RESEARCH ARTICLE OPEN ACCESS

Minimally Invasive and Low-Cost BCI System Interprets the Will of the Subject by means of an Artificial Neural Network

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ABSTRACT

The advances in BCI technology are evident and continuous, but the problems of portability and invasiveness of the devices that the subject must wear still remain to be solved. The paper presents a light, low-cost and non-invasive system that allows the disabled subject unable to communicate to interact with the environment and other people. Signals are acquired from a sensor applied to the finger, then are processed by an Artificial Neural Network. This allows the tetraplegic and anarthric subject to express their will and make choices through a graphic interface. The system can be greatly improved both in the quality and quantity of different signals acquired and in their simultaneous processing to discriminate different mental states, so as to improve communication, access to computer and home automation functions.

***Keywords* -** Brain Computer Interaction, Galvanic Skin Response, Artificial Neural Network, disability, domotics

Date of Submission: 16-10-2020 Date of Acceptance: 31-10-2020

I. INTRODUCTION

The visionary attempt of Neuralink, a company owned by Elon Musk and Neuralink [1,2] whose mission is to develop implantable neural interfaces, is the culmination of the progress of the BCI. However, the current state of the art [3-8] is limited to certain applications: in classic one-way BCIs, the external device receives commands directly from signals resulting from brain activity, such as EEG or EcoG [9,10]. One-way neural interfaces therefore represent the complementary function to neuroprostheses [11,12,13], which are typically dedicated to the peripheral nervous system. Bi-directional BCIs [14] combine the described communication channel with a return line that would allow the exchange of information between the external device and the brain.

Today, the role played by the BCI is mainly in the direction of functional support systems and aids for people with disabilities [15-18]. The acquisition and interpretation of electroencephalographic signals has been successfully used to control the movement of a wheelchair [19, 20], or the speech synthesis [21-23] of a word vocabulary. Applications are also being developed in the field of home automation [24-26].

Examples of clinical applications of these instruments include, in addition to motor prostheses, cochlear prostheses [27] and deep brain stimulation (DBS) [28,29]. In all these cases, the direction of research is to reduce the size of bioelectrical interfaces to minimize nerve tissue damage and maximize selectivity, and in this field nanotechnology is applied [30,31].

However, there are two problems that prevent a rapid development of this field of research.

The first, as we have seen, is linked to the biocompatibility of the implanted devices, which is gradually improving, the second - more critical - is linked to the relationship between the sophistication of the devices and microelectrodes to be implanted and the useful information content to be transmitted in a bidirectional sense. In other words, the progress of technologies is faster than that of neuroscience, which still cannot achieve the objective of understanding the code used by the network of neurons to store and transmit information.

The presence of different channels from which to acquire physiological signals useful for computational processing and its subsequent use by actuators is therefore not yet a guarantee of sufficient efficiency. And since the invasiveness of the sensors used remains a problem not only in the case of internal brain insertion, but also in the case of external application (think of the uncomfortable EEG headsets), it seems emblematic to us that a research carried out using a low-cost sensor commercially available for several years, which we will describe below, is still topical because it allows performances not dissimilar to those of many current more complex applications.

The research was carried out with the intent to distinguish two different signals produced by the mind and to use them for different purposes: communication, device activation and deactivation, word processing. The work was conducted at the IRCCS Istituto Neurologico Carlo Besta, Milan, Department of Developmental Neurology, which fully supported and funded this research.

Its topicality lies in the non-invasiveness and cost-effectiveness of the device used and in the computational aspect, which uses an *ad hoc* Artificial Neural Network able to discriminate two different mental states in real time.

We will see how the system shows useful performances and how it could be easily enhanced through other new available technologies, while maintaining its non-invasiveness and cost-effectiveness.

II. CLINICAL USE OF MINDDRIVE

The device adopted is called MindDrive [32,33] and consists of a sensor applied to the finger with a small plastic support.

MindDrive technology was first developed in the military field by US and former USSR scientists for aeronautics, then it was transferred to the civil field and has been perfected and patented by three companies: Softlab-Nsk (Russia) developed the programs, theOther90% Technologies (USA) protected the patent worldwide, and Discovogue Infotronics (Italy) designed and distributed the sensor.

The tool was put on sale in the form of a video game, which allowed anyone wearing it to influence the virtual route along ski slopes, bowling alleys, etc.

At the same time the device was being tested for research purposes in different areas.

The Hesperia Hospital in Modena tried MindDrive in operating room, during surgery on the heart of a child wearing MindDrive, in order to better understand the brain's reactions during a surgical procedure.

