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**A Low Complexity Algorithm to Control a Robotic Arm
Using the Emotiv EPOC Headset**
Artículo Académico

**Santiago Andrés Aguiar Del Pozo
Wilson Jonathan Yáñez Parreño**

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DE TRABAJO DE TITULACIÓN**

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Santiago Andrés Aguiar Del Pozo

Wilson Jonathan Yáñez Parreño

Calificación:

Nombre del profesor, Título académico

Diego Benítez, Ph.D.

Firma del profesor

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Firma del estudiante: _____
Nombres y apellidos: Santiago Andrés Aguiar Del Pozo
Código: 00102583
Cédula de Identidad: 1717667586
Lugar y fecha: Quito, 13 de mayo de 2016

Firma del estudiante: _____
Nombres y apellidos: Wilson Jonathan Yáñez Parreño
Código: 00133688
Cédula de Identidad: 1721334959
Lugar y fecha: Quito, 13 de mayo de 2016

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Agradezco a mis padres y a mi hermana que siempre me han apoyado incondicionalmente a lo largo de toda mi carrera universitaria.

Le doy las gracias a todos mis amigos y mi familia por apoyarme en todo.

Santiago

Agradezco a mis padres, los mejores padres del mundo y a mis amigos, mi segunda familia, no lo habría logrado sin ustedes.

Wilson

DEDICATORIA

A mis padres, mi hermana, mi familia y mis amigos,

Santiago

Para mis padres,

Wilson

RESUMEN

Esta investigación presenta el desarrollo de un algoritmo de baja complejidad, el cual usa el dispositivo Emotiv EPOC para medir la diferencia de potencial electrostático en la cabeza de un individuo, calcula la Transformada de Fourier de tiempo reducido de la señal y el área de una curva paramétrica en un espacio de eventos bidimensional, para así poder realizar el reconocimiento de un guiño con un ojo y un guiño con ambos ojos. Este enfoque usa solamente dos electrodos del dispositivo, que conjuntamente con la señal del giroscopio incorporado en el mismo, permiten el desarrollo de una interfaz cabeza-computador que posibilita la interacción con un brazo robótico.

Palabras clave: Interfaz, Cabeza-Computador, Emotiv EPOC, Algoritmo, Baja Complejidad, Brazo Robótico

ABSTRACT

This paper presents a low complexity algorithm which uses the Emotiv EPOC headset to measure the difference of electrostatic potential in the head of an individual, computes the Short Time Fourier Transform of the signal, and calculates the area of a parametric curve in a 2D event space to perform the recognition of a single eye and both eyes winks. This approach uses only two electrodes of the headset, which together with the use of signals from the gyroscope, available in the device, allowed the development of a Head-Computer Interface that enables the interaction with a robotic arm.

Keywords: Head Computer Interface, Emotiv EPOC Headset, Algorithm, Low Complexity, Robotic Arm.

A Low Complexity Algorithm to Control a Robotic Arm Using the Emotiv EPOC Headset

Santiago Aguiar, Wilson Yáñez, Diego Benítez
 Universidad San Francisco de Quito
 Colegio de Ciencias e Ingenierías "El Politécnico"
 Campus Cumbayá, Casilla Postal 17-1200-841
 Quito, Ecuador

Email:saguiar@estud.usfq.edu.ec, wyanez@estud.usfq.edu.ec, dbenitez@usfq.edu.ec

Abstract—This paper presents a low complexity algorithm which uses the Emotiv EPOC headset to measure the difference of electrostatic potential in the head of an individual, computes the Short Time Fourier Transform of the signal, and calculates the area of a parametric curve in a 2D event space to perform the recognition of a one eye and double eye winks. This approach uses only two electrodes of the headset, which together with the use of signals from the gyroscope available in the device, allowed the development of a Head-Computer Interface that enables the interaction with a robotic arm.

Index Terms—Head Computer Interface, Emotiv EPOC Headset, Algorithm, Low Complexity, Robotic Arm.

I. INTRODUCTION

There have been several approaches on controlling robots by using the electrostatic difference of potential in the head of an individual, formally known as electroencephalographic (EEG) and electromyographic (EMG) signals to develop a Brain Computer Interface (BCI) [1] [2]. The main problem with such approach is that by nature, these signals are to be noisy, non-stationary, complex and of high-dimensionality; which requires a strong signal processing, and in some cases, multiple stages in order to identify events and classify the former into usable information [3] [4].

Nonetheless, in recent years there has been an increase effort on finding ways to improve the algorithms, quality of extraction, and analysis of these types of signals. Several methods, either based on time, frequency domain and machine learning techniques (such as support vector machines) have been developed and studied [5].

