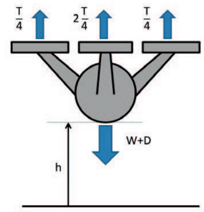
Classification of brain signals for RPAS control in the treatment of attention deficit hyperactivity disorder



Clasificación de señales cerebrales para el control de RPAS en el tratamiento del trastorno por déficit de atención e hiperactividad

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RESUMEN

- El Trastorno por Déficit de Atención e Hiperactividad (TDAH) se caracteriza por la dificultad en procesar la retroalimentación del estado actual de concentración de un individuo. Una de las principales líneas de investigación en el tratamiento del TDAH es el uso del Neurofeedback electroencefalográfico (EEG) como un medio de proporcionar una cuantificación y representación del nivel de concentración. Esta investigación constituye un primer paso en el desarrollo de una aplicación de un sistema aéreo no tripulado (RPAS) que ayude en el tratamiento del TDAH haciendo uso de una interfaz cerebro - ordenador, que se base en las medidas detectadas por un sensor EEG. Estas medidas modifican la altura de vuelo de un cuadricóptero de acuerdo con la evaluación de la señal. Para desarrollar el sistema propuesto, se ha diseñado una aplicación en tiempo real para procesar y clasificar los artefactos electrofisiológicos. Finalmente, las señales procesadas son enviadas al controlador de la aeronave, que modifica la altura de la misma función la deseada retroalimentación al usuario.
- Palabras Clave: BCI; drone; RPAS; EEG; TDAH; Neurofeedback; machine learning; red neuronal.

ABSTRACT

The Attention Deficit Hyperactivity Disorder (ADHD) is characterized by a difficulty in processing feedback regarding the current state of the concentration of an individual. One of the main lines of research in the treatment of ADHD involved the employment of electroencephalography (EEG) Neurofeedback as a means of providing a quantification and representation of the concentration level. The current investigation constitutes a first step in developing an application of Remotely Piloted Aircraft Systems aiding in the treatment of ADHD employing a Brain Computer Interface, based on the measurements detected by an EEG sensor. These measurements modify the flight height of a quadrotor according to the signal evaluation. In order to develop the proposed system, a real-time mechanism for processing and classifying the electrophysiological artifacts has been developed. Finally, the processed signals are then fed into the aircraft controller, modifying the aircraft flight and thus providing the desired feedback to the user.

Key words: BCI; drone; RPAS; EEG; ADHD; Neurofeedback; machine learning; neural network.

1. INTRODUCTION

Nowadays the Brain Computer Interface (BCI) technologies are in full swing, but the idea was born many years ago. The first scientist who demonstrated that the brain produces electrical current was dated on 1920s [1]. In fact, the concept of electroencephalography (EEG) was born nine years after that discovery [2]. From that point, the EEG has become a tool to better understand the neural processes, pathologies and, also, for studying correlations of cognitive functions. Evolving from this concept, one of the main lines of research in EEG has sought to perform an adequate processing of the information contained in these signals so as to develop a communication channel between a human brain and the environment [3]. This reference showed that certain features of EEG could be controlled on purpose by a human after the corresponding training, which resulted in the birth of Neurofeedback.

In last 30 years, the field of BCI has drawn the attention of an increasing number of researchers. By the way, the rise of the capacities of calculation processing of computers has caused that machine learning techniques are considered a key tool for classifying EEG signals. There are many different strategies to classify signals based on machine learning algorithms, but one of the most relevant strategies is deep learning [4]. This strategy has limitations, but its usage is extended because it helps the researcher to process a big data set and extract conclusions from that in a shorter period.

The applications of BCI are so diverse and from different nature [5]. Focusing in the treatment of ADHD through Neurofeedback application [6], some studies indicate that this technique can complement perfectly the habitual pharmacological approximation of this disorder [7]. In fact, several patented and commercial products deal with the use of Neurofeedback for this and other proposals, both medical and for entertainment [8].

Precisely, the combination of BCI capacities with the versatility of applications associated to Remoted Piloted Aircraft Systems (RPAS), has caused that the researching on the viability of controlling a drone making use of BCI techniques has grown during last years [9]. Therefore, the study proposed in this paper is the first step to design a Neurofeedback application, specifically developed for the treatment of ADHD, starting from the state of the art of the current BCI technologies. The use of Neurofeedback for the treatment of ADHD is not extended, neither the given feedback by the existing technologies is mature yet. Thus, this study proposes to give the feedback through the control of a quadrotor RPAS. Concretely, the feedback corresponds to the height hover flight of the quadrotor, which changes depending on the level of focus of a given patient. This paper presents how the process of the signal needs to be carried out in order to control the drone. Because of this study is not focused on the neurological part of the project, a similar brain signal than the concentration one has been selected in order to develop the study. It has been decided to choose the alpha rhythm because it has already used for Neurofeedback applications [10], and some studies reveal that these frequencies are activated while the subject is doing cognitive tasks, which is directly related with the level of focus of the patient [11]. In addition, alpha rhythm can be stimulated closing the eyes, thus it is an easy way to check the validation of the application developed in this study.

