Brain Human Interfaces

Gabriela ENE, Maria STANCIU
Bucharest University of Economic Studies, Romania
gabriela.ene02@gmail.com, stanciuu.mairaa@gmail.com

The interaction between human and external devices has reached new limits in the past decades. Brain Computer Interfaces require cross science learning and research, like computer programming, psychology, biology, design, and data mining. Direct interaction with human brain is possible through sensors that monitor the brain activity while performing various tasks. In this paper, we present the development done so far, the research methods, appliances in medicine and how systems can adapt dynamically to tasks required by the end user. We also analyze the impact and usefulness of such system in an economic environment, where the choices and decisions are made based on thoughts, comparisons, data series, data reports and many other factors, which need to be considered. In an economical system where efficiency is a requirement, cost reduction is necessary and making the right decision at the right time is the goal for any organization, implementation of brain human interfaces would be revolutionary.
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1 Introduction

Brain Human Interface **(**BCI) represents a communication system that allows a person to send an electronic command only through the voluntary variations coming from brain activity [1]. This term refers to an interface that takes signals from the brain and delivers them to an external hardware device.

Different types of brain-computer interfaces have been developed over time for different purposes. Some of the oldest BCI were used only for registration of brain activity signals. The first real BCI applications were neuro prostheses developed for the restoration and improvement of senses and functions such as hearing, sight and movement.

Due to the remarkable plasticity of the brain cortex, the sensors as obtained through natural stimuli, after adapting them to be handled by the brain, can assimilate signals from implanted prostheses. The ultimate goal of direct interfacing brain-computer is to enable an individual suffering from a disease that affects a motor function of his body to obtain effective control over a hardware that replaces the motor function simply by controlling his brain.

Such an interface would increase the person's independence, leading to an improved quality of life. Despite the rapid evolution since the occurrence and deepen this area in the 90's until now, the BCI field still remains an unexplored area of research.

The brain is the most complex known human part of the body, so the simulation of brain functions in an automated system is not the easiest task, but we are on track, thanks to the numerous achievements already made.

The aim of the paper is to outline the research and discoveries made in cognitive neuroscience and to present the progress made so far in brain imaging, along with the implications brought in medicine. The study of analyzing physical processes that are associated with a specific thought is based on signal processing and monitoring.

Brain imaging helps researchers to observe the electric, chemical or blood changes that happen into the brain when neurons communicate with each other. By studying those images, we can infer different cognitive processes that happen in the brain, at a specific moment.

2 Literature Review

During the lately phase of BCI development, all classification methods were based on algorithms that use an initial phase of training, so after the training phase, the algorithm can recognize or identify a state of mind. Of course, using those algorithms, we can see only a mental state, but we cannot see how the algorithm has concluded so that we can gather knowledge. These types of algorithms behave as a black box, we can only see inputs and outputs, and their processing is unknown.

An indistinct system (fuzzy system) allows us to view connections made to reach a conclusion, so data can be interpreted, and we can get insights into brain activity. This is the characteristic of interpretability of the data gained by using a fuzzy system.

The first experiments of electroencephalogram (EEG) on humans were conducted by Hans Berger in 1929 [2], and since then, the idea that brain activity could be monitored and be used as a channel of communication opened new horizons of research.

First recording device of Berger was made of silver foils affixed to the patient's head. The test results did not offer great and detailed information, but it was a start for brain signals recording. The dual-coil galvanometer Siemens device was more documented and it led to success, so electroencephalogram would allow the study of the brain activity. However, in 1973, the first prototype of BCI appeared, created by Vidal [3].

In the late 90's, the field of brain human interfaces started to gain more interest from researchers and great discoveries were made. More and more laboratories have begun to develop research studies in this area. Different types of interfaces were proposed and tested since then, many of them in the medical field.

Currently, researchers started developing another type of brain-computer interfaces, which are still at a theoretical level, but represent a ground for artificial intelligence development. The main goal is to load all the brain functions into a BCI, which would lead to the existence of a disembodied brain.