The primary focus of this research is to develop a low complexity algorithm for the development of a Head-Computer Interface (HCI) to be used for controlling a robotic arm using the raw sensor signals provided by the EPOC neuroheadset, as step toward the development of aid tools for people with severe disabilities

A. Emotiv EPOC Headset

The EPOC is a wireless, low cost, high resolution neuroheadset produced by the Australian company Emotiv Systems, which measures electrical impulses generated by brain activity. The headset has 14 electrodes that are located across the scalp following the international system 10-20 [6], plus 2 reference electrodes, which are labeled using the Common Mode Sense (CMS) active electrode and the Drive Right Leg (DRL) passive electrode reference [7]. They are named as follows: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, and P3 & P4 for the reference electrodes as shown on figure 1.

The headset offers a precision of $0.51\mu V$ and also includes: a gyroscope; a signal amplifier; a 0.16Hz high-pass filter; a 85Hz low-pass filter; a 50Hz notch filter implemented to block the noise introduced by the electric grid, and a simple analog to digital converter at 128 samples per second [8].

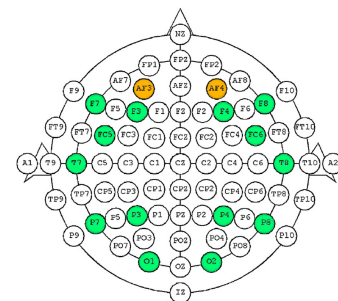


Fig. 1. 10-20 International System, Emotiv's electrodes placement (green) and electrodes used on this research (orange)

II. METHODOLOGY

For the development of the HCI we proposed the model shown on figure 2. All the raw electrostatic voltage differences and the gyroscope data were acquired using the EPOC neuroheadset. We developed two processes in parallel with these signals. First, we performed

an event detection and discrimination of the voltage signals, and at the same time we developed a head tracking system using the raw signal from the gyroscope. All the signal processing and the graphical user interface (GUI) was done on LabVIEW. Once we gather the control signals, we transformed them into pulse width modulated signals and transmitted them to the servos in the robotic arm using an Arduino Uno microcontroller board.

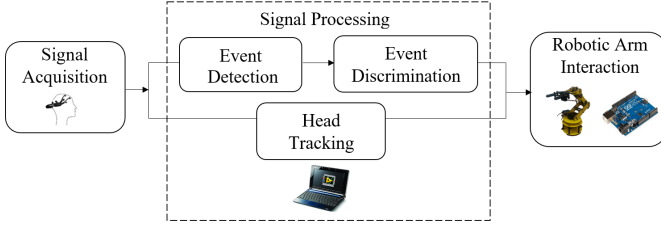


Fig. 2. Brain computer interface processing pipeline

A. Signal Acquisition

The signal acquisition was done by sending the raw data produced by the neuroheadset to LabVIEW. Communication between LabVIEW and the EPOC interface was done by using the API library from the EMOTIV SDK. The main pre-processing of the signal was done inside the EPOC headset, without the possibility to change it. Nevertheless, the acquired signal showed to have a good quality for developing the analysis.

B. Event Detection

The EEG activity has been widely classified in the frequency domain. That is: alpha (8-15 Hz), beta (16-31 Hz), delta (< 4 Hz) and theta (4 – 7 Hz) waves [9]. Therefore, is natural that the first step in order to analyze the EPOC signals is to compute the Fourier transform of the incoming signal.

Since for any practical application we need real time analysis, we decided to apply the Short Time Fourier Transform (STFT) in the incoming signal as shown in equation 1. This method has the advantage of computing the frequency spectrum of a signal as it is being recorded, and also gives the possibility of improving the resolution of the spectrum by means of changing the form of the window function ($W(t - T)$) and its width [10].

$$x(\omega, T) = \int_{-\infty}^{\infty} x(t)W(t - T)e^{j\omega t} dt \quad (1)$$

We used a Blackman-Harris window with a length of 512 samples which gives a reasonable compromise of resolution in both, frequency and time domains.

After this analysis, we concatenated the spectrum of the signal at consecutive times and computed the spectrogram as showed in figure 3 (bottom) as a graphical indicator of the strength of the signals in the frequency domain where the changes on electroencephalographic activity can be seen in real time.

Peaks on the frequency spectrum appeared every time a significant voltage signal amplitude was obtained. Thus, in order to accurately identify the presents of muscular facial activity produced by a winking action as a valid event, we measured the maximum of these peaks and considered that there was an event only if their amplitude overpass a certain threshold value which was established experimentally.