2. PROCESSING AND CLASSIFICATION STRATEGIES

2.1. BRAIN COMPUTER INTERFACE METHODOLOGIES

TA Brain Computer Interface is a system that allows a human to interact with the environment by control signals generated through electroencephalographic activity. To do that, these systems are based on five stages of processing: signal acquisition, signal improvement, feature extraction, classification and transmission to the control interface.

The first stage of acquiring the signal oversees receiving the brain signals through certain electronic equipment that allows to get the physiologic phenomena that the study is focused on. Among several techniques, the EEG is the most used because of it has lower risk for the individuals to whom it is applied, its higher temporal resolution and its relatively lower cost. The main drawback is the low quality of the signal because the origin of the signals is in the neurons and they must cross the cranium, the scalp and other layers.

The next stage is to improve the quality of the signal. The goal is to erase all the effects not directly related with the EEG activity, so that the EEG signal is clear. This stage becomes more difficult if the frequencies of the noise fonts and EEG signals are in the same band. Part of this noise can be reduced making use of an ultrasound gel, that improves the electrical conductance between the human skin and the electrodes.

The next step of a BCI application is the feature extraction. The aim of this stage is identifying the discriminative information in the brain signals and generating a joint of characteristic parameters that describe that information. These parameters are called features, and their selection and consequent extraction is not an easy task.

Once the features have been extracted, they must be passed to a classifier algorithm. It tries to recognise the kind of brain activity according to the features selected previously. The classifiers algorithms need to be trained in order to adjust the internal parameters for obtaining more accustomed results.

The final stage of a BCI application is to send the information to the control interface based on the results of the classification phase. This stage is specific for each application.

Figure 1 sums the BCI application developed in this study. The diagram represents the control loop through which the brain signal can control a system, in this case, a quadcopter. The loop is closed when the individual perceives the movement of the RPAS according the kind of EEG signal generated in his brain. This signal suffers a pre-processing phase in order to allow to better extract the features. After that, an algorithm decides if the signal contains the features in enough quantity and it classifies the signal in different categories. Depending the category reached, the command and control block sends the corresponding orders to the quadcopter.

This study has been carried out with the aid of an open source certified hardware called OpenBCI Cyton [12]. The final objective is to develop an application to identify if the subject is concentrated or not, in order to give the feedback to him/her. As it has been exposed in the Introduction, the team has decided to use the alpha-signal as testing signal, because its similarities with the concentration one. The alpha-signal is excited when the subject closes his/her eyes, so this process has two main advantages: the signal is like concentration signal and it is easy to label in the training phase, just registering if the subject has his/her eyes opened or closed. When the

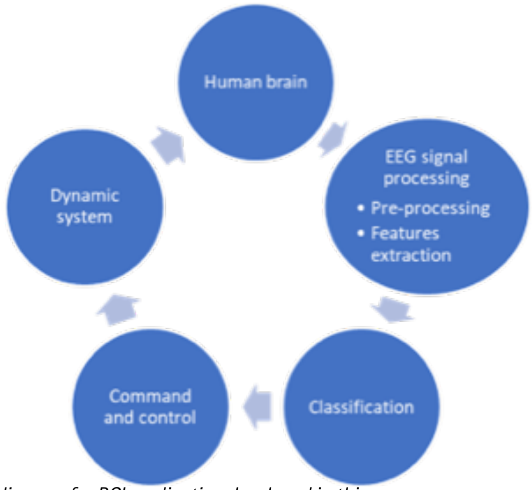

Fig. 1: Block diagram for BCI application developed in this paper

alpha-signal is excited, the energy associated to its frequency band, between 8 and 12 Hz, increases. In order to measure the alpha-signal with the board, it is only necessary to use one electrode located on the back zone of the cranium.

