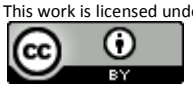
Available online at: https://ijact.in

Date of Submission	22/11/2018
Date of Acceptance	14/02/2019
Date of Publication	28/02/2019
Page numbers	3011-3020 (10 Pages)



ISSN:2320-0790

An International Journal of Advanced Computer Technology

METHODOLOGICAL APPROACH FOR EXTRACTION OF CHARACTERISTICS OF BIOLOGICAL SIGNALS

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Abstract: Generally, signal processing is applied to a set of data that is derived from the sampling of an acquired signal. This treatment is carried out with the help of a computer that in turn executes a series of logical and mathematical operations. The treatment of signals is linked to other techniques and scientific disciplines. Some of the applications of the signal treatments may be in the form of processing of audio signals, treatment of digital images, digital communications and biological signals.

In this case, the treatment was applied to biological signals such as ECG (Electrocardiogram signal: electrical activity of the heart), EEG (Electroencephalography signal: electrical activity of the brain recorded on the scalp), EMG (Electrocardiogram signal: electrical activity of muscle), and a dynamic prototype.

This work shows a method for the extraction of characteristics of biological signals. The proposed method is based on statistical parameters. First, a histogram was obtained for each biological signal. After the information obtained from the histogram, the frequency polygon of each biological signal was calculated. This process was performed with the brand class brand, including the lower and upper ranges of each class of biological signals (ECG, EEG, EMG and a dynamic prototype).

Keywords: Histogram; frequency polygon; biological signals; signals treatment; class mark, characteristics of biological signals

I. INTRODUCTION

Signal processing is applied to a set of data that is derived from the sampling of a signal obtained by any means and is performed with the help of a computer through a series of logical and mathematical operations.

The biological signals of the human body can come from many physical phenomena. Being able to process and draw conclusions about this phenomenon is a task of great interest for the scientific world. First, the physical phenomenon must be converted into electric character signals [1]. After obtaining the signals, it is necessary to translate them. This is possible using a translator to transform the digital signal into a tangible analogy signal in the real world.

The treatment of signals is linked to other techniques and scientific disciplines. Some of the applications of the signal treatments can be oriented to audio signals, digital image processing, digital communications and biological signals. In this case, the treatment was applied to biological signals such as ECG (Electrocardiogram signal: electrical activity of the heart), EEG (Electroencephalography signal: electrical activity of the brain recorded on the scalp), EMG (Electrocardiogram signal: electrical activity of muscle), and a dynamic prototype [2].

The process applied to the biological signals was:

• Histogram
• Frequency polygon

There are several methods to treat biological signals. One of them is the Dynalet's method [3], which was based on Liénard (differential equations) to model and compress signals, such as the case of the ECG and the pulse. Once this process is completed, a comparison is made with the original signal using the Dynalet and Fourier transformation as a whole.
The biomedical signal can be processed using the wavelet technique [4]. There are additional techniques based on the decomposition of the value (SVD) and the reduction of the wave difference (WDR) for the compression of the ECG signal [5].
Another way to obtain information on biological signals is by decomposition in the empirical way (EMD) [6]. In this method, they are not stationary signals derived from non-linear systems that decompose. When this process is applied to real biomedical signals, it is possible to obtain components to represent physiological phenomena.
Time domain analysis techniques involve data handling as parametric functions to obtain computer or mathematical models from the original system [7].
When working with non-periodic and non-repeated signals that the brain generates from any stimulus, it is a complex investigation in which information is constantly obtained.

With this new information is possible to expand and to understand the acquired knowledge.
Many time signals consist of points quantities over time, however, samples obtained from replicas of biological data are usually scarce [8].
The biological signals that are characterized in the frequency domain are very useful for making diagnoses. The problem with these signals lies in their infinite waveform and their great length.

There are many techniques to analyze signals, among them we can find the Wavelet transform, the Fourier transforms and the neural networks [9]. There is also the Hilbert Huang transform to recognize patterns in biological signals such as EMG, and then obtain a characteristic vector from them [10].There is no systematic model to deal specifically with the data obtained from biological signals, that is to say, an established method cannot be applied to perform the treatment of biological signals[11].

In this document, a computational analysis is performed on signs of biological origin; this analysis is divided into two parts. On the one hand, we worked with trigonometric functions; Sinusoidal function, composite function and damped sinusoidal function. From which is obtained its respective histogram to know its potential action and obtain the frequency polygon for each function and in this way Perform, understand and interpret the information contained in these functions to model and treat them.

