IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 22, Issue 3, Ser. III (May - June 2020), PP 01-12
www.iosrjournals.org

High Accuracy of Brain Signals Predictions Using Electroencephalography

Carlos J. O. Santos[1], Rodrigo M. de Figueiredo[2], Sandro J. Rigo[3]
[1]*(Graduation on Automation Engineering, Unisinos University, Brazil)*
[2]*(Graduation on Electrical Engineering, Unisinos University, Brazil)*
[3]*(Graduation on Applied Computing, Unisinos University, Brazil)*

Abstract:
Background*: To accurately interpret the human brain has been a desire of humankind since the creation of the first device capable of reading its electrical impulses. The applications resulting from this knowledge can represent a significant advance in current technology for brain-computer interaction. A device called Electroencephalogram can read electrical signals from the scalp, and that signals can be treated and comprehended. Nevertheless, the literature in this field has some gaps to be fulfilled, mostly related to the signals processing and its efficient classification regarding human movements.*
Materials and Methods*: The objective of this research was to develop a method capable of receiving, processing, and understanding the electrical impulses of the brain related to different body movements, using an electroencephalography device with a non-invasive approach. To this end, a commercial electroencephalography device called Emotiv Epoc+® was used to capture brain signals. The obtained data is used in an artificial neural network, which can determine which movement was performed. We developed the pre-processing of the data using the Parseval Theorem as a contribution to this research, regarding the precision increase in data interpretation.*
Results*: The device created was able to determine, given a certain period, the movements with a high accuracy and performance.*
Conclusion: *This research also contributes by providing a method capable of predict with 100% accuracy movements from signals obtained with an electroencephalography device and how to manipulate the data to achieve such high accuracy.*
Key Word*: Brain; Electroencephalography; Artificial Neural Networks.*

Date of Submission: 22-05-2020 Date of Acceptance: 09-06-2020

I. Introduction

Living in a connected world in which concepts such as the Internet of Things (IoT) and AI (Artificial Intelligence) are becoming part of our everyday life, the human being perceives himself within a computerized environment, and his connection with the machines becomes more intimate in conjunction with the industry 4.0 revolution. The objective proposed in this project is to develop a stable system, which allows the reading and connection of the human brain to computers - developing a brain-computer interface - and, later, connecting this interface to other programs or applications that make use of signals collected. The development of this method allows higher speed in processes performed usually with a mouse and keyboard and make available to impaired people the convenience of using computer systems.

Some techniques already used today allow this brain signal reading operations and among them we find the electroencephalogram, a non-invasive exam widely used in the medical field for the diagnosis of brain diseases or abnormal neurological behavior. The electroencephalogram is one of the bases used in this work because, in addition to enabling the reading of brain signals by a non-invasive method, it also has an acceptable compatibility for the subsequent treatment of these signals.

As the general process of electroencephalography (signal capture - signal treatment - application development with the signal) is quite extensive, a commercial data capture device will be used to validate the development carried out so that, in this way, it is possible to direct the focus of this project to the improvements in the treatment of the signal itself. Once treated, it is possible to use this signal, for example, to send commands to external equipment such as mechanical arms and legs (examples of evolution in accessibility), to communicate the program with various other programs that perform direct contact with human beings (reading the level of emotions like happiness) or integrating it with digital games using movement readings. To read brain signals and send these data to the computer, an Emotiv Epoc+® will be used, a commercial EEG device which consists of electrodes connected to the scalp to capture electrical signals from the brain and these signals will be sent to the computer, which will receive this data, and enable the development of diverse applications.

The research was conducted entirely with open source tools such as the programming language Python and the ScikitLearn programming library. This contributes to the construction and sharing of a method to predict data using an artificial neural network (ANN) with high accuracy. The data read from the brain is manipulated with various methods which are capable to adjust it to a better format, resulting in better predictions from the ANN. This is regarded as the main contribution of this research. The device used during the data acquisition is portable and its specifications fit very well the objective presented.

The rest of this paper is organized as follows. During section 2, called Background, basic concepts necessary to contextualize the phenomena involved in the development of this project will be presented, besides other projects with related subjects. In section 3, called Methodology, the steps developed will be presented with diagrams and descriptions of the proposed system. In section 4, steps taken to validate this system, together with the experiments carried out, are presented, providing an analysis of what objectives have been achieved. Finally, chapter 5 will contain the conclusions and the feasibility analysis, along with future works indication.

II. Material And Methods

The method known as electroencephalography (EEG) consists of measurements of the electrical functions of the human brain performed by means of electrodes, which may be intracranial, implanting the electrodes surgically in the skull - a method called invasive -, or extracranial, placing these electrodes on the scalp - method called non-invasive -.Thus, it is characterized as a graphic visualization of a potential difference between two points in the brain, after some time (TATUM, 2014). Zeyu et al. (2018) explains that the electroencephalogram is an electrical signal generated in the cerebral cortex or on the surface of the scalp considered weak and of low amplitude and, therefore, difficult to obtain.

Nervous System

The cerebral cortex is part of the Central Nervous System (CNS) - the focus of brain signal uptake in this work - and it consists of two parts of the human nervous system, the brain and the spinal cord. The brain is located inside the skull and is subdivided into 3 parts: the brain, the cerebellum and the brain stem. The spinal cord is responsible for the diversification of signals from the muscles, joints and skin to the brain and vice versa. It is connected to the brain stem and the human peripheral nervous system. The Peripheral Nervous System (PNS) is another part of the human nervous system, acting in the transport of information from the muscles and glands in the human body to the central nervous system and vice versa. The central nervous system receives this information, analyzes it and performs actions based on these analyzes (BEAR, 2017).