C. Event Discrimination

The spectrum was a good tool for detecting changes in the electrical activity from the base line. However, the changes on the spectrum were not significant enough to discriminate between different activities such as: mental commands, face gestures, arms and legs extensions, moving fingers, performing hops, etc. After several different trials, we decided to focus on the analysis of winks, since they had the most notorious changes in electrical activity given the fact that electromyographic signals ($\sim mV$) are several orders of magnitude greater than electroencefalographic signals ($\sim \mu V$) [11] [12], and since the electrodes used by the EPOC capture both the EMG and EEG signals when performing such activity.

However, the difficulty on the analysis is that EMG activity related to winks varies among people, obtaining a different amplitude and form of the signal during wink events in different parts of the head, as can be seen from figure 3 (top) where the signals obtained from electrodes in positions AF3 and AF4 for two different subjects can be observed. As it can be notice, the shape and amplitude of the signals differ from one subject to another in the time domain, however in the frequency domain there are peaks in the power spectrum that still can be related to the event and therefore can be used for event detection.

After a profound analysis using different electrodes of the headset, we notice that the signal from the electrodes placed in positions AF3 and AF4 showed the most significant changes during winks, and therefore measuring these electrodes was enough to recognize wink activity.

Thus, in order to recognize different events we decided to use the signals from these two channels as a system of parametric equations, using the time as the independent variable, to plot the parametric curve in real time after an event was detected by a significant change in electrical activity indicated by the peaks in frequency spectrum,

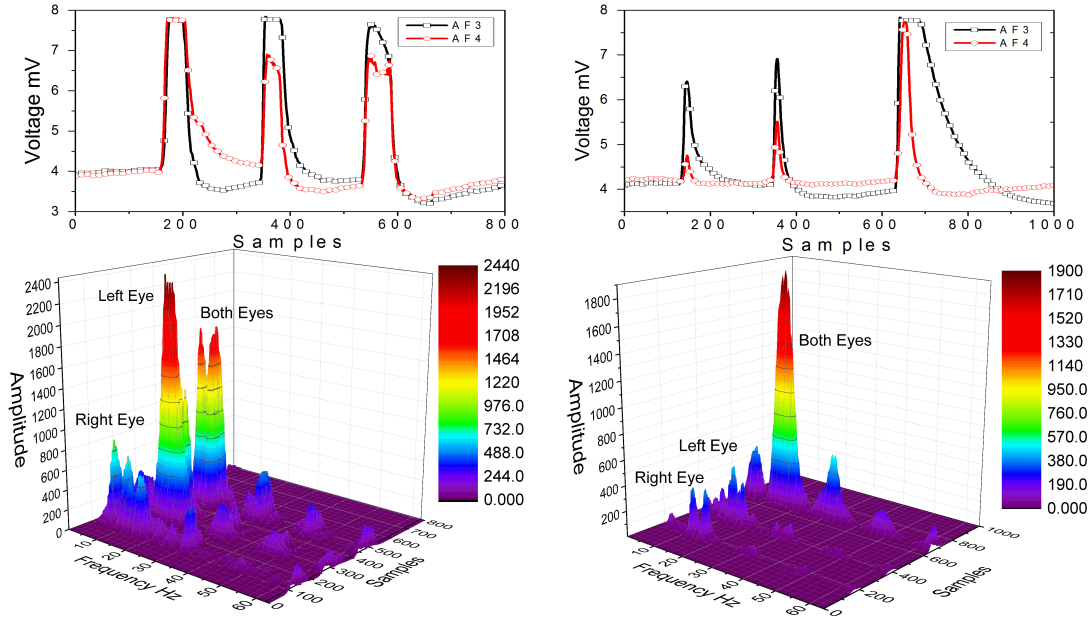


Fig. 3. Top: Raw data from the channels AF3 and AF4 as obtained from the EPOC headset. The peaks in the signal correspond to a sequence of right wink, left wink and both eyes wink. Bottom: Spectrogram of the channel AF3 with the amplitude of the power spectrum represented by coloring scale

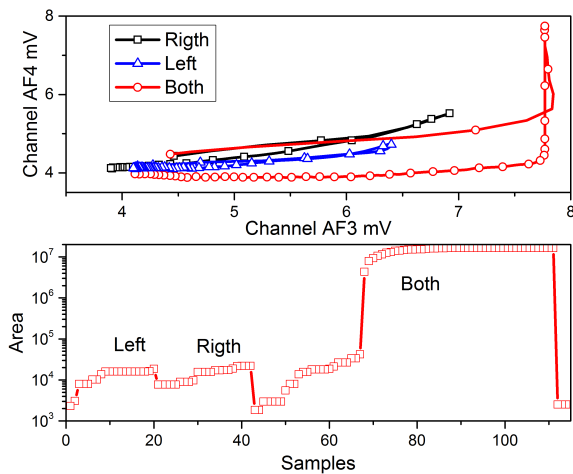


Fig. 4. Top: 2D Event space using the Channels AF3 and AF4 as the axis. Bottom: Calculated Area of the Cluster of data during the different events