At the Resuscitation Division of the hospital in Lugo (Ravenna), MindDrive was applied to a woman in awake coma, to monitor her reactions while talking to her, managing to identify simple moods and her preferences among the people present in the room.

The Ferrari automotive company tested the technology as a first step to replace some of the driver's operations through mental command.

However, it is clear, especially in light of recent developments of the BCI, that the most interesting and usable applications in the immediate future remain those dedicated to the world of disability.

In this paper we intend to describe the application developed at the Istituto Neurologico Carlo Besta, Milan to foster interaction with the environment by tetraplegic anarthric children under treatment at the Institute.

Usually people with this pathology use a large transparent plastic sheet with the letters of the alphabet printed on it to communicate: the person assisting the subject holds it in front of him and understands which letters he wants to indicate by following his gaze.

The use of the computer has not made things easier, because a residual movement (foot, hand, eyes) is used to activate a scanning keyboard, i.e. every time the cursor on the screen passes over the desired letter, this is chosen by activating this movement.

Using the mind to interact with the computer, and through the computer with the outside world, instead of this long and tiring system, would take an important advantage.

The children involved in the study experienced a brand new emotion playing the video games offered by MindDrive (skiing, bowling, drawing, etc.) and interacting for the first time with the world like their peers.

But the aim of the research work was to go beyond commercial applications and to develop a system that processes the signals coming from the sensor and allows interaction with the computer based on the mental state of the subject.

III. METHODS

The human brain is a bioelectric source in continuous activity; in fact it is composed of about 10 million neurons connected to each other with about one million billion interconnections. When a neuron is activated, it sends an electrochemical impulse to the neurons to which it is connected, so that electrical impulses start from the brain, which travel through the spinal cord, inside the vertebral canal, and finally are used to control the muscles.

By intercepting and processing these electrical impulses by means of sensors placed on the skin we can acquire physiological signals.

The mental state can be correlated to the variation of the subject's physiological signals, which can be monitored by sensors.

In our case the sensor placed in contact with the skin is able to obtain 3 fundamental parameters:

- blood pressure;
- average heartbeat;
- GSR (Galvanic Skin Response), which is a tension measured on the skin [34-37].

The first two parameters are evaluated using a plethysmographic sensor [38-40].

GSR (Galvanic Skin Resistance) measures

the change in the electrical properties of the skin. It is calculated through the measurement of skin resistance through a weak constant current passed over two microelectrodes on the skin surface. The skin behaves approximately like a resistor. A voltage is generated between the two electrodes from which the skin's resistance can be calculated.

External emotional stimuli (a sudden noise, a phrase, etc.) or internal emotional stimuli, e.g. imagining frightening scenes, cause an alteration of electrical resistance in some skin areas, particularly at the palm of the hands and the sole of the feet. The sweat secreted by the sweat glands is probably the origin of the variation in resistance and conductivity, although vaso-dilatation and -constriction are also involved. Therefore the GSR measurement can be considered to be a simple and useful tool for examination of the autonomous nervous system function, and especially the peripheral sympathetic system. The measurement is relatively simple, and has a good repeatability.

The GSR transient response, called the psycho-galvanic reflex, has a characteristic waveform with a rise time of about 1-2 seconds and a longer fall time. GSR signals can vary in different individuals and situations and are best measured on the hand surface of the fingers, with typical values from 50k to 500kΩ/cm^2. Values above 200 kΩ are typical of relaxed individuals; if the subject is emotionally agitated, skin resistance decreases progressively.

For the intended use of the system we decided to use only the GSR signal, because it is faster variable than the pressure, whereas the heart rate is considered too much influenced by various internal or external factors (e.g. movement).

The sensor consists of a printed circuit that has many points of contact with the skin. The sensor is placed in close contact with the skin thanks to the plastic support in which it is encapsulated, which is inserted on the finger and fixed to it by means of a strap. The signals coming from the skin are filtered and acquired by the analog port of a microprocessor, that converts, normalizes and filters them with another digital band pass filter to eliminate any noise collected from the environment.

Then the signals are transmitted through a standard serial port to the computer, where they are processed by our software, written in C. The software acquires the signals from the device and process them in real time with an Artificial Neural Network developed *ad hoc*.

In the following the Artificial Neural Network procedure is analyzed.