To execute a movement, several regions of the human brain are activated, requiring an interaction between the control of sensations captured by the sensors and the coordination of the muscles that will perform the movement. These impulses are conducted by neurons, individual cells capable of transferring the necessary electrical potentials throughout the body. The transport of the necessary data for the body structures is characterized by the load generated traversing this structure until reaching its ends, certain axonal terminals. These terminals have several branches and in them the electrical signal that traversed the axon is converted into a chemical signal, being transmitted to another neuron via its dendrite and later transformed again into an electrical signal in a process called synapse. The dendrites receive several of these synapses, so in this way, if we use the axon analogy as the neuron's conducting wires, we can also use the analogy that the dendrites are the “antennas”, receiving the signals that arrive at a neuron coming from another neuron and thus propagating information. Multiple neuron dendrites and axons form the nerve, identified as the major conductor of electrical signals throughout the body (BEAR, 2017).

The process of creating electrical signals involves electrical reactions generated when electrical charges move through the nervous system. For these signals to be captured and treated by the computer, it is necessary that there are a considerable duration and amplitude and, thus, the EEG shows the continuous change of tension between different places of the scalp comparing the signals captured in the electrodes (TATUM, 2014). The selected electrodes are arranged in regions of the brain (anterior and posterior, left and right) and signals with an amplitude of few microvolts are detected. The output of these measurements forms parallel plots showing the voltage changes between these electrodes. These variations occur when currents flow in the cerebral cortex and generate tension since neuron dendrites are excited by this movement of electrical currents and the EEG, in relation to the biological issues of the central nervous system, measures these variations that occur just below the end of the skull (BEAR, 2017).

For potential differences to be detected, thousands of electrical contributions from neurons must be added, since, as the electrodes are placed on the skull, these signals need to pass through layers of tissue, fluids, bones and skin. Thus, the EEG has the limitation of better capturing signals that occur in the same periods of time: when several neurons are excited in similar periods, the generated signals add up and are captured.

However, when several neurons are excited at different times, the signals end up being small and irregular, and cannot be properly captured, thus indicating that the moment when the activity occurs is an important factor in this reading because it directly influences the amplitude of the electrical signal. For two signals that activate the same number of neurons, for example, different readings may occur, depending on their interaction with the time of occurrence. These singularities during the measurement of electrical signals influence the electroencephalogram, the method of collecting these data (BEAR, 2017).

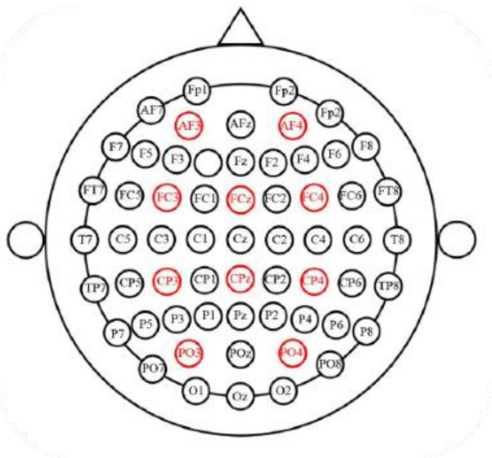
Electroencephalogram

The practice known as electroencephalography (EEG) is an evolution in medical engineering that has been commonly used since 1970, when the methods used were being discovered and two cameras were used on a split screen: one to capture EEG results with their waveforms and the other to monitor the patient. EEG is widely used for medical research and verification of the existence or not of mental illnesses, but it can also be used to obtain brain waves, that is, the functions that the brain generates, mentioned above. These brain waves are divided into five categories according to their frequency, which are:

- Delta, for values less than 4 Hz;
- Theta, for values between 4 and 7 Hz;
- Alpha, for values between 8 and 11 Hz;
- Beta, for values between 12 and 36 Hz;
- Gamma, for values bigger than 36 Hz.

Different states related to the human mind are related to different types of brain waves (RAMDINMAWII, MITTAL, 2017). These signals are obtained according to a standard positioning of the electrodes on the scalp, which is essential to avoid repetition in obtaining the necessary data on the EEG. The 10-20 international system is the most widely used positioning method, based on obtaining anatomical points distributed on the scalp, as shown in Figure 1 (SONG et al., 2018).

Figure no 1: Positioning according to the international 10-20 system.



EEG Equipment

This section will present commercial products that can be used in the electroencephalogram application. The study of this product's details contributes to this research allowing us to know better the specifications of the products available on the market. Thus, a comparison between them is valid to visualize the data in a succinct and easy to understand way. Table 1 shows this comparison and the values considered for this study. The table relates the product with positive and negative aspects, together with the perceived main differential.

Table no 1: Comparison of the devices studied.

Device	Positive Aspect	Negative Aspect	Differential
Emotiv Epoc+®	Portable for application	High market price	Autonomy of up to 12 h
Mark IV®	Open programming in codes	High market price	Reading up to 35 positions
MCScap Clinic®	Low price	Simple structure	Various sizes
EEG WaveGuard®	Quick application with labeling	High market price	Use of up to 251 channels
Electrodes Pray Med®	Copper wire core	Expensive materials like gold and silver	Labeling colors for cables
Electrodes disco	Low price	Less durable	Up to 1.5m

EEG BIOPAC®	Has own amplifier	Less portable by its wires	Easy and organized connection
VErGE®	Valuable for research purposes	High electromagnetic interference	Data in the order of mV and µV

With the data collected, we could verify opportunities with the current technologies for the construction of devices in the area of electroencephalography.