This rather simple approach of constructing a 2D event space, using the signals from channels AF3 and AF4 as a basis, allows the possibility of recognizing the difference between a wink with both eyes and only with one eye as shown on figure 4 (top).

In order to analytically compute the difference, we calculated the area of the cluster of data in the 2D event space using the extrema values (ie. maxima and minima), and carefully placed a threshold to recognize the two

different events as shown on figure 4 (bottom).

Finally the wink detection and discrimination algorithm can be summarized with the process diagram shown on figure 5

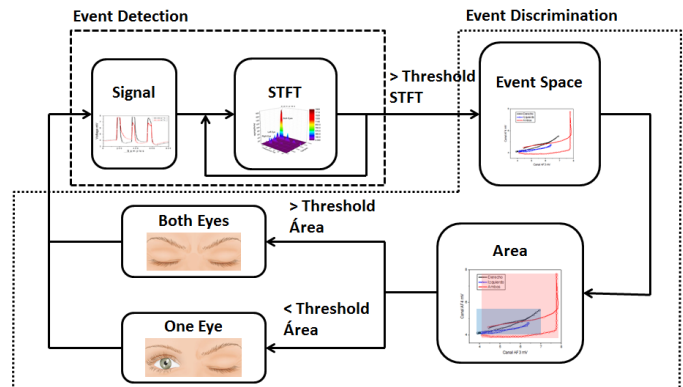


Fig. 5. Diagram of the detection and discrimination of events

D. Head tracking

For the development of any possible application of the head computer interface more control signals are required. In order to do so, we developed a head tracking system, which added the gyroscope signal available from the EPOC headset (that registered the velocity of the head movements in both horizontal and vertical axis) and summed over its previous value in time. This method,

was used as an equivalent to integrating the velocity in order to have the position, it showed a great accuracy for performing head tracking in real time.

One of the drawbacks of this approach was that for sudden and fast head movements the gyroscope signal reached its saturation value. This caused a loss of calibration in the origin of the reference system for the tracking. Therefore, in order to account for this problem we also enabled the user to reset the reference axis when needed.

E. Robotic Arm Interaction

The wink detection and head tracking provided six control signals (head up, head down, head right, head left, single eye wink and double eye wink) that were enough to interact with the robotic arm using an Arduino Uno microcontroller board. The robotic arm has six servos that run independently as shown in figure 6. Servo 1 and servo 5 were controlled by the signal obtained from the gyroscope. This signal allowed two independent movements: one to rotate the arm clockwise and counter clockwise using the servo 1, and another to move the arm up and down using servo 5 to control the vertical axis. The servo 6 was controlled by the wink detection, winking with one eye opened the claw while winking with both eyes closed the claw. Furthermore, we decided to use only three of the available servos and keep the other fixed in order to give mechanical stability to the arm. These movements were enough to perform basic actions as explained in the results and accuracy section.

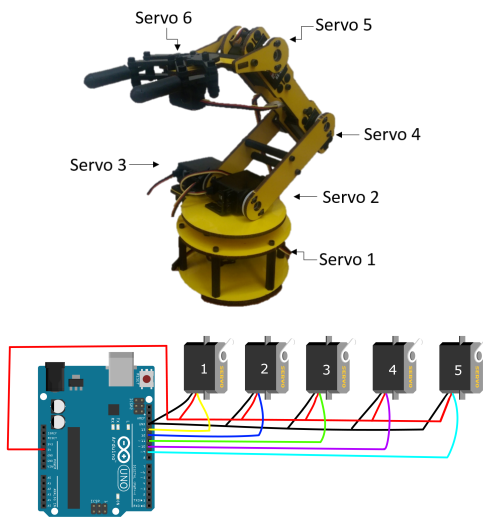


Fig. 6. Top: Robotic Arm Diagram. Bottom: Controller Diagram

F. Graphical User Interface

To have a better user experience we developed the graphical user interface (GUI) shown on figure 7 (top),

where the wink recognition and the head tracking can be seen in real time. The GUI consists on a diagram that shows the quality of the contact of each electrode on the headset; a light indicator and an animation that demonstrates the detection of each of the two types of winks; an event recognition graph, which shows the calculated area to show if the event surpasses the given threshold and a graph of the head tracking system showing the horizontal and vertical movements. The proposed system can also be externally monitored by a mobile device (such as a tablet) using the LabVIEW Data Dashboard application