On the other hand, the next part of this document is to analyze the biological signals (ECG, EEG and EMG) and the dynamic prototype [2]. From the signal his histogram was obtained to see its potential action, and to obtain the frequency polygon for each function in the same way, perform, understand and interpret the information contained in these functions to model and treat them. In this document, the software implemented was RStudio.

II. THEORETICAL DESCRIPTION

The essential part of this document is the treatment of biological signals obtained from stimuli applied to various areas of the body. The biological signals with which we worked were; ECG (electrocardiogram, heart activity), EEG (encephalogram, neuronal activity of the brain) and, finally, EMG (electromyogram, muscle activity).

A. Biological signals

Signals are a way of transmitting information. When these signals are obtained, it is possible to obtain information about the source that generated it. The biological signals originate from different physiological systems of the organism, which allows the doctor to extract information about how the organs that emit these signals work and obtain a diagnosis [11].
The bioelectrical signals are used mainly to obtain a medical diagnosis and to detect pathologies in the organs. However, there are also bioelectrical signals that are produced voluntarily to control man-machine interfaces. These signals originate in the membrane of various cells of the body and have behaviour similar to that of some electrical components [12].
These signals can be obtained from signals from electrophysiological sensors, such as arterial pulse sensors. The signals can also be obtained from molecular devices, such as nuclear magnetic resonance (NMR) spectrometry [3].
These signals come from the human body and are produced due to the displacement of ions in solutions that correspond mainly to Na+, K+ and C1. Displacement occurs due to differences in the concentration of organic fluids [13].
As mentioned above, in the work a treatment was made to several biological signals (ECG, EEG and EMG) and a dynamic prototype. Below is a brief description of each of these.

a. Electrocardiogram

ECG (see figure 1) is a biopotential generated by the heart's muscles movement. To understand the origin of the ECG, it is necessary to have a brief knowledge of the heart's anatomy.

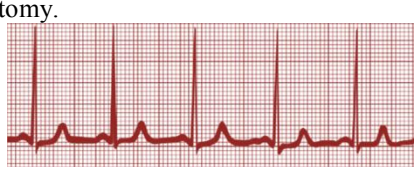

Figure 1 Electrocardiogram representation

The process begins with the pacemaker, a cellular group specifically commissioned to generate actions of regular rhythm potentials which are controlled through innervations. The potential generated by the pacemaker moves in all directions along the surface of the atria and travels to the union of them and the ventricles. The wave ends at a point called the atrioventricular nodule.
The process continues when the nerve fibres act as delay lines in the muscles of the ventricles. And they get adequate timing between the atria and the ventricles. On the other hand, the wave front crosses the surface of the ventricles and terminates the path at the tip of the apex of the heart.
On the other hand, a depolarization wave is followed by a re-polarization wave; this last wave lasts between 0.2 and 0.4 seconds. Now to represent the ECG waves to each characteristic that stands out in the record is assigned a letter. These characteristics are identified with actions related to the propagation of the action potential. In Figure 2, you can see the various waves that make up an ECG.

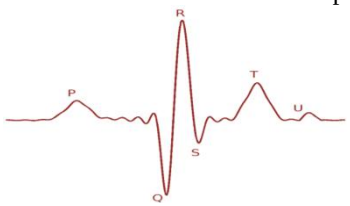

Figure 2 Waves that conformed an ECG.

The representation begins with a horizontal segment that precedes the P wave and is designated as a baseline or isopotential, now the P wave is a depolarization of the atrial musculature. On the other hand, the QRS complex is the result of the combination of repolarization of the atria and in the depolarization of the ventricles, these actions occur almost at the same time.
While the T wave is ventricular repolarization, the U wave, if it appears, may be the result of the posterior potentials of the muscles of the ventricles. Finally, the P-Q interval is the time when the excitation wave is delayed in nearby fibres in the atrioventricular node [15].

b. Encephalogram

EEG is a representation that registers bioelectric potential that is generated in the neuronal activity of the brain. The brain has a complex shape and waveforms that vary depending on the location of the electrodes on the surface of the scalp, see figure 3.