Related Work

In this section, other projects that have similar themes to this one will be presented. As the focus here will be on signal processing, most of the works commented on will also be in this segment, but complementary works that address capturing signals and focus on specific development of will be covered too.

The signals obtained during the application of an electroencephalogram are typically weak, being less than 100 µV and, in most cases, the equipment for collecting these data is large and difficult to operate. The project by Zeyu et al. (ZEYU et al. 2018) focuses on developing a simple EEG acquisition system with characteristics of being configurable, portable and with less energy consumption than those normally used. For this, the first characteristic of a normal EEG addressed for simplification was the design of the electrodes because, in standard exams, the application of thermal pastes by doctors on patients is necessary, which results in a long time. In this project, electrodes with porous material and with water absorption at the end were used, which facilitates the capture of electrical signals. In addition, a gold structure (meaning high conductivity) and a protective cap are added to these electrodes in order to obtain the best possible signal resolution (ZEYU et al. 2018).

The conclusion expressed by the developers was that, despite presenting problems with the electrodes created in relation to their durability, the signals read are acceptable and, as this product has characteristics of low energy consumption and portability, it can be applied in other areas of the medicine such as electrocardiogram and electromyography exams, also of great importance for identifying problems related to human health (ZEYU et al., 2018).

One of the possible applications for using the signals treated in this project is virtual reality: systems that can be applied for the detection, prevention and treatment of mental illnesses, and this is the focus of the work developed by Horvat et al. (2018). During this development, a commercial device was used to capture the three-dimensional space around the user and detect the movements performed during its use. In addition, movements of the headset itself are considered during its rendering, so that it is possible to simulate the movement of the user's head and move the camera within the virtual reality simulation.

With this project it was possible to recognize the feasibility of using the electroencephalogram in virtual reality in detecting emotions, for example. Portable commercial devices such as the presented can be reconciled to obtain acceptable and stable results, although not comparable to those obtained in laboratory devices, since simple movements such as discomfort due to using a device can also influence the measurements performed (HORVAT et al., 2018).

The EEG system, as a human-machine interface, aims to develop applications, for example, for people with brain problems, whether for voice control, movements or external prostheses. The project presented here aims to develop a human-machine interface based on electroencephalography and verify that, depending on the movement and speed of the eyes, different waves can be read. In addition, this developed interface should be fast, simple and with the possibility of being applied to real devices (MALEKI, MANSHOURI, KAYIKÇIOĞLU, 2018).

With the objective of producing a non-invasive, fast, simple and asynchronous method of human-machine interface for reading EEG signals, the project mentions, as possible applications, moving a wheelchair or driving a car, decreasing the negative effect of brain diseases (MALEKI, MANSHOURI, KAYIKÇIOĞLU, 2018).

According to Ramdinmawii and Mittal (2017), the human brain is a complex network of nerve cells with different connections and the communication between this large network is given by electrical signals called brain waves. These signals can be captured by an electroencephalogram device and divided into five main frequencies: Delta (<4 Hz), Theta (4 to 7 Hz), Alpha (8 to 12 Hz), Beta (12 to 36 Hz) and Gamma (> 36 Hz), and certain human behaviors reflect different frequencies within the ranges seen above. For the study seen here, the behavior of music in brain waves will be studied with differentiation between genders, thus verifying the brain's response to each of these.

In the project developed by Chen, Gao and Wang (2016), the objective is to identify human emotions using signals read on an EEG, in addition to peripheral signals. The union of these two capture methods becomes a tool for recognizing emotions, using the verified data to compare with patterns and obtain human states as a result. For peripheral signals, electro-oculography, electromyography, electrocardiogram, skin responses and temperature, breath measurements and, finally, plethysmograph signals were used. For the EEG signals, the data obtained with a passband filter with a lower cutoff frequency of 0.3 Hz and a higher cutoff frequency of 45 Hz were processed and, later, these obtained frequencies were separated into Theta, Alpha, Beta categories. and Gamma. Thus, the data read in two groups of experiments was joined while watching videos for stimulation. At the end of their project, the authors compare their results with other measurements made in related works, concluding that the method of joining several peripheral measurements with the electroencephalogram results in outputs consistent with the verified emotions.

Table no 2: Comparison of the related work studied.