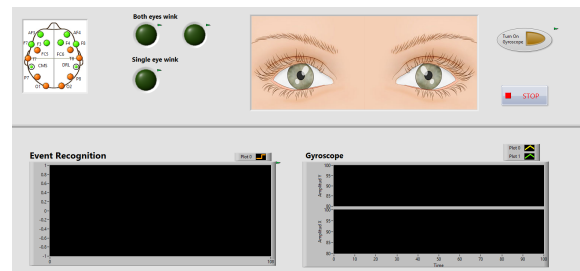


Fig. 7. Graphical User Interface (GUI)

III. RESULTS AND EXPERIMENTATION

The greatest advantage of this algorithm is that enables the interaction with the robotic arm without any previous training. Thus in order to prove the effectiveness of the HCI, we developed a simple task where 20 subjects had to move an object from one glass to another glass using the robotic arm controlled only by the HCI, the glasses were separated by a distance of 15 centimeters as shown on figure 8.

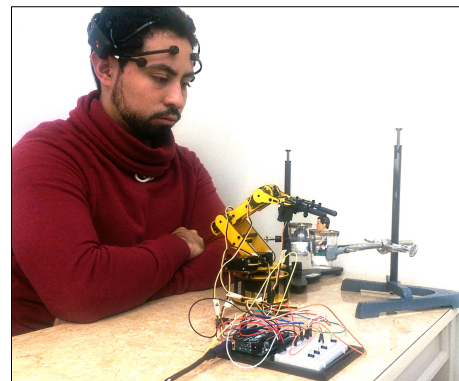


Fig. 8. Experimental Setup

The main inconveniences that the subjects seem to have was that, certain individuals have trouble winking with a single eye (either right or left), or had trouble putting on the headset and getting good contact signals. Nevertheless, the experiment showed a great degree of

success given the fact that all of the individuals were able to perform the task with a time varying from 19 to 150 seconds with an average time of 66 seconds as shown on figure 9.

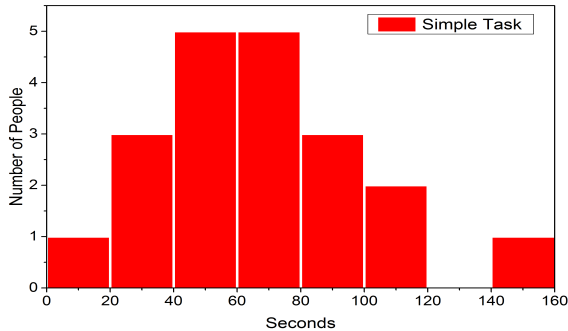


Fig. 9. Histogram of the time required to complete the proposed task for a testing sample of twenty individuals.

To further test the accuracy of the algorithm, we performed a second evaluation experiment with two different subjects which consisted on repeating 20 times a sequence consisting on a left eye wink, a right eye wink, and a wink with both eyes. After that, We asked the subjects to use their preferred eye to open the claw and close it winking with both eyes and again repeated the procedure 20 times. This two experiments gave the results shown on table I, were the number of correct and wrong detection guesses obtained by the HCI system are presented. In order to calculate the accuracy of the algorithm we compute the ratio of the number of correct guesses over the total number of events. The results indicate a great degree of accuracy considering that is a low complexity approach.

TABLE I
RESULTS AND ACCURACY

Subject A	Left	Right	Both	Open Claw	Close Claw
Correct	20	19	17	19	17
Wrong	0	1	3	1	3
Accuracy %	100	95	85	95	85
Subject B	Left	Right	Both	Open Claw	Close Claw
Correct	19	18	16	20	18
Wrong	1	2	4	0	0
Accuracy %	95	90	80	100	90

IV. CONCLUSION

In this work, we showed that it is possible to implement a low complexity algorithm that enables wink recognition without any training performed by the user.

Moreover, for this purpose it is just sufficient to compute the STFT and calculate an area using only the AF3

and AF4 channels of the device. In addition, to develop the HCI, the wink detection can be complemented by performing the head tracking using the gyroscope signal included in the device. This approach was enough to successfully control a robotic arm and perform simple tasks with it.