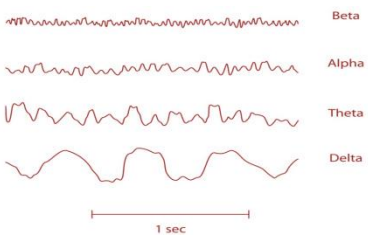

Figure 3 Encephalogram representation

EEG potentials that are measured in the surface of the scalp are a representation of the combinatorial effect of neuronal potentials of the big cortex region and diverse interiors points [15].

c. Electromyogram

EMGs are bioelectric potentials associated with muscle activity and can be measured on the surface of the body near the muscle of interest. Or you can also enter directly into the muscle with the help of needle electrodes that pass through the skin, see Figure 4.
The signal obtained from EMG is generally a sum of potentials that act individually on the fibers and constitute a muscle, or muscles, in which this potential is measured. The electrodes of the EMG gathered muscle potentials within reach. That is, the closest muscle potentials can interfere with attempts to measure EMG in small muscles, although electrodes are placed in small muscles [15].

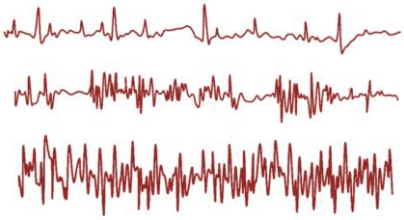

Figure 4 Electromyogram representation

B. Signals treatment

a. Histogram

A histogram is a graph that attempts to show the shape of the sample and indicate where the highest concentration and the least amount of sampling points can be found. The first step is to build a frequency table and create class intervals, these intervals divide the sampling into groups and show where each group starts and ends.
An important element is also the total frequency. It is the amount of data that you have within each class interval while the relative frequency is the frequency but divided by the total number of data.

Finally, the density is the relative frequency but now divided by the width of the class. The purpose of the density of the relative frequency is to adjust the relative frequency with the width of the class without any change in the representation. A wider class is a class with more elements of sampling and a higher relative frequency, then, when the relative frequency is divided by the width of the class, the trend is adjusted and the density is the relative frequency per unit.

The class intervals are represented by rectangles, in each of them a rectangle height is the sampling density in this interval. The area in each rectangle is the relative frequency in each class interval and the area under the entire histogram must be equal to 1 [16].

b. Classmark

The class mark is a representative value in each of the classes of a histogram; it is the central value of each interval. What is measured when calculating the arithmetic mean between the limits of the interval, that is, the arithmetic means between the lowest limit and the highest limit [17].

c. Cumulative frequency polygon.

The cumulative frequency polygon is a representation of absolute and relative simple frequencies; it is represented by a line that unites all class mark [17].

III. EXPERIMENTAL SETUP AND RESULTS

This document consists of two parts, in the first part there is a simulation stage in which tests are performed on trigonometric functions; Sinusoidal function, composite function and damped sinusoidal function.

The treatment applied for these functions were the creation of the graph, the making of the histogram and with this information to generate a frequency polygon.

The first function generated was: $f(x)=\sin(x)$, which can be seen in Figure 5.

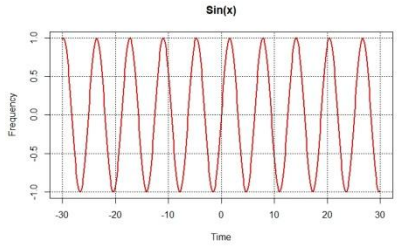

Figure 5: Plot of the Sin(x) function

The next step was to create a histogram of the function, which can be seen in Figure 6.

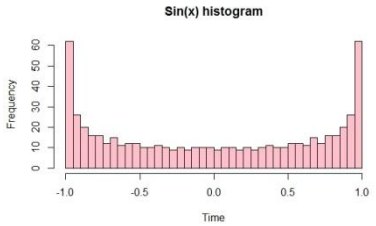

Figure 6: histogram of Sin(x)

Once the histogram function was obtained, it was plotted in the graphical form of the frequency polygon of the histogram, as shown in Figure 7.

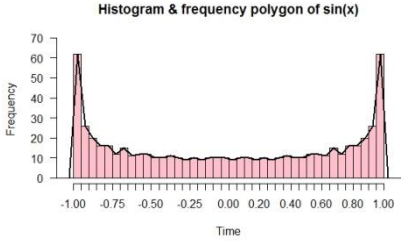

Figure 7: Histogram & frequency of sin(x)

A table was also prepared that contained relevant information about the original function. The parameters in this table are; lower and upper limit, class and frequency mark (the table only showed a small part of the function data), as shown in Table 1.