Authors	Area	Description
ZEYU et al. 2018	Simple EEG acquisition	Low cost device equipment with good configuration and low energy usage
HORVAT et al., 2018	Capture three-dimensional space around user	Usage of a commercial device combined with considering head movements on virtual reality
MALEKI, MANSHOURI, KAYIKÇIOĞLU, 2018	Human-machine interface to detect eye movements	Fast and simple project to capture different waves depending on the eye's movement and speed
RAMDINMAWII, MITTAL, 2017	Music in brain waves	Capture different brain waves according to the music user is listening
CHEN, GAO, WANG, 2016	Identify human emotions	Combine EEG with several other methods (electro-oculography, electromyography, electrocardiogram, skin responses and temperature, breath measurements and plethysmograph signals) to understand emotions

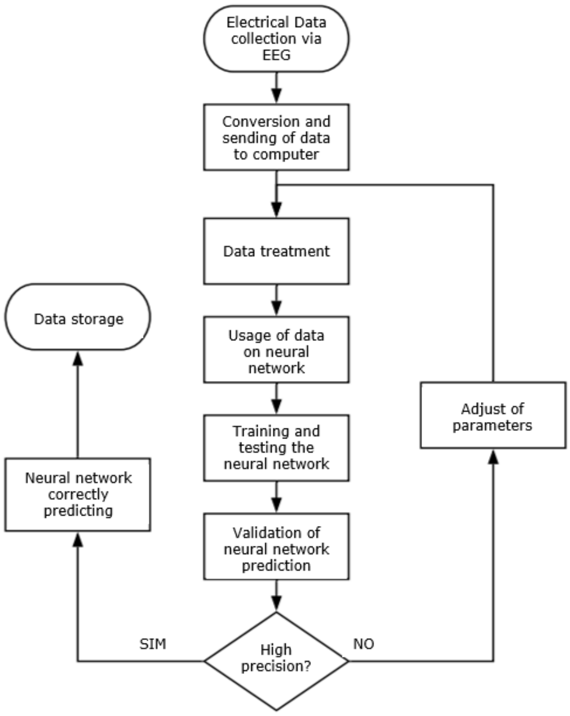
During the next chapter, the methodology used to achieve this research objectives will be presented.

Methodology

In this methodology section, we present the procedures that were performed, the descriptions of each step and how, technically, these steps were connected. In addition, the instruments used were determined according to their capacity and compatibility with the characteristics required in the project.

An overview of the steps adopted can be seen in Figure 2, showing a complete flowchart with the steps contemplated in the project. The first action in this process is the capture of electrical signals. In this stage, a commercial equipment was used and the signals that will be later treated were obtained. The second stage includes the initial part of the treatment of these signals on the computer, receiving the signals from the EEG device, converting and reading the signals to direct them to the next stage, in which the final treatment was carried out. These steps on the computer were developed in a programming environment with the Python language, used to create an application to transform the signals making them suitable for training an artificial neural network that will learn the movements and later present predictions according to test data. Finally, the last step contemplates the comparison of these data provided by the artificial neural network with the data carried out in the practical experiment, making it possible to carry out an analysis of precision and reliability of the results obtained. In this step, the accuracy of the network can be viewed and analyzed on the computer screen, indicating the direction of movement and informing the accuracy of the test performed, enabling the user to define whether the training of the neural network was satisfactory.

Figure no 2: Project flowchart.



In the flowchart, we can see the steps described in the block diagram and an adjustment step, to determine the parameters of the neural network and ensure that the variables used to treat the data contribute to a high precision in the network predictions.

Signal capture with EEG device

To carry out the first stage of the project, that is, to capture electrical signals on the scalp, the equipment used has the characteristics of an item mentioned in the equipment research, the Emotic Epoc+®. An image of this equipment available for purchase by the manufacturer Emotiv® can be seen in Figure 3.

Figure no 3: Emotiv Epoc +® EEG device used.

This component has as its main premise an easy use and configuration with professional results. Its main characteristics can be verified below (EPOC, 2018).

- 14 monitored channels;
- Quick setup, between 3 to 5 minutes;
- Salt-based sensors, making the use of conductive gel unnecessary;
- Wireless connection;
- Portable with battery up to 12 hours;
- 9 motion sensors to detect different head movements.

As can be seen in Table 2, it has 14 channels for reading the scalp, in addition to two reference channels. These channels are classified according to the international 10-20 system (SONG et al., 2018).

Table no 3: Classification of EEG cap.

Channel	Position
1	AF3
2	F7
3	F3
4	FC5
5	T7
6	P7
7	O1
8	O2
9	P8
10	T8
11	FC6
12	F4
13	F8
14	AF4
Ref1	P3
Ref2	P4

At the time of data acquisition, the equipment was mounted on the head of a voluntary for this project and quickly configured, following the equipment's characteristics. For the measurements, four movements were used: move the arms to the right, to the left, up and down, as shown in Table 3.

Table no 4: Measurements performed.

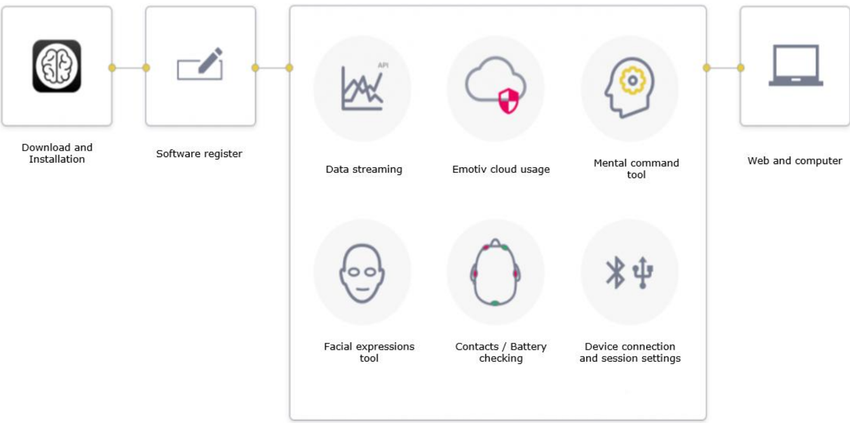
Measurement	Movement performed	Time and topology
1	Move your arms to the right	Movement performed for 10 seconds, moving your arms and returning to the center repeatedly
2	Move your arms to the left	Movement performed for 10 seconds, moving your arms and returning to the center repeatedly
3	Move your arms up	Movement performed for 10 seconds, moving your arms and returning to the center repeatedly
4	Move your arms down	Movement performed for 10 seconds, moving your arms and returning to the center repeatedly

After collecting the data, a new step was necessary: converting this data into files that can be accessed by the program that was developed. In the next session, the details of this conversion are presented according to the characteristics of the used electroencephalogram device.