As future work, the described analysis shows that is possible to manufacture a low cost headsets for HCI applications such as the control of a robotic arm, given the fact that just two electrodes and a gyroscope are needed to obtain the required signals. The algorithm developed can also be easily implemented in embedded devices, for instance a Ni MyRIO (FPGA) or a Raspberry Pi, and with further refinements it may be used for the manipulation of different machinery such as more complex robotic arms, wheelchairs or even Unmanned Aerial Vehicles.

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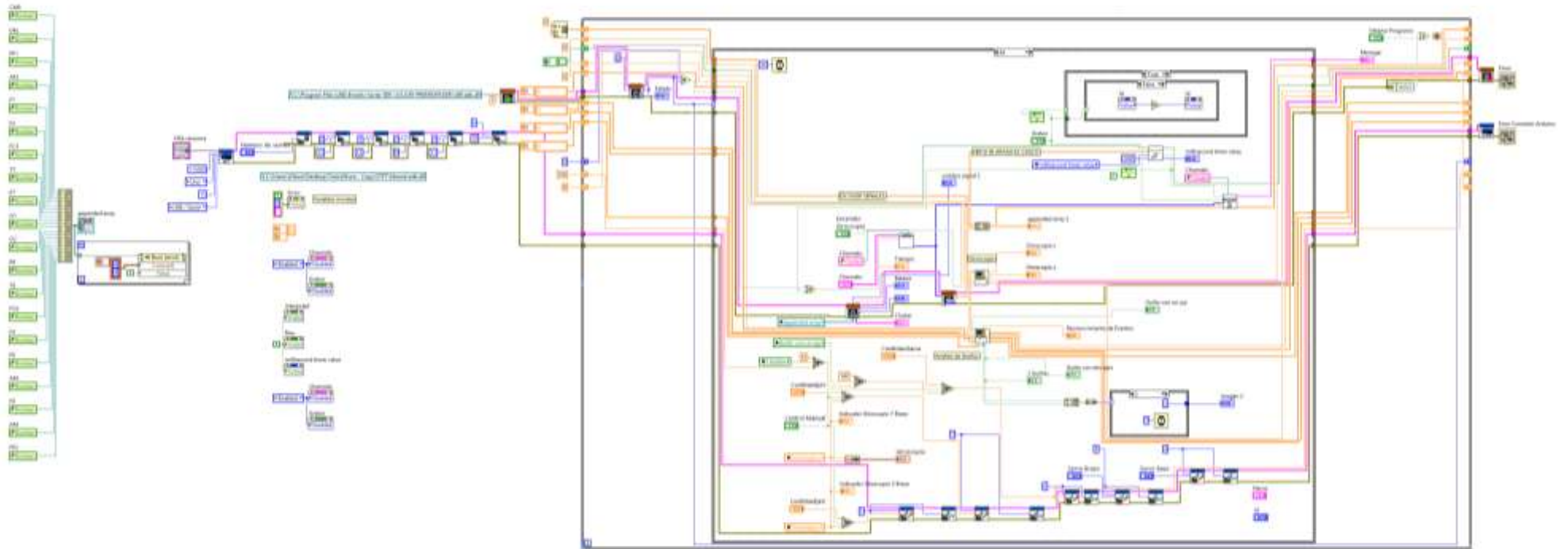
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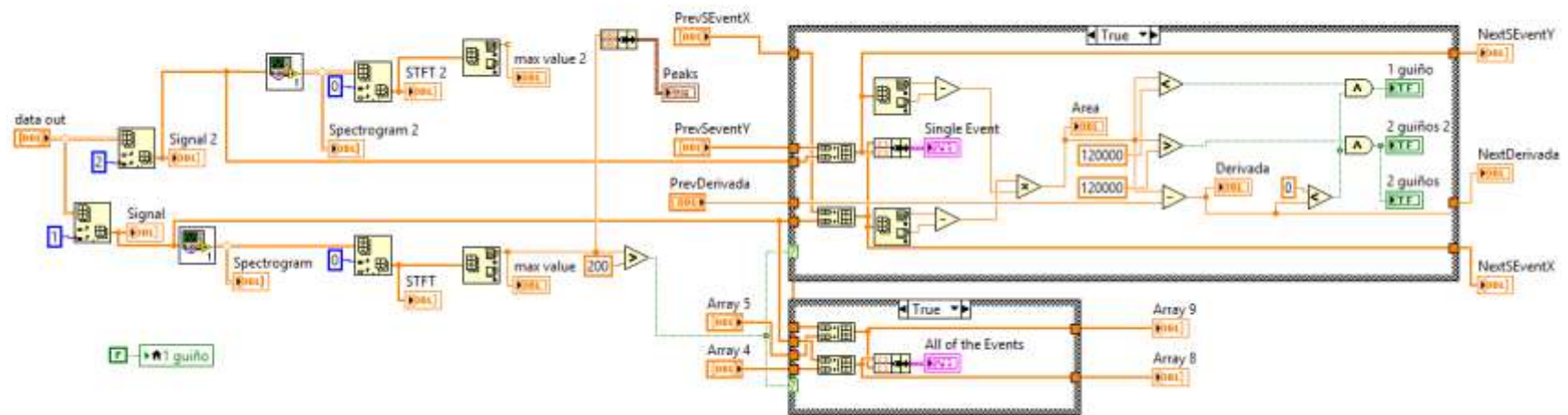
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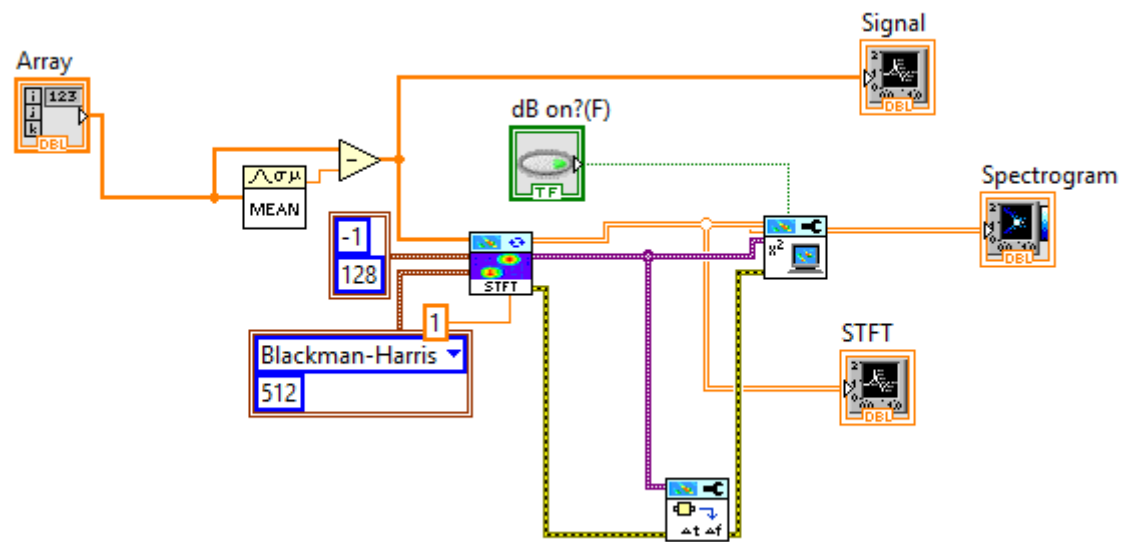
ANEXOS