2.2. EEG SIGNAL PRE-PROCESSING

The application must identify if the channel is measuring an increase of alpha-signal to classify if the subject has the eyes opened or closed. In order to develop a real-time application, the classification must be based on the last N data samples received by the sensor. N should be as low as possible, in order to reduce the width of the time window that is used for the analysis of the signal. On the other hand, N should be large enough so as to represent the relevant features of the EEG signal. The drawback is that the alpha-signal is a low frequency EEG effect, so it is necessary to register enough data to be identified. The most ambitious objective is that the program be able to process the classification algorithm in a lower time than the next sample is received, that is the maximum overlapping.

Once the overlapping degree has been selected, the next step is to choose the algorithm to pre-process the signal and extract the features. In this study, the pre-processing has been carried out through Wavelet Transform. The main difference with Fourier Transform is that Wavelet Transform uses functions that are well localized in both the time and the frequency domains. Amongst the possibilities, it has decided to use the Morlet Wavelet. This wavelet is composed by a complex exponential function multiplied by a Gaussian window (Figure 2).

2.3. CLASSIFICATION AND TRAINING

The last step is to determine the number of wavelet functions used to extract the features and their central frequencies. It has been decided to take a distribution of frequencies that follows a logarithm scale. This rule is not arbitrary such as it has been demonstrated that several physical systems follows this behaviour. Experimentally, it has been decided to extract 26 frequencies located in the band between 7.4 Hz and 42 Hz, where the alpha-signal is contained for all the people.

The strategy followed for classifying the signal based on the 26 features extracted by the Wavelet Transform is training a neural network. This network used for classifying the brain signal has a typical architecture for pattern recognition problems in order to classify inputs into a set of target categories. In this case, two categories has been selected: opened-eyes and closed-eyes. Because of the model requiring a numerical value of the output, closed-eyes has been assigned to 1 and opened-eyes to 0.

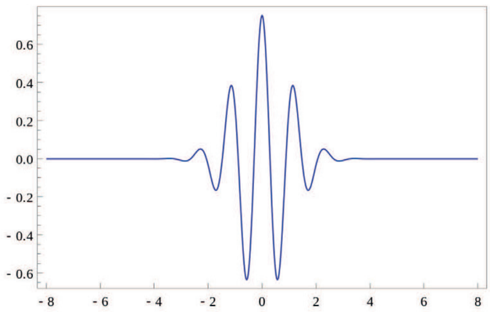

Fig. 2: Wavelet Morlet example

The main properties of the neural network selected for this study are the following:

- Pure feedforward scheme.
- 26 inputs, 1 hidden layer with 10 neurons and 1 output.
- Hidden layer function transfer: hyperbolic tangent sigmoid function.
- Output function: soft max function.
- Sets: the samples are divided randomly into three sets: training (70%), validation (15%) and testing (15%).
- Training process: scaled conjugated gradient backpropagation.
- Objective function: cross-entropy error.

To sum up, the training process is as follows:

1. The electrodes are located and connected to the patient.
2. The application collects data for five minutes, alternating the subject opened-eyes and closed-eyes according to the indications of the program, in order to give enough data for the neural network training process.
3. The application extracts the features through the Wavelet Transform strategy.
4. The resultant features are used to train the neural network. Perhaps, several training processes are needed if the accuracy is not good enough.

After this training phase, the application is prepared to determine if the subject has the eyes opened or closed, according to the alpha-signal. This can be used to control a physical system. For instance, this could be used to control a quadcopter drone flying in hover to increase its altitude. In this way, the system gives the subject a feedback of the state of his eyes, depending on the drone increases its altitude or not.

3. SIMPLIFIED QUADROTOR DYNAMIC MODEL, COMMAND AND CONTROL

In order to demonstrate how to integrate the outputs of the classification process with the control of a drone, a simplified model of a quadrotor has been developed. The objective of the autopilot is to use the results of the classification to control the altitude of the aircraft. If the subject stays with the eyes opened, the autopilot

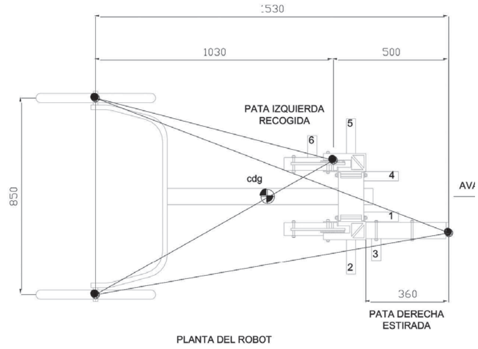

Fig. 3: Hybrid robot plant (dimensions in mm.). Stability

commands the drone to hover at a determined height. On the other hand, if the subject closes his eyes, the drone must climb until reached certain height and stay there while the subject has the eyes closed. Thus, the dynamic system has been developed assuming that the movement of the aircraft has just one degree of freedom, which is the altitude of the drone *h*. The dynamic system is based on the schema pictured in Figure 3, where *W* is the weight of the aircraft, *T* is the total thrust of the motors under the hypothesis that the four of them developed the same thrust in this simplified unidirectional model, and *D* is the aerodynamic drag of the drone. Thus, it is possible to say that the thrust only depends on the vertical speed v=dh/dt and the control parameter. It has been decided to take as control parameter the revolutions of the motor, *n*.