Designing a BCI requires hard work and information gathered from multiple fields of expertise. It requires knowledge of neurology, engineering, programming and signal processing.

"In principle, the activity of the brain, from the basic sensory functions to moving ability, decision-making capacity and memory functions are based on the micro-volts electrical pulses generated by the action of billions of neurons" [4].

If all or, at least, a part of the neurons action would be recorded then, at a theoretical level, ongoing brain activity could be stored and analyzed.

The electrical activity originating from the billions of neurons is propagated not only in the dura - matter membrane and skull, but also it propagates on the surface of the scalp, making it possible to register non-invasive interfaces and interpreting neural electrical signals.

However, captured EEG signal on the scalp is a blurred version of the local potential within dura matter.

In addition, eye movement, for example, or in general, any muscle activity that is recorded at the same time leads to a more contaminated signal, making it impossible to make a relevant and direct interpretation of such signals.

In the context of BCI, the challenge to interpret noisy EEG signals is even harder because a BCI system requires real-time processing on-line.

3 BCI Types

There are several types of Brain Human Interface:

- *Invasive BCI*: For the most part, they were aimed for repairing damaged sight and providing new functionality to paralyzed people. An invasive BCI is implanted directly into the gray matter during a neurosurgical intervention. The signal quality is very good, because it is focused only on critical areas, in areas that gather information so that the signal is not disrupted. A disadvantage of this method is that each foreign object within the body is treated as an enemy, so these types of BCI are prone to scarring of tissue. This will make signal weaker in time and it is possible to completely disappear. Of course, the main drawback is that this procedure carries a high degree of risk for the patient due to the neurosurgical intervention.
- *Partially invasive BCI*: These kind of BCIs are implanted inside the skull but not

inside gray matter. This will prevent scar tissue. The signal is weaker than a BCI invasive, but better than a non-invasive, because the skull will not divert the signal.

- *Non-invasive BCI*: The electrodes are placed over the skull, with no need for surgery. This type of interface is the most common nowadays because there is no risk for the patient, but the received signal is very diffuse and in the same time it can be deviated from the skull.
- *Dependent BCI*: These kind of interfaces assume that patient controls some of his motor functions during testing, but for severely paralyzed people who can not control movement functions, this is not a solution. Training and saving mental states is mandatory for dependent interfaces.
- *Independent BCI*: Motor capacities are not required, so an independent interface is suitable when patient movement is impossible due loss of motor functions control.
- *Synchronous interfaces*: Using a synchronous BCI, the user can interact with the application concerned only in a specific period of time imposed by the system.
- In this case, the user can execute a movement, only when a stimulus (visual or audible) appears. If the motion occurs within the time specified, the user will have a feedback, otherwise nothing will happen. The main advantage of synchronous interfaces is that we will always know when a movement happens and we have an image of a signal representing a movement task. The main disadvantage of this interface is that the user is held to perform a motor function only in a certain time, so this interface cannot be implemented with a long-term scope.
- *Asynchronous interfaces:* In this case, the user can perform a task whenever he wants and the interface must respond accordingly. This is also called a "self-paced brain computer interface.

The principle that lies behind this method is that the interface permanently examines the brain in order to determine if the user performs a task. Of course, when performing a task, the interface must decide what kind of task is performed (to interpret correctly the stimuli, process the signal and reach a correct conclusion), therefore, the complexity of an asynchronous interface is much higher. The design of this type of BCI is one of the main objectives set for the next research years, because it really is a major challenge.

A common qEEG-based BCI system consists of important components:

- Intent sent by the brain(“encoding”),
- Control command received by a computer algorithm „decoding”,
- Feedback received in real-time
- Decoding represents the kernel of a BCI system, connecting the brain with external devices.