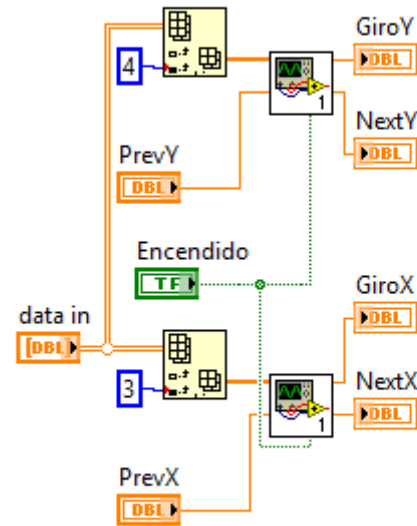
Anexo 1: Diagrama de bloques principal



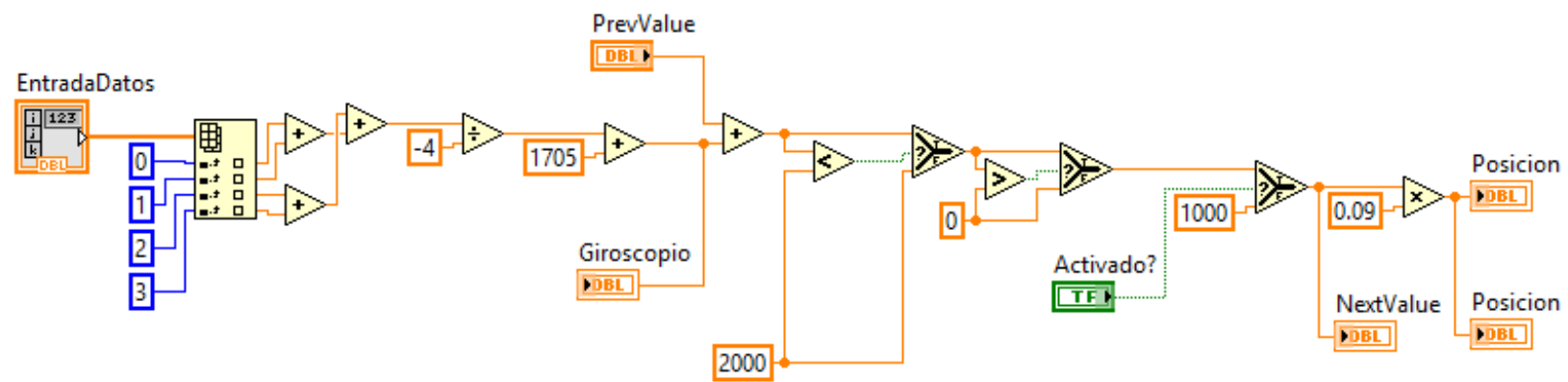
Anexo 2: Diagrama de bloques para el análisis de guiños