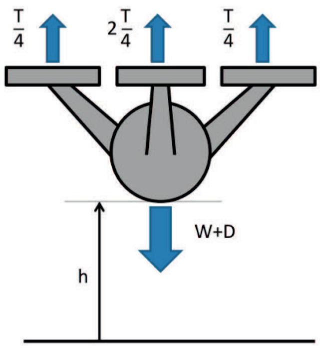

Fig. 3: Schemae of the dynamic system representing the quadrotor

In the case of this study, the drone is a quadrotor manufactured by SOLARDRON, which is a small Spanish company. Therefore, the final simplified dynamic equation for this drone is:

$$d\Delta v/dt = -0.691\Delta v + 0.204\Delta n \quad (1)$$

where the units of Δv are m/s and in the case of Δn rev/s. The actual model of a drone in order to control the real aircraft must be more detailed. However, this model is enough for the objectives of this study, because only a simulation of the dynamic of the quadrotor is enough to demonstrate the viability of the research.

Once the model is reached, it is necessary to develop a system whose objective is to guarantee the vertical position of the aircraft depending on the brain signal. This autopilot has been designed through the PID strategy, which generates control commands from the addition of three terms: Proportional, Integral and Derivative. In the case of the quadrotor considered in this study, the height associated to opened eyes is 1 meter above ground and to closed eyes is 2 meters. Thus, the resultant values of the PID coefficients are: kp=35, kI=5 and kD=20.

4. RESULTS

4.1. CLASSIFICATION SUCCESS

The first aspect to analyze is the quality of the classification following the procedure exposed in this paper. For that proposal, it is necessary to explain the concept of confusion matrix. It is a table in which the rows represent the possible outputs reached by the neural network and the columns represent the actual output that may be reached. Therefore, when reached and target outputs coincide, the network provide a positive estimation. However, if they do not coincide, the result corresponds to false estimations. The confusion matrix provides the number and percentage of true positives, true negatives, false positives and false negatives. In the case of this study, there are only two possible outputs of the network: 0, corresponding to opened eyes, or 1, corresponding to closed eyes. The confusion matrix has been built with Matlab software, and it is showed in Figure 4 corresponding to that obtained after five minutes training.

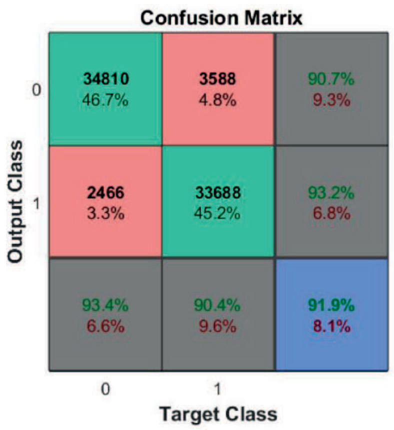

Fig. 4: Confusion Matrix after 5 minutes training, being 0 the case of opened eyes and 1 closed eyes one.

Analyzing the values of the last row of the confusion matrix, it is possible to say that the model predicts in a worse way when the subject has his eyes closed than when he/she has his/her eyes opened. Anyway, both cases present an error under 10%. This last row measures the recall of the application. On the other hand, the accuracy of each category is showed in the last column of the confusion matrix. In this case, it is higher when the network predicts that the subject has his/her eyes closed than when it says that the eyes are opened. Finally, the last cell of the matrix with the background in blue represents an average success considering the recall and the accuracy.

These classification errors are acceptable from a neurological standpoint, because the brain signals are not "black or white". There are many interference sources, interdependent processes, hence a certain degree of uncertainty is assumed. However, from the standpoint of the control of the drone, these errors are more relevant. If the dynamic of the quadrotor is quick, which is this case, the variability of the results suppose that the aircraft is continuously going up and down so fast, in accordance with the output of the classification process (Figure 5).