Conversion of acquired signals

The conversion of the signals acquired during the measurements is carried out by Emotiv Epoc+®. To read the signals captured by the EEG during the experiments performed for data collection, the Cortex® software, API developed by Emotiv®, was used. In this software it is possible to check the variation of the 14 channels in real time, which allows a quick configuration and the guarantee that the signals are not being influenced by external factors such as magnetic fields existing in the measurement room, for example. An outline of the features available in this software can be seen in Figure 4, which details options such as use in the cloud, facial expression tool and mental command tool.

Figure no 4: Cortex Software.

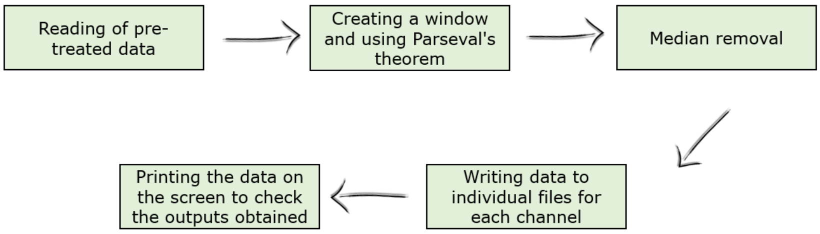


A monitoring window was created while the movements were executed for 10 seconds. After taking the 4 different measurements, the output provided by the program was cataloged according to the handled side, exported in CSV data format and shared with those involved in data collection. This data export was performed directly in the program, since the EEG device is connected to the computer via wireless network, as detailed in its specifications. These data then served as a basis for the program developed and for the training of the neural network that should predict the movements.

Data processing

After the stage of data collection and separation, some techniques were implemented so that these data were in the necessary format to serve as an input to the artificial neural network used. We can see which procedures were used in the diagram in Figure 5, which illustrates the steps taken during the treatment of the acquired information. First, the reading of the pre-treated data (that is, the files obtained directly from the Cortex program, generated in CSV format) was performed, storing the information in an internal data frame. After that, a parameterizable window with a value of 1000 was created so that with this window it was possible to detect peaks in the input data. The data were then divided into ranges of 1000 samples, according to the parameterized size, and in these data the Parseval Theorem was applied (IWASAKI, 2020).

Figure no 5: Block diagram of the data processing step.



To better identify the system's peaks, Parseval's theorem was used. This theorem says that the total energy of a system, in a wave form and throughout the time of observation, is equal to the total energy of the Fourier transform of the same system, adding all its components. To apply the Parseval Theorem to the data, the sum function of the Numpy library was used, raising all the values of the window to the square and adding to find a result, in terms of power, for the parameterized window. In addition, the median of 1000 values were calculated, and this was subtracted from the power value found. This made it possible that unnecessary data in the signal worked were eliminated, focusing only on the peaks, part that is essential for a good training of the artificial neural network.

This process was performed for all input data, resulting in a new data set that was again exported to files in XLSX format. This time, the files were exported individually, that is, each of the 14 channels generated a file and this was repeated for the 4 directions measured in this project. With the data ready, the matplotlib library was used to generate a graph, comparing the data in potency (when applying Parseval's theorem) and the data without the median. An example of these graphs can be seen in Figure 6, where in the data without median the peaks are more evident and consequently more suitable for the next stage of training the neural network.

Figure no 6: Comparison graph of channel AF3 for the 'up' movement.

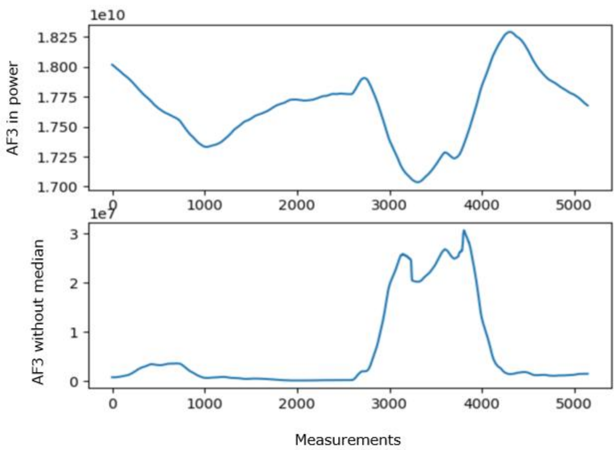
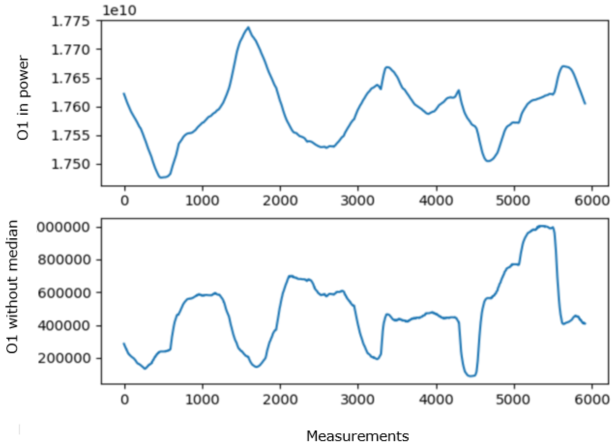


Figure no 7: Comparison graph of channel O1 to the 'right' side.