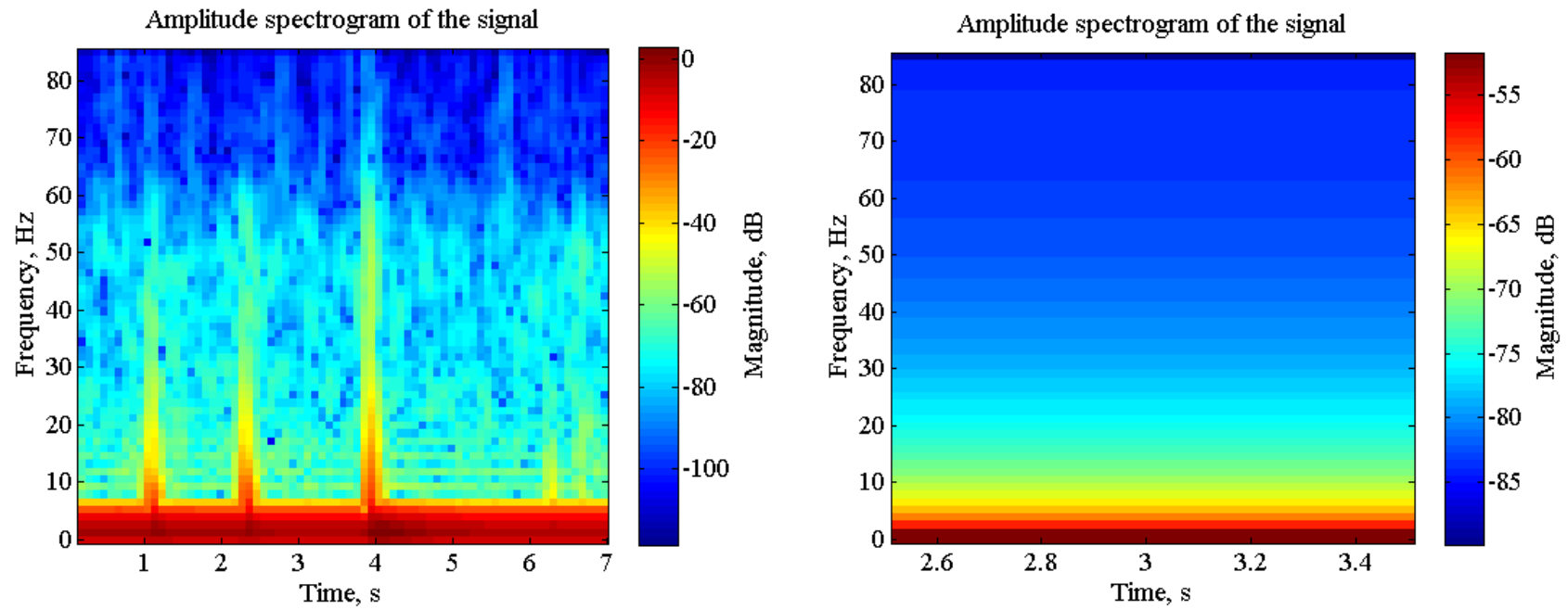
Anexo 3: Diagrama de bloques para el cálculo del espectrograma y la transformada de Fourier de tiempo reducido



Anexo 4: Diagrama de bloques para la obtención de datos del giroscopio



Anexo 5: Análisis de datos del giroscopio para realizar el posicionamiento de cabeza



Anexo 6: Comparación del efecto del tamaño de la ventana para el cálculo de la STFT usando una ventana de 64 muestras (izquierda) y de 1024 muestras (derecha)