The first necessary processing phase is the training phase, during which the system begins to acquire two samples of signals referred to two different mental states: a sample composed of mental states of relaxation and one composed of states of stress. This is achieved by presenting the subject sharply different sound/visual situations or by simply suggesting the subject to think about relaxing situations and breathing slowly for ten seconds, or vice versa to think about possible physical efforts accompanied by shortness of breath for another ten seconds. The system acquires the corresponding signals and makes them available for a comparison with the subject's future mental states.

This phase must be repeated every time the subject wears the sensor, because the variability of the psychophysical state can induce differences in the detected signals, which are processed in real time.

After the training we obtain two samples of signals, one potentially associated with states of relaxation and another potentially associated with states of stress. In order to process the data with the ANN, the filtered data are divided into sub-sections 2000 samples long. These sub-sections represent the input patterns to the ANN that will be used to train the ANN.

In this way the ANN stores configurations of neurons associated with states of relaxation (Value 0) and others associated with states of stress (Value 1).

In the meantime, the system continues to sample data from the sensor. After the training phase, the ANN is now ready to process signals in real time. Again, the signal is divided into patterns and applied as input to the ANN, whose output is the value of the current mental state of the subject (Fig. 1).

The comparison between the training signals and those acquired in runtime is achieved exploiting the characteristics of the ANN developed *ad hoc*, the ITSOM (Inductive Tracing Self-Organizing Map) [41,42].

The ANN model core is similar to the T. Kohonen's SOM (Self Organizing Map). We observed that the time sequence of the SOM winning neurons tends to repeat creating chaotic attractors that uniquely characterize the input that produced them. In fact at every epoch the new winning weight, along with the weight that won in the previous epoch, constitutes a second order approximation of the input value, and so on.

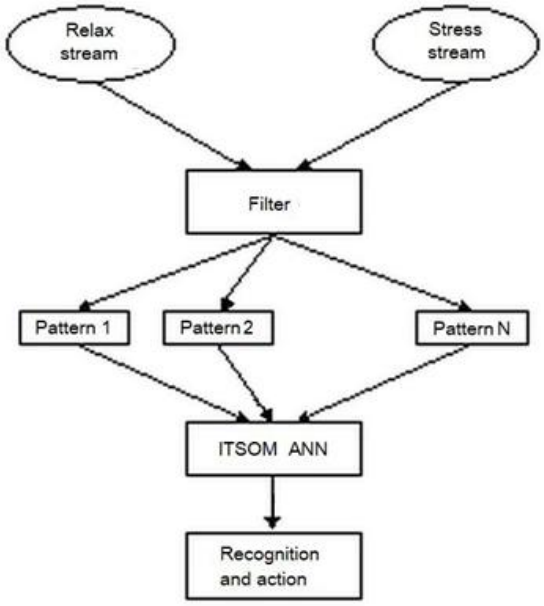


Fig. 1 - Flow-chart of the signal processing system

So it is possible to derive the input value by comparing the characteristic configurations of each input with a set of reference configurations, whose value is known.

In this way a real process of induction is realized, because once a vector quantization many-to-few from the input layer on the weight layer is carried out, a few-to-many step is operated from reference configurations to the whole input (Fig. 2).

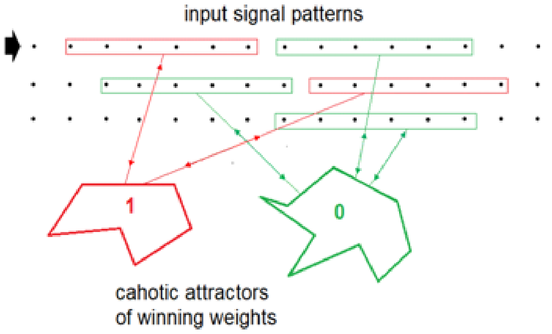


Fig. 2 - ITSOM ANN Architecture

In our case, the induction is produced in real time after the training by comparing the chaotic attractors produced by the time series of winning neurons during the training, coded in "0" and "1", with the attractors produced during the use of the sensor.

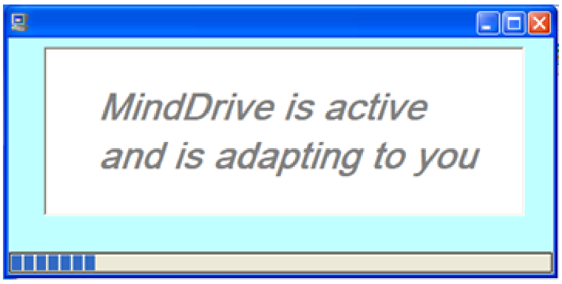
This is possible through a coding procedure of the attractors in the form of binary codes, easily comparable, carried out through a z-score procedure.