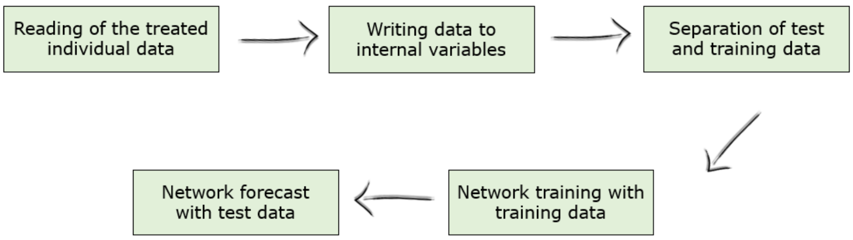


In addition, the treatment of the data enabled a comparison between the channels from a correlation point of view: it was possible that some of the channels had a high correlation with each other (for this project, the value of 85% was defined as the limit). If there were cases where two channels were above this correlation limit, one of these channels would be disregarded, since they would have the same information to train the neural network. However, during the tests performed, there were no cases of correlations above the limit.

MLPClassifier neural network training

After processing the data, the stage of construction of the neural network that should predict the movements is necessary. For this, the Scikit Learn library was used because it contains several tools for data modeling and because it contains a ready-made artificial neural network, the MLPClassifier. This network was then trained according to the steps obtained in the previous steps, identifying parameters to present predictions later. In this step, the steps highlighted in the diagram in Figure 8 were developed.

Figure no 8: Block diagram of neural network training.



According to the diagram, the first action for training the network was to read the data previously treated, these being individual for each of the 14 available channels. These data were then transferred to internal variables, where they could be manipulated with the Scikitlearn library. Using the function train_test_split from this library, these data were separated into two sets: the first, containing 20% of the available information, became a set for testing the neural network. The second, containing the remaining 80% of the information, will be used for training. The data from all 14 channels and all directions were merged to perform these steps, since the network must receive data from any direction, understand and predict the informed direction.

With the data ready, the artificial neural network was trained. The amount of three layers were used, containing 30, 20 and 10 levels each, in addition to a maximum of 500 iterations. These layers received this configuration according to a pattern exposed in the experiments performed. Initially, the value used was 10 levels per layer, but after several tests the new value proved to be much more effective for the neural network. The data captured by the EEG served as an input, as well as an additional column indicating the respective direction to each of the measured sides. On figure 9, data from the obtained channels is presented after the processing performed.

Figure no 9: Data after processing performed.