Lower	Upper	Main	Frequency
-1.00	-0.95	-0.975	62
-0.95	-0.90	-0.925	26
-0.90	-0.85	-0.875	20
-0.85	-0.80	-0.825	16
-0.80	-0.75	-0.775	16
-0.75	-0.70	-0.725	12
-0.70	-0.65	-0.675	15
-0.65	-0.60	-0.625	11
-0.60	-0.55	-0.575	12
-0.55	-0.50	-0.525	12
-0.50	-0.45	-0.475	10
-0.45	-0.40	-0.425	10
-0.40	-0.35	-0.375	11
-0.35	-0.30	-0.325	10
-0.30	-0.25	-0.275	9

Table 1 Sin(x) summary

From Table 1, we worked with the classmark and the frequency to obtain the frequency polygon graphically and mathematically, as seen in Figure 8.

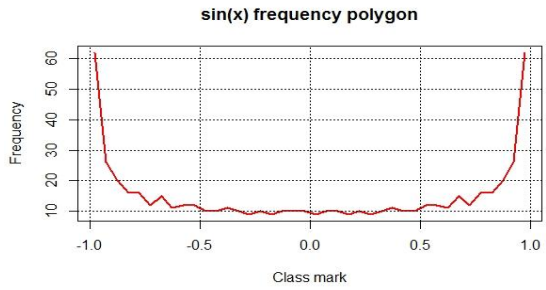

Figure 8: Frequency polygon of Sin(x)

The second function generated was:

$f(x)=\sin(x)+\cos(x)$ This can be seen in Figure 5:

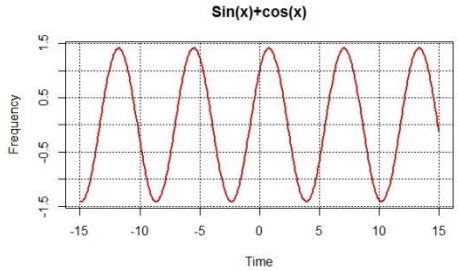

Figure 9: plot of the Sin(x)+cos(x) function

The next step was to elaborate a histogram of the function, which can be seen in Figure 10.

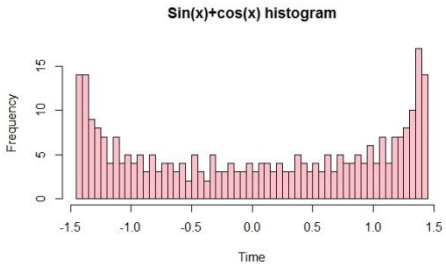

Figure 10: Histogram of Sin(x)+cos(x)

Once the function histogram was obtained, it was represented in the graphic shape of histogram frequency polygon, as shown in Figure 7.

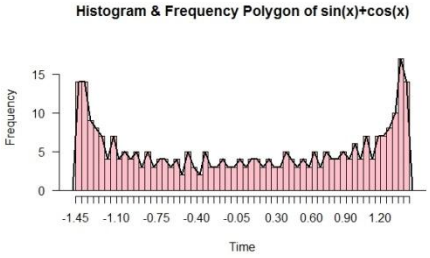

Figure 11: Histogram & frequency polygon of sin(x)+cos(x)

The following table shows relevant information about the original function. The parameters in this table are; lower and upper limit, class and frequency mark (the table only showed a small part of the function data), as shown in Table 2.

Lower	Upper	Main	Frequency
-1.45	-1.40	-1.425	14
-1.40	-1.35	-1.375	14
-1.35	-1.30	-1.325	9
-1.30	-1.25	-1.275	8
-1.25	-1.20	-1.225	7
-1.20	-1.15	-1.175	4
-1.15	-1.10	-1.125	7
-1.10	-1.05	-1.075	4
-1.05	-1.00	-1.025	5
-1.00	-0.95	-0.975	4
-0.95	-0.90	-0.925	5
-0.90	-0.85	-0.875	3
-0.85	-0.80	-0.825	5
-0.80	-0.75	-0.775	3
-0.75	-0.70	-0.725	4

Table 2: sin(x)+cos(x) summary

From Table 2, we worked with the classmark and the frequency to obtain the frequency polygon graphically and mathematically, as seen in Figure 12.

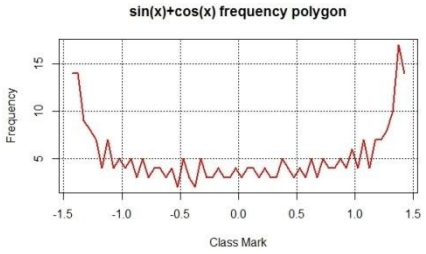

Figure 12: Sin(x)+cos(x) frequency polygon

The second function generated was:
$f(x)=10*\sin(2*x)\exp(-0.2*x)$ This can be seen in Figure 13.