This behavior does not correspond to the speed of the brain processes that are studied in this research. The alpha-signal associated to the state of the eyes changes slowly, so it is not expected that the drone can change its position very fast. Thus, one possibility is to include a low pass filter after the classification process. The transfer function of the filter needs to be selected considering also the dynamic of the quadrotor to be controlled. In this way, the commands sent to the aircraft will not be so abrupt and the movement of the drone will be in accordance with the signal brain behavior.

4.3. CLASSIFICATION DELAY

In line with the previous section, there is the time that the algorithm needs to realize that the state of the eyes has changed. For measuring that, after training the network, several tests have been carried out registering the output of the algorithm and, simultaneously, filming a video of the face of the subject. Thus, a comparison between the real instant of opening or closing the eyes and the instant when the application decided that the state has changed is available. The averages of these intervals are included in the Table 1, for both cases and in two tests.

The second test was developed after finishing the first one but without retraining the neural network. In both tests, the average delay associated to open the eyes are lower than the corresponding to close the eyes. This fact is related with the brain processes. After the subject has closed his eyes, the brain takes some time to synchronize the neurons until the amplitude of alpha-signal increases. However, the inverse process of desynchronizing is faster. Because of that, the algorithm takes more time to identify that the eyes are closed than the eyes are opened.

Action	Test 1	Test 2
Closing eyes	2.15 s	3.77 s
Opening eyes	1.72 s	3.02 s

Table 1: Average delays for two tests

Another relevant conclusion extracted from the obtained delays is the differences between the results of the two tests. As it has been exposed previously, the second test was carried out without retraining the neural network. So, the differences are caused by the signal received in the application. This variation of the signal can be caused by the losing of effectiveness in the electrode connection.

One explanation is the loosing of ultrasound gel, which is necessary for reducing the noise in the communication between the brain and the electrode. Another possibility is that the brain signal generated during the training process is more similar to the signal generated in the first test than the one generated in the second, because they are nearer in time. This result is very interesting, because it opens the researching to determine how much time after the training process the network is valid, the algorithm stops working and a new training process is needed.

4.3. QUADROTOR BEHAVIOR

The behavior of the aircraft has been simulated for a unitary step input in the case of neglecting the signal noise, on one hand, and, in the other, the case of considering the noise associated to a typical ultrasound sensor.

The time in reaching the commanded height is around one second, with a maximum vertical speed of 1m/s approximately. In addition, the maximum overshoot is 17 cm, which is under the maximum admissible. On the other hand, the behaviour of the aircraft considering the noise is quite similar to the results reached neglecting it, fulfilling the initial criteria established for the autopilot design.

5. DISCUSSION AND CONCLUSIONS

The success rate of the classification obtained with the methodology presented in this study is adequate to the proposals of this research. The goal was to demonstrate that Neurofeedback technique can be carried out providing the feedback with a drone. The analysis of the alpha rhythm associated to the action of having the eyes opened or closed has been a perfect choice for demonstrating the viability of the technique. The behavior of this signal is expected to be like the concentration one, and the drone has been capable to change its flight hover height according to the level of the alpha-signal energy.

Going in depth into the procedure for carrying out this research, the strategy chosen for classifying the signals based on a combination of neural networks and Wavelet Transform is adequate for this proposal. The evolution of this work to Neurofeedback should start with this same strategy, especially for removing interferences of the signal and artifacts such as eyes blinking or heartbeat. Of course, as the signal is more complex, more difficult to be characterized and harder to learn for the neural network. Because of that, in future works, a deeper knowledge of the characteristics of the brain concentration signal is a key input for the success of this application to the treatment of ADHD. It is possible to consider the option of using information of several electrodes for a better characterization of the signal. Depending on the results of these advances, maybe a new neural network structure will be needed or different pre-processing filters.

Another issue to be studied in the future is the dependency on the test duration, because the ultrasound gel is progressively lost as the test evolves. This drawback can be solved by using a higher quality board than the one chosen for this study. In addition, a sensitive study for analyzing the best location of the electrode in order to maximize the success of the classification should be undertaken in future stages of this research. These two lines of future work will provide robustness to the application.

From the standpoint of the quadrotor, the autopilot developed in this study is very simple. It has allowed to demonstrate the viability of the connection and communication between the outputs of the classification process and the command inputs for the control of the drone. For an actual application, a whole autopilot needs to be developed, based on the complete tridimensional dynamic of the aircraft and based on the real output of the onboard sensors..

The final step of the research will be to measure the success of the therapy itself. Once all these improvements are incorporated, it will be the moment to analyze if the expected results on the treatment of ADHD are good enough. For that, the application allows making the feedback more demanding using the capability of commanding intermediate altitudes, just by classifying into more categories associated to several levels of concentration.

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