IV. APPLICATION

A graphic module allows the subject to autonomously manage different functions through the activation of the two signals "0" and "1" processed by the ANN in real time starting from the acquired signals.

The screenshots that the subject sees when the MindDrive is activated are shown below.

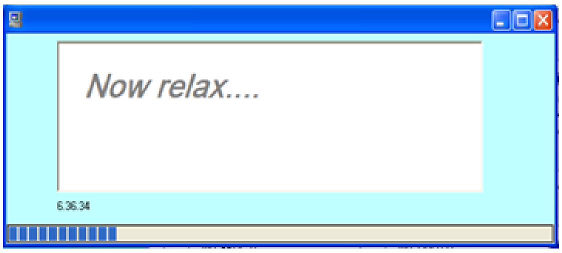
In Fig. 3 MindDrive indicates that it is beginning to adapt to the physiological signals of the subject.



MindDrive is active and is adapting to you

Fig. 3 - MindDrive is activated

Then the training phase begins: the subject reads that first he must relax. As before mentioned, the best results are obtained by presenting the subject peaceful images and sounds or just suggesting the subject to imagine a relaxing peaceful situation and to breathe deeply and slowly (Fig. 4).

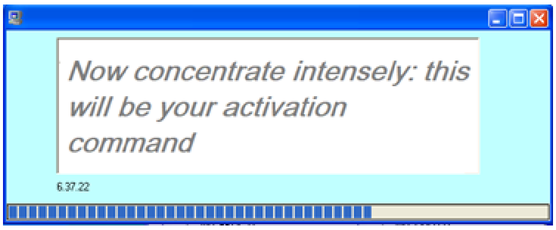


Now relax....

6.36.34

Fig. 4 - Relax training

After 10 seconds (Fig. 5) the subject is suggested to activate a strong mental effort. The best results were obtained presenting the subject stressful images and sounds or just by suggesting the subject to imagine a strong physical effort and to breathe quickly.



Now concentrate intensely: this will be your activation command

6.37.22

Fig. 5 - Stress training (activation signal)

Once the training phase is over, the system is ready to work in real time reacting to the subject's mental state.

To get started, a panel with four possible functions is displayed (Fig. 6).

Fig. 6 - System Dashboard

A red flashing light passes every four seconds from one frame to the other, and the subject can give its activation command when the flashing light illuminates the selected frame:
Writing, Yes/No communication, Alarm communication, Switch.

The subject selects a frame, that becomes green and activates a corresponding panel.

A slider, adjustable by a helper, allows the system sensitivity tuning, balancing the accuracy of the choice with the ease of activating the control.

The Switch function (Fig.7) allows the subject to turn on and off electrical devices that must be interfaced with the software: bulbs, TV, computer, etc..

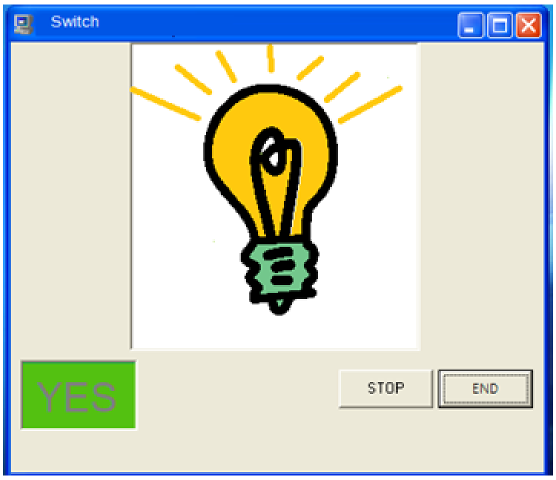


Fig. 7 - Switch function

The Alarm function (Fig. 8) can be connected to a beeper in another room or in other location.

Fig. 8 - Alarm function

The Yes/No function (Fig. 9) allows the subject to communicate with an interlocutor who asks a question: if she/he activates one of the three possible commands (YES/NO/MAYBE), the answer will appear in the large box below, and the interlocutor can read it.