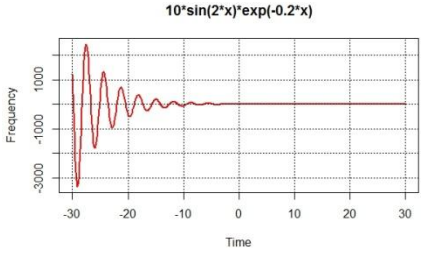

Figure 13: Plot of the 10*sin(2*x)*exp(-0.2*x) function

The next step was to elaborate a histogram of the function, which can be seen in Figure 14.

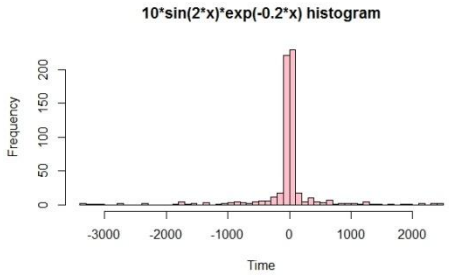

Figure 14: 10*sin(2*x)*exp(-0.2*x) histogram

Once the function histogram was obtained, it was represented in the graphic shape of histogram frequency polygon, as shown in Figure 15.

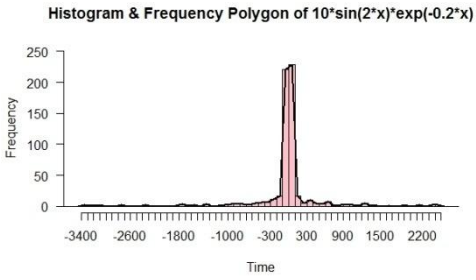

Figure 15: Histogram & frequency polygon of 10*sin(2*x)*exp(-0.2*x).

The relevant information regarding the original function, including the parameters lower and upper limit, class mark, and frequency, (the table only showed a little part of data about the function), are shown in Table 3.

Lower	Upper	Main	Frequency
-3400	-3300	-3350	2
-3300	-3200	-3250	1
-3200	-3100	-3150	1
-3100	-3000	-3050	1
-3000	-2900	-2950	0
-2900	-2800	-2850	0
-2800	-2700	-2750	2
-2700	-2600	-2650	0
-2600	-2500	-2550	0
-2500	-2400	-2450	0
-2400	-2300	-2350	2
-2300	-2200	-2250	0
-2200	-2100	-2150	0
-2100	-2000	-2050	0
-2000	-1900	-1950	0

Table 3: 10*sin(2*x)*exp(-0.2*x) summary

From Table 3, we worked with the classmark and the frequency to obtain the frequency polygon graphically and mathematically, as seen in Figure 16.

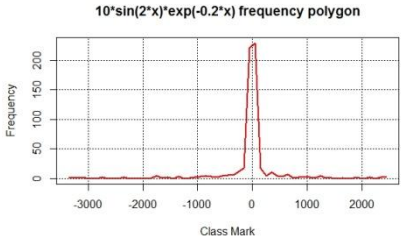

Figure 16: 10*sin(2*x)*exp(-0.2*x) frequency polygon

The second part of this document shows the results obtained by applying the same treatment in trigonometric functions but now in biological signals (EEG, ECG, EMG [18]) and a dynamic prototype [2], to avoid the loss of information for the analysis of these signals.

The first graphic obtained was of a dynamic prototype. In the same way as in the simulation, an important factor to consider is the sampling frequency, which, in this case, is 5 Hz. The formula applied was: original signal / sampling frequency and the result are shown in the Figure 17.

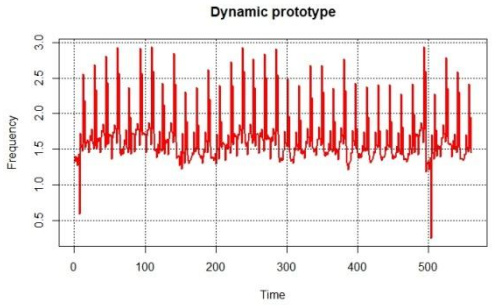

Figure 17: Dynamic prototype

The next step was to elaborate a histogram of the function, which can be seen in Figure 18.