There are three representative steps in the whole process:

- *EEG acquisition*
- *EEG signal processing*
- *Pattern classification*

In neuron-based BCI, the voluntary intent of the person is direct. If the person wants to move his arm along on a desired trajectory, he just needs to think that he is controlling his arm [6].

In an EEG BCI system, the information contained in EEG is not enough due to noisy signal received. Usually, the control command, like moving the arm has assigned a specific mental state beforehand.

The person needs to imagine the corresponding mental task to “encode” the command, either through attention shift or by voluntary regulation of his EEG.

Different types of EEG signals exist:

- Sensorimotor Rhythm [6],
- Visual Evoked Potential (SSVEP) [7],
- Slow Cortical Potential (SCP) [8],
- P300 [9]

Among these, sensorimotor rhythm and slow cortical potential types can be adapted by the subject's voluntary intent after training, whereas the visual evoked potential and P300 can be modulated by the subject's attention shift. Actually, the implementation and research of the EEG-based BCI paradigm is largely about how to help the BCI user to express (“encode”) his voluntary intent efficiently. The more efficient the subject's brain encodes voluntary intent, the stronger the target EEG signal is and the decoding will be more efficient.

4 BCIs development

The control interface of a BCI is a component that translates control signals produced by a neural signal into semantic control signals to operate a device [15]

Usually two phases are required in the development of a brain-computer interface:

- *Offline phase* represents an initial phase, a phase of training that allows a researcher to gather information about the system, allowing him then to calibrate it. This step is necessary because each individual has a different brain response to a stimulus, and data gathered is different from individual to individual. This phase is implemented by training the patient, see the reactions to different stimuli and record the brain activity.
- *Online phase* represents a later stage implemented when training is conducted and completed and data on brain activity responses is complete and consistent.
  The interface is used to recognize different mental states and turn them into commands for external devices.

The online stage usually consists of six steps in this order:

1. *Measurement of brain activity*: this step consists of measuring brain activity (for example, a technology for measuring EEG).
2. *Preprocessing*: EEG signals have incorporated a lot of disturbance, so this phase involves cleaning redundant data and analyze the correctness and accuracy in order to increase the signal strength that interests us.
3. *Extraction of characteristics*: the stage where only the features extracted from the received signals are kept for future processing. After this phase, the data collected will be more accurate and adapted to the purpose.
4. *Classification*: in this stage, the developer assigns a class to a set of features extracted from the analyzed signals. This class corresponds to an identified mental state.
5. *Translation in a command*: after identifying the class, a command representing the class is given to an external device.
6. *Feedback*: this step gives the user feedback on the state of mind that has been identified. This aims to help the user to control brain activity.

The entire CBI architecture is summarized in Fig.1

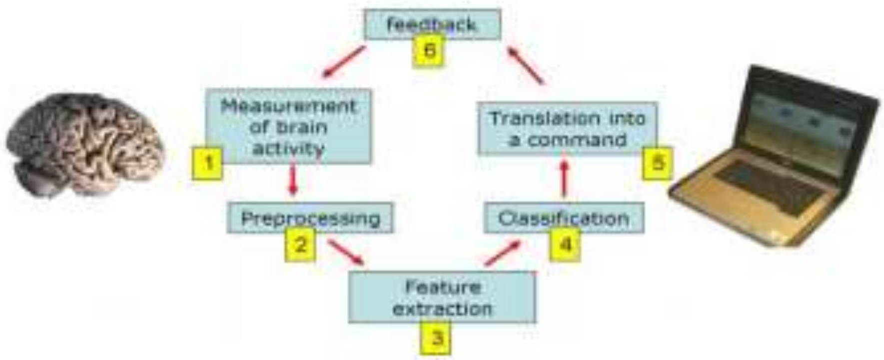

Fig. 1 The CBI online phase

Electroencephalograph measures generated electrical activity by the brain using electrodes placed on the scalp. The man who invented this technique is Hans Berger in 1929 and named this technique electroencephalogram. EEG signals recorded had a very low amplitude of the order of microvolts, so the signal needed to be amplified before processing it.