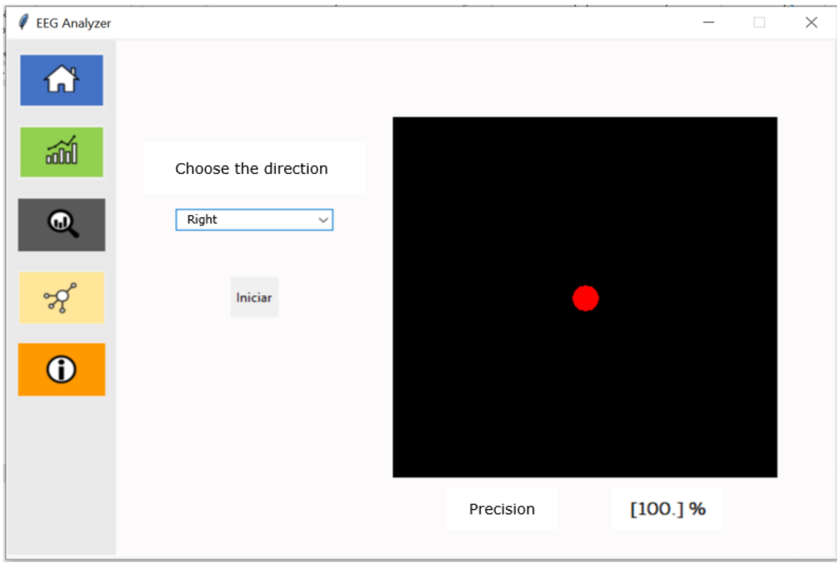
	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
0	4227,692	4221,539	4228,205	4201,539	4207,692	4263,077	4229,744	4222,051	4228,718	4232,308	4180,513	4202,051	4265,128	4215,384
1	4225,641	4219,487	4224,615	4200,513	4212,82	4274,872	4229,744	4220,513	4226,154	4228,205	4182,051	4202,564	4259,487	4218,461
2	4224,615	4216,923	4221,025	4201,025	4217,436	4280,513	4229,744	4220,513	4226,667	4226,154	4181,539	4202,564	4254,359	4220,513
3	4225,641	4215,384	4220,513	4202,564	4219,487	4281,539	4230,256	4222,051	4229,23	4227,692	4178,461	4202,564	4251,282	4220,513
4	4227,692	4214,872	4222,564	4204,103	4217,436	4280	4231,282	4223,59	4232,308	4232,82	4173,333	4202,564	4251,282	4218,461
5	4228,718	4215,384	4225,641	4204,615	4214,359	4277,436	4231,795	4224,615	4235,384	4237,436	4169,23	4202,051	4253,846	4215,384
6	4228,205	4216,923	4226,154	4204,103	4212,82	4273,846	4231,795	4224,103	4235,897	4238,974	4167,179	4201,539	4255,897	4213,333
7	4226,667	4217,949	4225,128	4204,103	4215,897	4268,718	4231,282	4223,077	4234,359	4234,872	4168,205	4202,564	4255,897	4212,308
8	4224,615	4217,949	4223,59	4203,59	4222,051	4262,051	4230,256	4222,051	4231,795	4227,692	4169,23	4204,103	4252,82	4211,795
9	4222,564	4216,41	4222,564	4202,564	4227,692	4254,872	4228,718	4221,025	4229,744	4221,539	4169,23	4205,128	4249,23	4209,744
10	4222,051	4215,384	4221,539	4201,025	4230,769	4251,282	4227,179	4220,513	4228,718	4219,487	4167,692	4204,103	4245,641	4206,667
11	4223,077	4214,359	4220,513	4200,513	4229,744	4256,923	4227,179	4219,487	4228,205	4221,025	4166,154	4202,051	4244,615	4203,59
12	4224,103	4214,359	4220	4201,539	4226,154	4272,308	4227,692	4217,436	4227,179	4223,077	4165,128	4201,025	4245,641	4202,564
13	4224,615	4214,872	4220,513	4202,564	4224,615	4292,308	4228,205	4216,41	4225,641	4224,615	4166,667	4201,539	4248,718	4203,59
14	4224,615	4216,41	4221,025	4203,077	4225,128	4309,23	4227,692	4216,41	4224,615	4225,641	4168,718	4202,564	4252,308	4205,128
15	4224,615	4217,949	4221,025	4202,564	4227,179	4318,974	4226,667	4217,436	4225,641	4226,667	4170,769	4203,59	4253,333	4205,128
16	4224,615	4218,974	4219,487	4202,051	4227,692	4322,564	4225,641	4217,949	4227,179	4226,667	4169,744	4204,103	4250,256	4203,59
17	4224,103	4218,974	4217,436	4201,539	4225,641	4325,128	4225,128	4217,436	4227,692	4225,641	4166,667	4204,103	4244,615	4201,025
18	4223,077	4217,949	4215,384	4201,539	4222,564	4330,256	4223,59	4214,872	4226,667	4224,103	4164,615	4203,077	4241,025	4201,539

After the data is processed, we can notice it is labelled by channel (columns) and measurement (lines). This ensures it can be easily manipulated when programmed on Python. Each measurement generated thousands of lines and is divided into the channels, which values are based on the device reference. There is one file per movement performed and those files were joined when used as test/train for the neural network. When performing this training, all the data was used as input and the output is always referenced to the exact moment captured (one output per line).

Comparison of neural network predictions

With the trained neural network, the predict function was used to check what the response of the network would be depending on the test input. In addition, a user interface screen was created, where it would be possible to check the percentage of accuracy of the network. This percentage was measured by comparing how many results were correct in relation to the total number of data, since the network must predict one side for each measurement portion of the EEG device - for reference, more than 16,000 lines were generated for each side measured, meaning 16,000 individual network forecasts and more than 30 MB of data collected. An image of the developed interface can be seen in Figure 10.

Figure no 10: Data after processing performed.



On the presented screen, we can check the interface created to determine the neural network predictions. On the left menu, there are options to navigate through each screen, in this order:

- Home: Initial screen to input the data collected from the electroencephalography device;
- Data Processing: This screen is used to start applying the processes implemented to modify data for a better output on the neural network;
- Network training: To start the training of the neural work based on the preprocessed data.
- Predictions: To select a movement and check what is the precision of the neural network when predicting that movement.
- Information: Screen presenting the interface information such as version, author and university.

When predicting on figure 10, user have an input box to choose which movement will be predicted. When the process starts, the red circle moves to the side predicted by the neural network, and when it is over the precision is displayed on the screen.

During the next section, the results of the network forecasts will be presented, allowing an analysis in relation to the precision of the obtained output.

III. Result

During the development of this research for the treatment of signals obtained via electroencephalogram, an application was developed, and this application can predict, with the help of an artificial neural network, the movements made during the data capture. The development obtained can be analyzed in relation to three points:

- Technical performance analysis: To check if it would be possible, within technical limitations, for the project to function properly and within its specifications;
- Financial feasibility analysis: To verify that, even with good functionality, the project will not become too expensive to be valid;
- Analysis of performance in relation to time: To verify that the project would not take too long to be executed, in order to make it unfeasible or impossible.

Therefore, the topics mentioned above are analyzed below, highlighting possible advantages and disadvantages and raising points of improvement to be mentioned later.

The first step to be analyzed in this section of the work will be technical performance, thus verifying whether it was technically possible to achieve the objectives defined during the project. It is verified, therefore, that according to the references studied and the base projects consulted, the work is technically feasible, since the steps carried out using open programming libraries and well-known languages. Python programming makes it possible to use a wide variety of libraries and therefore applications that can be developed. The use of the computer adds several possibilities and one of these was used, Visual Studio Code, having several tools suitable for the execution of the project, being free and configurable together with Python. This combination of tools and the fundamentals, logics and methods of the programming language used provide elements that make the elaboration of this project possible.