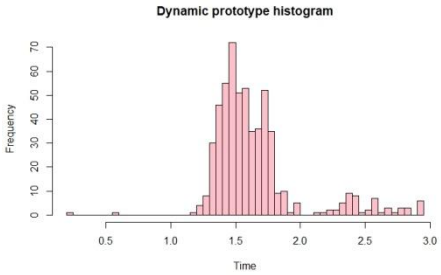

Figure 18: Dynamic prototype histogram

Once the function histogram was obtained, it was represented in the graphic shape of histogram frequency polygon, as shown in Figure 19.

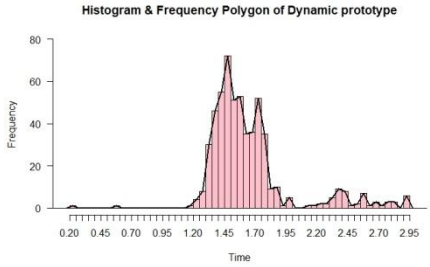

Figure 19 Histogram & frequency polygon of Dynamic prototype

And again, a table was elaborated, which contained relevant information regarding the original function. Parameters in this table are; lower and upper limit, class mark, and frequency, (the table only showed a little part of data about the function), as shown in Table 4.

Lower	Upper	Main	Frequency
0.20	0.25	0.225	1
0.25	0.30	0.275	0
0.30	0.35	0.325	0
0.35	0.40	0.375	0
0.40	0.45	0.425	0
0.45	0.50	0.475	0
0.50	0.55	0.525	0
0.55	0.60	0.575	1
0.60	0.65	0.625	0
0.65	0.70	0.675	0
0.70	0.75	0.725	0
0.75	0.80	0.775	0
0.80	0.85	0.825	0
0.85	0.90	0.875	0
0.90	0.95	0.925	0

Table 4: Dynamic prototype summary

From Table 4, we worked with the classmark and the frequency to obtain the frequency polygon graphically and mathematically, as seen in Figure 20.

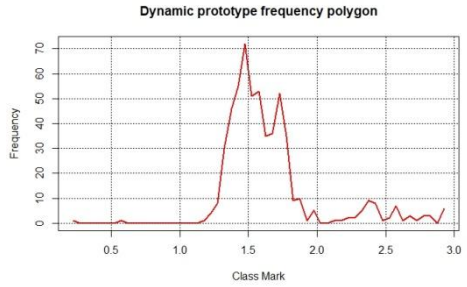

Figure 20: Dynamic prototype frequency polygon

The second graphic generated was from an ECG. An important fact to consider in this case is the sampling frequency which is 500 Hz. The formula applied was: original signal / sampling frequency and the result is shown in Figure 21.

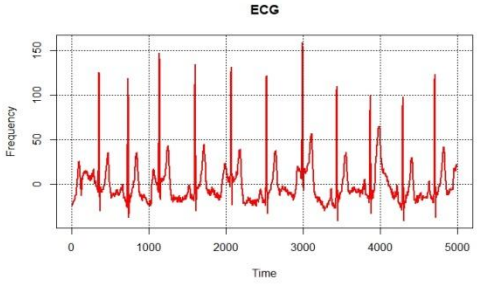

Figure 21: Graphic of an ECG

The next step was to make a histogram of the function, which is shown in Figure 22.

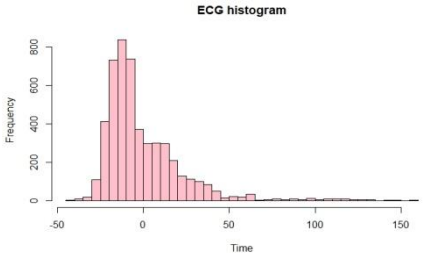

Figure 22: ECG histogram

Once the histogram function was obtained, it was plotted in the graphical form of the frequency polygon of the histogram, as shown in Figure 23.

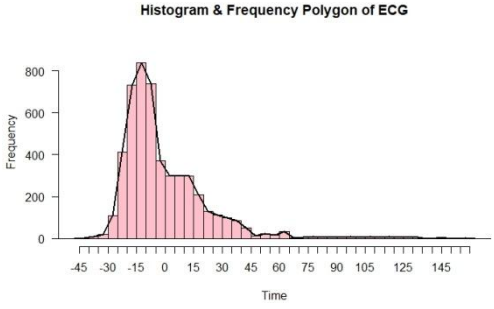

Figure 23: Histogram & frequency of ECG

In the same way as in the previous cases, a table was prepared that contains relevant information about the original function. The parameters in this table are; lower and upper limit, class and frequency mark (the table only showed a small part of the function data), as shown in Table 5.