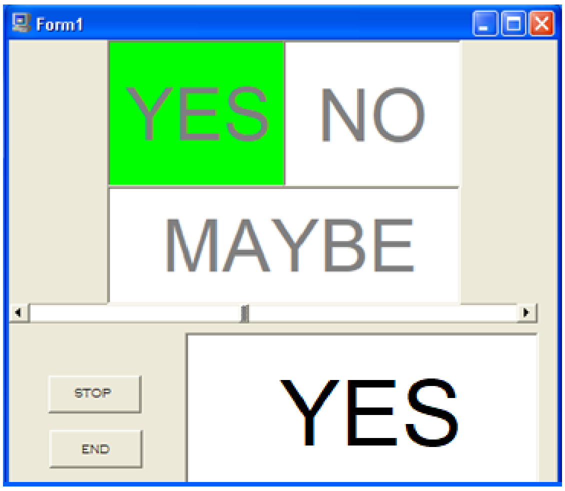


Fig. 9 - YES/NO function

Finally, a prototypal writing system (Fig. 10) allows to choose the letters, which are accumulated on the bottom lines.

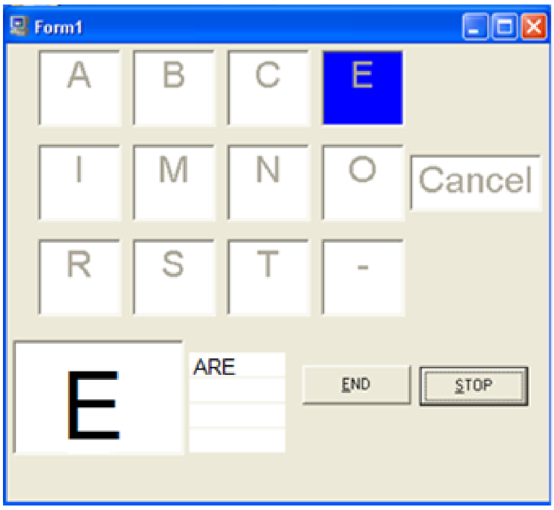


Fig. 10 - Writing system

V. CONCLUSION

Although prototypal, the system has been successfully tested on three tetraplegic anarthric children undergoing therapy in the Department of Developmental Neurology at the Istituto Neurologico Carlo Besta in Milan. The children actually managed to activate the buttons, with great enthusiasm on their part and on the part of their parents.

The next step is to move from the prototype to an engineered functional system, that is easily expandable to provide:

- A complete and functional word processor, possibly applicable to a speech synthesizer
- An interface to various external devices: domotic devices, wheelchair joysticks, PC environments, mobile phone, etc.

In particular, the group has developed a system devoted to disabled persons that allows the full management of any PC environment with a unique command [43] (Fig. 11).

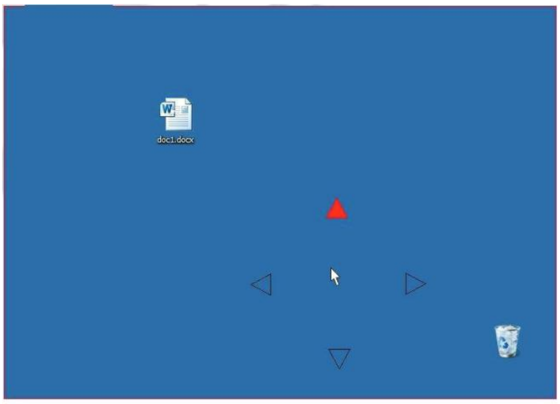


Fig. 11 - The mono-command system emulates the mouse click

Applying this software to the BCI system would allow to make available not only a complete and functional writing system, not bound to a slow and frustrating scanning input system, but also all full computer related activities, from the web environment (with social media, study and work possibilities, documents, real time information etc.) to all the available software applications, that allow, among others, IoT functions for remote interacting with any device and environment.

The system could also, with an appropriate interface, be used in biofeedback applications. Biofeedback instrumentation is often used to induce rapid and deep relaxation in the treatment of anxiety, phobias, panic attacks and generally in the therapy of all the most common somatizations, such as headaches, gastritis, ulcers, and in general for pain management. The advantage of this system would be its low cost and portability, which makes it easy to use at the patient's home, thus making it possible to enhance the therapeutic effects compared to the biofeedback instruments currently used in hospitals.

An important improvement of the system would be the simultaneous use of many different physiological parameters without increasing the size and cost of the device, in the light of recent developments in technology, which provide commercial low-cost sensors for the detection of physiological parameters, used also on fit-bands and smart phones.

Recent researches by our group have shown that the same ANN model has been able to process simultaneous signals to discriminate between several mental states [44, 45, 46]: this method may be used to improve the performances of the described system, increasing the discrimination between several mental states within the acquired signals, therefore increasing the number of functions available to the subject.

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