The measurements are carried out with electrodes attached to the head in a number from 1 to 256, pointing to various areas of the scalp.

Electroencephalography (EEG) has the greatest potential to study the non-invasive interface, mainly due to timing resolution, ease of use, portability and low cost, but as every good thing comes with some disadvantages, as well, EEG signal is very sensitive to disturbances and an interface using electroencephalography always comes with an extensive training period for the subject before the user can exploit real results from it.

The goal underlying to any interface is identifying more specific neurophysiological signals of motor activities and to assign a command to each of these signals (models of the brain).

These signals are divided into two main categories:

1. *Evoked Signals*, which are generated by the user in response to a stimulus, unconscious. They are known as Evoked Potentials (EP)
2. *Spontaneous signals generated* voluntarily by the subject without receiving any stimulus.

4.1 Evoked signals

An evoked potential response is an electrical potential recorded in the nervous system of a human or animal after the presentation of a stimulus, distinct from the spontaneous potential detected by EEG, EMG or other electrophysiological recording method. These kind of systems based on EPs have been studied for a long time since the 1970s. This is because it is easy to set up such a system and it has a fast transfer rate of the gathered information and the period spent for the user training is reduced [10]. The research focused on BCI signals visually evoked (VEP), because it is easier for the user to perform a motor function as a response to a visual stimulus. VEPS mechanism reflects the visual information processing mechanism in the brain. On a large scale, there are three types of stimuli used: *diffuse light flashing*, *chessboard*, and *grid type patterns*. In the field of BCI research, the most popular type is chessboard.

Placing electrodes is a very important step in order to get the best results.

International Society for Clinical Electrophysiology Vision (ISCEV) recommends specific standards for testing VEP namely: electrode placement system after 10 to 20 system [11].

The active recording electrodes are placed over the active source, which for the visual evoked potential signals is the cortex. A reference electrode is placed on a surface that does not respond to visual stimuli, and the base electrode is connected to a second inactive terminal of the device. The electrical signal is recorded from the scalp.

To extract information from the experiment, average repeated responses have to be used. VEPs are blocked for some time on a stimulus so, when a stimulus is presented to the subject, the time after electrical activity in the brain should change is known. Evoked potential signals of small amplitudes (1-20 μV) are incorporated into larger potential amplitude signals.

According to the knowledge of electrophysiology, VEPS with corresponding low rates of stimulation are classified as transient VEP (TVEP) and ones with corresponding rapid repetitive stimulation are classified as steady state SSVEP. VEP introduces transient responses of the visual system, but using long channels in order to stimulate a response. An equilibrium (steady) response is obtained, which can be estimated from the average, resulting the SSVEP. Potential signals to steady state are distinguished from the transient potential, as constituent components of discrete frequencies that remain constant in amplitude. SSVEP has the same fundamental frequency (first harmonic), but usually they also include SSI or higher subharmonics.

P300 is a very extensively response studied in the field of BCI, because it appears that this occurs in response to a significant stimuli, or a stimulus that is quite rare [12].

For example, if the subject is presented a list of names, and every 7 seconds his name appears, a value of P3 is instantiated because it was registered a significant stimulus. P3 wave latency is 300-1000 milliseconds, hence the name P300. Latency depends on the complexity of the stimulus. P3 amplitude is inversely proportional to the frequency of presentation of the stimulus material.