Lower	Upper	Main	Frequency
-45	-40	-42.5	4
-40	-35	-37.5	10
-35	-30	-32.5	19
-30	-25	-27.5	108
-25	-20	-22.5	411
-20	-15	-17.5	730
-15	-10	-12.5	837
-10	-5	-7.5	738
-5	0	-2.5	370
0	5	2.5	297
5	10	7.5	299
10	15	12.5	297
15	20	17.5	208
20	25	22.5	129
25	30	27.5	113

Table 5: ECG summary

From Table 5, we work with the class mark and the frequency to obtain the frequency polygon graphically and mathematically, as shown in Figure 24.

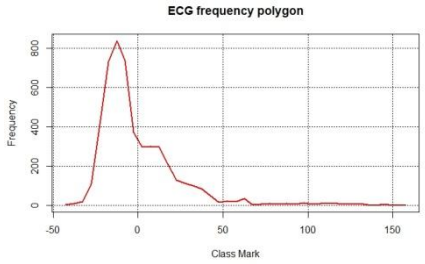

Figure 24: ECG frequency polygon

The third graphic generated was of an EEG, an important data to consider is a sampling frequency, in this case, the EEG sampling frequency is 500 Hz, the formula applied was: original signal / sampling frequency and the result was shown in Figure 25.

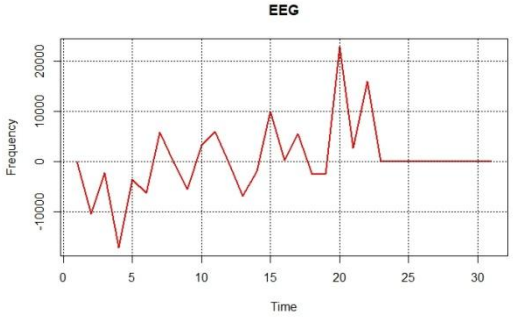

Figure 25 EEG plot

The next step was to elaborate a histogram of the function, which can be seen in Figure 26.

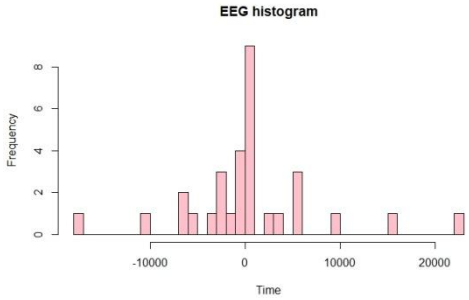

Figure 26: EEG histogram of the current EEG function

Once the function histogram was obtained, it was represented in the graphic shape of histogram frequency polygon, as shown in Figure 27.

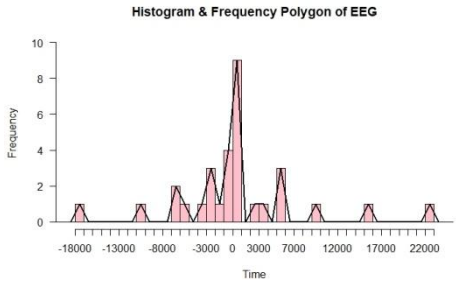

Figure 27: Histogram & frequency polygon of EEG

As in the previous cases, a table was prepared that contains relevant information about the original function. In the same way the parameters in this table are; lower and upper limit, class and frequency mark (the table only showed a small part of the function data), as shown in Table 6.

Lower	Upper	Main	Frequency
-18000	-17000	-17500	1
-17000	-16000	-16500	0
-16000	-15000	-15500	0
-15000	-14000	-14500	0
-14000	-13000	-13500	0
-13000	-12000	-12500	0
-12000	-11000	-11500	0
-11000	-10000	-10500	1
-10000	-9000	-9500	0
-9000	-8000	-8500	0
-8000	-7000	-7500	0
-7000	-6000	-6500	2
-6000	-5000	-5500	1
-5000	-4000	-4500	0
-4000	-3000	-3500	1

Table 6: EEG summary

From Table 6, we worked with the classmark and the frequency to obtain the frequency polygon graphically and mathematically, as seen in Figure 28.

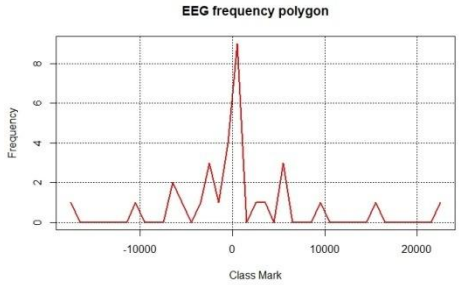

Figure 28: EEG frequency polygon

The last generated graph was of an EMG [18], for this case the sampling frequency of the EMG is 30 Hz, the formula applied was: original signal / sampling frequency and the result is shown in Figure 29.