For the analysis of financial viability, it is possible to verify that the project does not prove to be cheap, since, as previously mentioned, it uses adaptable devices and has expensive resources, such as the EEG cap, available at the university where the project was carried out, and the computer. In the case of purchasing the equipment for the elaboration of the entire project from scratch, it would still not characterize a work with high cost, since only the cap would be specific for this application, while the computer could be used for other applications, even in the health area. Regarding the use in this project, the necessary set for the application and execution of the desired objectives is found to be viable.

Finally, for the analysis of time, it is concluded that this would be the biggest limitation of the project. During the methodology and the analysis of results, the time required for a complete data forecast (sum of reading, processing and forecasting times by computer) was verified. In addition, the time taken to assemble the equipment is 5 minutes during the data collection and export to CSV files. The table 4 presents how much time was required for each task.

Table no 5: Time for each step.

Step	Average time
Data collect	100,354 s + 5 minutes for preparing the device
Data reading	58,537 s
Data training	1092,905 s
Neural network training	7,333 s
Neural network predictions	0,0722 s
Total	1.559,2 s = 25.986 min

In this way, the total time of 25.986 minutes or 0,43 hours can be considered high for this application, where quick responses are necessary to develop projects and systems that operate in real time.

IV. Conclusion

Brain data collecting and artificial neural network training are terms very often used in this research. Those dimensions are explored during the experiments performed, from which we can conclude a high precision can be obtained when working with the presented scenario. A commercial device was used to collect the data, and preprocessing methods were used to make this information clearer to the artificial neural network. Therefore, preprocessing stage was carried out applying Parseval Theorem as one of the overall improvements in data manipulation before the use of the ANN for the movement's classification. This classification included steps with test and training inputs and was designed to provide an output with high accuracy, adjusting the network parameters to obtain the best scenario.

As an improvement of the project, the time issue discussed above should be the main factor. The application works well for reading data and forecasts, with high precision, so that time was the only aggravating factor in this development. One can think about using devices with greater processing capacity or optimize the code with libraries that assist in performance as methods to decrease the time required for each execution, in addition to some libraries that use only one standard of data processing.

This work contributes with techniques involving programming and computational methods to predict movements capturing the signals from the human brain, thus demonstrating that it is possible to predict combinations of these signals with anticipation and develop technologies to understand a greater range of movements.

In addition, as indication of future works, it is possible to go deeper into issues such as emotions, intentions and several other areas of study in-depth in understanding the signals generated in the brain.

Acknowledgments

To achieve the results presented on this project, many assistances was obtained from several people and labs. As a first mention, a special thank you for the coordination of the Control and Automation Engineering course at Unisinos University. His support was fundamental to structure and follow the right steps during the development of this project. On the same university, the coordination from the Applied Computing course for Master and PhD helped a lot with valuable inputs and precise comments.

Also, a thank you for the colleague Lucian Joseph, which is developing his doctorate degree at the same university. This colleague was responsible for helping to capture the electrical signals from the brain with activities such as performing the data collection with the author and helping using the API used. Apart from this, thank you also for the Electrical Engineering laboratory from Unisinos University for all the support during this development.

References

[1]. BEAR, M. F. Neurociências: desvendando o sistema nervoso. 4. Porto Alegre: ArtMed, 2017.
[2]. CHEN, S.; GAO, Z.; WANG, S. Emotion recognition from peripheral physiological signals enhanced by EEG. International Conference on Acoustics, Speech and Signal Processing: IEEE, 2016.
[3]. EPOC. Emotiv Epoc+. Emotiv, 2018. Available on: <https://www.emotiv.com/epoc/>. Accessed on Oct 11th, 2018.
[4]. HORVAT, M. et al. Assessing emotional responses induced in virtual reality using a consumer EEG headset: A preliminar report. 41st International Convention on Information and Communication Technology, Electronics and Microelectronics: IEEE, 2018.
[5]. IWASAKI, A. Deriving the Variance of the Discrete Fourier Transform Test Using Parseval's Theorem. IEEE Transactions on Information Theory: IEEE, 2020.
[6]. MALEKI, M.; MANSHOURI, N.; KAYIKÇIOĞLU, T. Fast and Accurate Classifier-Based Brain-Computer Interface System Using Single Channel EEG Data. 26th Signal Processing and Communications Applications Conference: IEEE, 2018
[7]. RAMDINMAWII, E.; MITTAL, V. K. The Effect of Music on The Human Mind: A Study Using Brainwaves and Binaural Beats. 2nd International Conference on Telecommunication and Networks (TEL-NET): IEEE, 2017.
[8]. SONG, C. el at. Augmented reality‑ based electrode guidance system for reliable electroencephalography. Biomedical Engineering Online [Biomed Eng Online]: BioMed Central, 2018.
[9]. TATUM, W. O. Handbook of EEG Interpretation. 4. New York: Demos Medical, 2014.
[10]. ZEYU, W. et al. A Multichannel Reconfigurable EEG Acquisition System Design with Felt-based Soft Material. International Instrumentation and Measurement Technology Conference (I2MTC): IEEE, 2018.

Carlos J. O. Santos, et. al. "High Accuracy of Brain Signals Predictions Using Electroencephalography." *IOSR Journal of Computer Engineering (IOSR-JCE)*, 22(3), 2020, pp. 01-12.