4.2 Spontaneous signals

Spontaneous signals do not depend on stimulation. A BCI system can use the spontaneous signals as input generated by a controlled signal issued by the brain activity at a certain time, depending on the classification of EEG patterns taken from a specific mental activity.
The most common spontaneous signals are sensory-motor rhythms. These are brain activities (rhythms), related to motor actions such as movement of the leg or hand movement. They are located mainly in the frequency ranges μ (8-13 Hz ≃) and β (≃ 13 to 30 Hz) and these type of rhythms amplitude can be controlled by the end-user, so there are two control strategies proposed to this phenomenon:

- *operand conditioning*
- *imaginary movements*

In *an operand conditioning strategy*, a subject can learn to voluntarily modify amplitude rhythms by a sensory-motor training. The user is free to choose his own mental control strategy. Feedback is the most important part of a system based on operant conditioning, because after feedback, the user can understand what it should be changed in mental activity to increase the control accuracy. The main drawback of this method consists of a long training period of the patient, but after the calibration of the system, very good results were observed.
For a user, *imaginary movements coordination and mobility* lies in imagining his own mental states while doing them. Imagining leg movements represents a spatial placement determined frequently and temporal features assumed. For example, imagining the left or right movement of a member is associated with an ERD (event-related desynchronization) to the opposite side during the movement and ERS (event-related synchronization) with the related side.
Using this feature, the type of task that the user is trying to imagine can be determined.
The advantage of such a system is that the user does not need a long period of training, and in some cases, it works on the first try, but the complexity of such a system is the main disadvantage.
This strategy uses techniques of signal processing and devices implementation with advanced algorithms.
All signals presented so far, have been successfully used in the design of brain-computer interfaces, but the problem is that no one can say that a signal is "better" than another in this area, because they all have advantages and disadvantages. Signals are evoked unnatural because they require the use of a stimulus. Spontaneous signals are natural and a user should be able to perform a mental task whenever he wants, but tiring, due to the long training. However, it has been demonstrated that the use and high-performance signal processing learning algorithms reduce the training period, which could be subsequently eliminated.
Imagining movement is an effective approach in the development of brain-computer interfaces.
The following step is to implement signal processing and machine learning algorithms. With fuzzy classification system user can understand the ways of functioning of the brain and adjust the interface to his needs, so they can learn, as well as automatic learning algorithms implemented on the device.

5 BCI applications in the field of economic informatics

The machine learning research, brain human interfaces and artificial intelligence are closely related to the notion of rationality. Generic representation of agents in an AI system is enclosed in entities that perceive the world (or an environment) and act in it [13].
The quality of a BCI model is guaranteed by the level at which the agent's actions model the objects of the environment, evaluating the actions and interactions on and with the objects after certain observed perceptions. The link and coherence of objectives, the methods of achieving these goals and understanding perceptions is the core of rationality.
If the objectives are determined according to the desired preferences, and the decision making process is outlined in uncertainty, then we

can assimilate an AI agent to a standard situation of making a rational choice simulating a real world environment.
Thus, within an AI system, the task of the system designer is to build agents that have a higher degree of rationality within a given context.
To some extent, the abstraction of the notion of rationality is a basis for the development of intelligent algorithms in a field like economy. Assuming that AI can build an agent that can interact with other AI agents, research can focus on AI systems that interact with other intelligent systems to carry out transactions, negotiations etc. Because such a system would be much more complex than the cognitive human level, AI-connected systems can implement interfaces that are more complex, more difficult task calculations, and the ability to predict economics evolutions and make economic decisions more effective and accurate.
The design of a rational AI agent obviously involves many technical challenges. From an economic point of view, the preferences, desires, motives of an economic agent are notions of a conceptual nature.
From the point of view of consumer theory, a customer choice is also influenced by these elements, which do not have a necessarily rational applicability.
A customer can make the decision of buying something even though there is not a real need for that. Representing an economic environment in which agents interact means considering such assumptions.
Therefore, in the development of an AI agent, the automation of calculations and operations according to environmental variables is the basis of such representation.
In this case, specialized literature talks about getting conclusions based on different premises. At the same time, the agent's preferences can be represented as probability distributions.
This approach is based on the Bayesian theory, according to which it is possible to know the probability of an event depending on certain conditions related to the known event.
Researchers in the field of machine learning have taken over from the animal welfare model, the reward model. Thus, they try to associate a certain state with a given action (it is intended to map the evolution sequences from a perception to a certain action), following the signal of receiving a reward after an action is done [13].
The probabilistic mapping method was greatly avoided 30 years ago, but today it is a much more commonly adopted technique due to the representation and deduction evolution used in the Bayesian networks [13].
Statistical approaches dominate the outline of machine learning algorithms.
If such an AI system can be built, it will need to be able to interact rationally with other such systems. These systems should work on a game theory approach, where each agent will rationally react to the behavior of other agents, so that joint decisions achieve a balance, similar to a standard economic system.
Specialist literature on game theory provides for numerous conditions in which various strategies approached as adaptations to different situations can lead to a state of strategic balance, which is why the games theory is a reference in the implementation of artificial intelligence systems, due to multiple methods of applying strategies according to a given context, as well as the impact of these strategies viewed as a series of actions on an environment defined by variables and conditions.
In a multi-agent system, one's AI behavior cannot be programmed independently, but following the definition of rules and conditions describing the activity of all the system's agents. The goal is to change the agent's behavior, to change the "rules of the game" by associating rewards with certain actions that bring some results. In general, it is intended to achieve objectives assigned to a whole system, such as maximizing total value, allocating effectively resources etc.
The objectives of the system could include, for example, promoting a resource allocation to maximize total value. Obtaining performance would be a goal for a whole system, not to design an agent to achieve singular performance through some action. A new approach is to introduce into the system some mediator-type entities that can interact with and act on