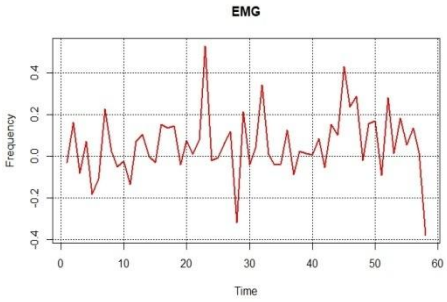

Figure 29: Plot of the EMG

The next step was to elaborate a histogram of the function, which can be seen in Figure 30.

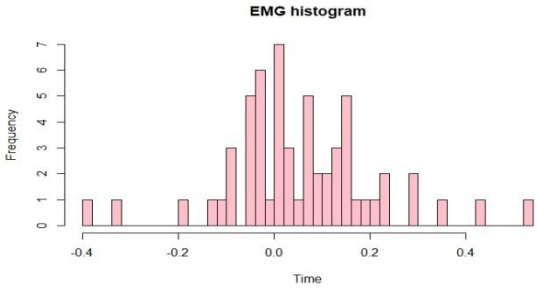

Figure 30: EMG histogram

Once the function histogram was obtained, it was represented in the graphic shape of histogram frequency polygon, as shown in Figure 31.

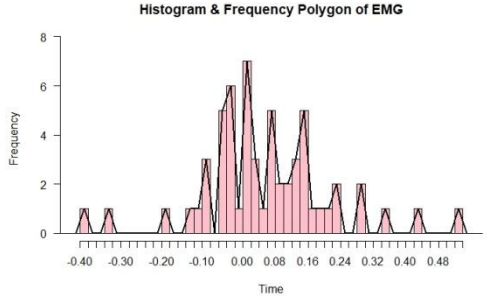

Figure 31: Histogram & frequency polygon of EMG. Self-image

Finally, also for this case, a table was created that contains relevant information about the original function. The parameters in this table are; lower and upper limit, class and frequency mark (the table only showed a small part of the function data), as shown in Table 7.

Lower	Upper	Main	Frequency
-0.40	-0.38	-0.39	1
-0.38	-0.36	-0.37	0
-0.36	-0.34	-0.35	0
-0.34	-0.32	-0.33	1
-0.32	-0.30	-0.31	0
-0.30	-0.28	-0.29	0
-0.28	-0.26	-0.27	0
-0.26	-0.24	-0.25	0
-0.24	-0.22	-0.23	0
-0.22	-0.20	-0.21	0
-0.20	-0.18	-0.19	1
-0.18	-0.16	-0.17	0
-0.16	-0.14	-0.15	0
-0.14	-0.12	-0.13	1
-0.12	-0.10	-0.11	1

Table 7: EMG summary

From Table 7, we worked with the classmark and the frequency to obtain the frequency polygon graphically and mathematically, as seen in Figure 32.

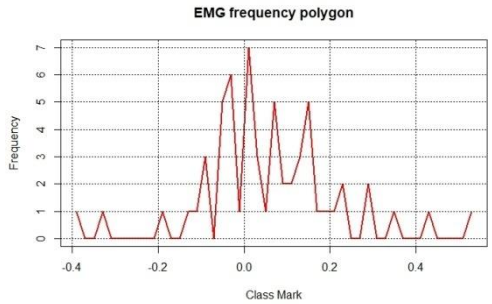

Figure 32: EMG frequency polygon. Self-image

IV. Conclusion

An optimal way to avoid the loss of important information from a biological signal for analysis purposes is by creating histograms in which your information is separated by classes and where the frequency with which the data is represented is shown.

On the other hand, the class mark allows obtaining a representative point of each histogram interval and then creating a frequency polygon. In this case, it is possible to obtain a graphic form to represent the original data.

It was possible to identify that through the frequency polygon, there is a graphic way to represent the information contained in the dynamic prototype and the biological signals (EEG, EMG and ECG).

It is an optimal way to preserve the greatest amount of information, since the frequency polygon maintains the form of the original data.

For a future document, with the information obtained with this work, it is proposed to work with classifiers in which the processed information will be introduced, to identify if it is possible or not to make a good classification of data.

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