic system in order to have enough time to move and change the sensor values.

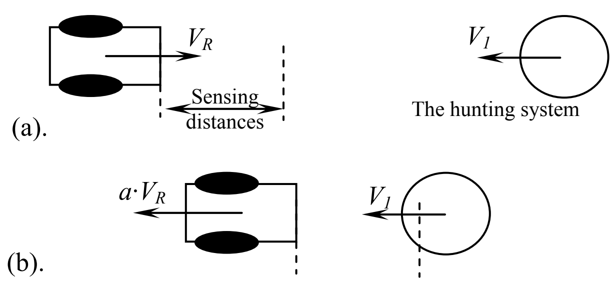

Fig. 3. A self-organized behavior acquired by the robot (a > 1)

V. Results

The task performed by the robot, for which it had to learn a suitable self-organizing behavior, was to navigate through a delimited zone while avoiding collisions with obstacles randomly placed within. Since the robot did not have a global map of the work zone this was not a path planning problem, but one of local navigation and collision avoidance. The learning task was to evolve an intelligent self-organizing behavior represented as a set of stimulus-response rules that map the current sensors distances state into velocity mode commands for the robot to execute. The learning rate was approximately 0.4 hertz.

One interesting behavior obtained consisted in avoiding an imminent collision. When the robot came closed enough to an obstacle it stopped and after that the ISoRSy took quickly back. This interesting behavior was developed further by the intelligent self-organizing robot in the form of the hounding behavior, see Fig. 3. If a "hunting" system (HS) followed the ISoRSy, when the HS was in the sensor range the ISoRSy stopped from its dynamic movements and took quickly in the opposite direction (with a superior speed) trying continuously to increase the distance between itself and the HS, Fig. 3.

VI. Conclusions

In this paper we presented a new concept for a BCI bio-instrumental complex, namely the iBiAoRS – inspired from the HMS hierarchical organization and able to deal with the compromise between the online processing and the classification accuracy. Using an adaptive controller, with a continuous self-organizing structure given by the local representation of the external world, the iBiAoRS was able to avoid obstacles without any supplementary control of the BCI system. Hence, the user of the system had only to initiate and to finish a global action (e.g. "take left", "go forward") without paying attention to local obstacles. Thus, the time between two different brain commands increased providing the user and the BCI system with more time to initiate and sustain a correct brain task and, respectively, to process the EEG signals. In the last part of the paper the second level of the movement dynamics controller was implemented and tested. The obtained results came to support the validity of the main iBiAoRS concepts.

References

[1] C. Guger, A. Schlögl, C. Neuper, D. Walterspacher, T. Strein, and G. Pfurtscheller, "Rapid prototyping of an EEG-based brain-computer interface (BCI)," IEEE Trans. on Neural Syst. and Rehab. Eng, vol. 9, no. 1, pp. 49-58, March 2001

[2] J. Lehtonen, P. Jylanki, L. Kauhanen, M. Sams, "Online Classification of Single EEG Trials During Finger Movements," IEEE Trans. on Biomed. Eng., vol. 55, no 2 pp. 713 – 720, Feb. 2008

[3] S. J. Roberts, W. D. Penny, "Real-time brain-computer interfacing: a preliminary study using Bayesian learning," Med. & Biol. Eng, & Comp., vol. 38, 2000, pp. 56-61

[4] W. Penny, and S. Roberts, "Imagined hand movements identified from the EEG Mu-Rhythm," 1998 Technical report, Imperial College, University of London. Available via http://www.ee.ic.ac.uk.

[5] C. Vidaurre, A. Schlogl, R. Cabeza, R. Scherer, and G. Pfurtscheller, "Study of On-Line Adaptive Discriminant Analysis for EEG-Based Brain Computer Interfaces," IEEE Trans. on Biomed. Eng., vol. 54, no. 3, pp. 550 – 556, March 2007

[6] R. R. Angevin, and A. D. Estrella, "Brain-computer interface: Changes in performance using virtual reality techniques," Neurosci. Let., vol. 449, no. 2, pp. 123-127, 2009

[7] H. Serby, E. Yom-Tov, and G.F. Inbar, "An improved P300-based brain-computer interface," IEEE Trans. on Neural Sys. and Rehab. Eng., Volume 13, Issue 1, March 2005, pp. 89 – 98

[8] G. Schalk, D. J. McFarland, T. Hinterberger, N. Birbaumer, and J. R. Wolpaw, "BCI2000: a general-purpose brain-computer interface (BCI) system," IEEE Trans. on Biomed. Eng., vol. 51, no. 6, pp. 1034 – 1043, June 2004

[9] S. T. Grafton, and A. F. de C. Hamilton, "Evidence for a distributed hierarchy of action representation in the brain," Hum. Movement. Sci., vol. 26, no. 4, pp. 590-616, 2007

[10] B. Schepens, and T. Drew, "Strategies for the Integration of Posture and Movement During Reaching," J Neurophysiology, 90, pp. 3066-3086, 2003.

[11] J. Michel, H.J.A. van Hedel, and V. Dietz, "Facilitation of spinal reflexes assists performing but not learning an obstacle-avoidance locomotor task", Eur. J Neurosci., vol. 26, no. 5, pp. 1299-306, Sept. 2007

[12] L. Dănăilă, and M. Golu, "Tratat de neuropsihologie," vol. 1, Editura Medicală, 2002

[13] C. Ghez, The control of movement, în E.R. Kandel, J.H. Schwartz, T.M. Jessell, Principles of neural science, Elsevier, pp. 533-547, 1991

[14] M. R. Dimitrijevic, Y. Gerasimenko, M. Pinter, "Evidence for a Spinal Central Pattern Generator in Humans," Annals of the New York Acad. of Sci. 860, pp. 360-376, 1998