behalf of AI systems [14].
So given the early stage of research in the field of artificial intelligence and learning algorithms, BCIs can also have non-medical applicability, meaning that they can be used by perfectly healthy people to accomplish different tasks, which can be programmed to anticipate and understand the user's status and intentions.
At the same time, an application in the field of economic informatics would be to combine a human computer interface with human reason, intertwined with conceptual variables as: curiosity, preference, reasons that cannot be quantified and abstracted in a calculation algorithm.
Thus, such a device would facilitate problem-resolving tasks through the complexity of the interface and the computing power. Also, it would make possible to be sure on decision making effects and results, giving a higher degree of predictability in a well-defined context.
Improving performance is another direction of applicability of brain – computer interfaces, with the ability to solve multiple tasks at the same time. Decreasing the time of analysis of economic strategies, analyzing the effects of a certain movement on the economic equilibrium of an organization or a system with accurate results obtained in real time on the basis of prerequisites would improve the quality of life and the evolution of a system from an economic point of view. Another applicability would be the rapid analysis of large data sets (elimination of redundancy, extraction of necessary coefficients).

6 Conclusions

Although in the early stages of research, brain computer interfaces open a new approach to quality of life and improving life for people with medical problems. The high ranges of applicability of these technologies open up new development horizons in various fields, not only medical.
Active BCIs accumulates results from brain activity, as a result of a process that is consciously assumed by the user, and is not necessarily influenced by external events.
Reactive BCI allows focusing on stimuli from a particular system and evoking certain brain responses.
Passive BCI involves obtaining results from unconditional voluntary brain control activity in the field of facilitating human machine interaction by providing implicit information on the user's state.
The progress made in research and the evolution of wireless technologies, the development of signal processing and the development of learning algorithms allow the real-time monitoring of cognitive activity, attention and brain activity. The development of BCI technologies leads to a new level of notion of human-robot interaction and automation of actions based on certain brain stimuli.

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Gabriela ENE has graduated the Faculty of Cybernetics, Statistics and Economic Informatics in 2015. Currently is studying for Master's degree in Economic Informatics at the same university. Main fields of interest are big data technologies, artificial intelligence, web development, algorithms and data structures.

Maria STANCIU has graduated the Faculty of Cybernetics, Statistics and Economic Informatics in 2015 and this year will graduate The Master of Economic Informatics on Faculty of Cybernetics, Statistics and Economic Informatics. Main areas of interest are: cloud technologies, web development and machine learning algorithms.