Evaluation of Hjorth parameters using synthetic signals

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***Abstract*—The Hjorth parameters, so-called activity, mobility; and complexity were proposed by Hjorth to describe the electroencephalogram (EEG) in terms of amplitude, mean frequency; and shape of the curve. Since these parameters are in the time domain, the method requires less computational resources for calculation when compared to related techniques. Several studies have been employing these descriptive parameters to assess biomedical signals. In this context, this study evaluated the behavior of these parameters, estimated from synthetic signals in six different controlled experimental scenarios. These measurements allowed us to observe the sensitivity of these descriptors in the presence of noise, trends, different frequencies, amplitudes, and number of samples. The findings of this study may support the understanding of the application of Hjorth parameters to real datasets.**

Keywords — Hjorth parameters, mobility, activity, complexity.

I. Introduction

In 1970 Hjorth proposed a set of three descriptors to assess the EEG signal in time domain [1]. These descriptors are based on the variance of the signal, resulting in minimal computational complexity compared to other similar time-frequency methods such as Fast Fourier Transform (FFT) and wavelets [1][2].

According to Hjorth, the first parameter, the so-called activity, provides the mean power of signals. The mobility, the second one, refers to the mean frequency of the signal. The third one is complexity and refers to the shape of the curve. The complexity value for a pure sine wave, for instance, converges to one [1].

Hjorth combined these three parameters for characterizing the patterns of EEG signals related to amplitude, the scale of time, and complexity in the time domain [1]. Several studies have been employing these parameters in analyses involving different biomedical signals [2]–[6].

M. Mouzé-Amady and F. Horwat compared the Hjorth parameters with the traditional spectral analyses (FFT) from the data collection of electromyographic (EMG) signals from nine subjects. The results showed a strong correlation (0.81 to 0.93) between mobility and mean frequency obtained from FFT, corroborating with the literature [2][1]. Moreover, Shafiul Hasan et al. evaluated a method to predict the intention of gait initiation and termination through pre-movement EEG signals. The Hjorth parameters were estimated and used as features for the classification through a supervised learning algorithm, Support Vector Machine (SVM). As a result, they obtained a promising ability to predict movement intention with mean accuracy, sensitivity, and specificity higher than 70% [3].

Also, these parameters have been investigated in studies involving tremor detection. For instance, Yao et al. extracted features and used them to increase the accuracy in tremor detection in the early stages of individuals with Parkinson's disease. They investigated a set of features, including the Hjorth parameters. The complexity showed a higher correlation with tremor compared to other features [4]. Similarly, in another study, Yao et al. showed that Hjorth parameters achieved a high performance to detect tremor from local field potentials (LFPs) recorded from the subthalamic nucleus in patients with Parkinson's disease [6].

Although the results reported in the literature using Hjorth parameters are encouraging, they do not allow to understand the behavior of these descriptors in different scenarios in data collection. Noise, trend, frequency and amplitude variations, and the different numbers of samples are present in a real data collection, and they may interfere with the results of the estimated features. Characterizing the behavior of these parameters in these different scenarios allows a better understanding of the results. A method used to evaluate the behavior is through synthetic signals. Synthetic signals allow testing specific aspects of a dataset in controlled experimental scenarios. Moreover, they simplify the representation of real complex signals [7][8].

Therefore, this study, based on artificial signals, proposes exploring the behavior of Hjorth parameters in different scenarios of data collection.

II. METHODS

The results of this research were obtained by using R. A pure sinusoidal signal corrupted by distinct types of noise was employed. The noise was introduced to cause distinct changes in the signal, e.g., addition of trend, frequency and amplitude variations [9][10].

A. Equations

The Hjorth parameters were implemented according to the descriptions by Hjorth [1].

Activity provides a measure of the squared deviation of the amplitude (1).

$$\boldsymbol{Activity = \sigma_a^2} \tag{1}$$

Mobility provides a measure of the standard deviation of the slope concerning the standard deviation of the amplitude (2).

$$\boldsymbol{Mobility = {}^{\sigma_d}/_{\sigma_a}} \tag{2}$$

Complexity gives us the number of standard slopes obtained through the average time required for generation of one standard amplitude (3).

$$\boldsymbol{Complexity = \frac{\sigma_{dd}}{\sigma_d} \bigg/ \frac{\sigma_{dd}}{\sigma_a}} \tag{3}$$

The assessment of these parameters, Equations (1-3), was carried out from the sine wave. Equation (4) describes this sine wave.

$$\boldsymbol{y\,(t) = Asin(2\pi ft)} \tag{4}$$

Where:

$y\,(t)$: Sine wave
A: Amplitude
f: Frequency (Hz)
t: Time (s)

In order to simulate a linear trend, a signal was generated according to (5).

$$\boldsymbol{y(t) = mt + n} \tag{5}$$

Where:

$y\,(t)$: Signal
m and n: Angular and linear coefficients, respectively
t: Time (s)
The nonlinear trend was estimated based on (4).

B. Simulations

The advantage of a method for generating the synthetic signal is that it allows testing the sensitivity of descriptors more rigorously, including only specific aspects such as fluctuations and artifacts. Six steps were considered to evaluate the sensitivity of the parameters. Steps 1, 2, and 3 varied the parameters of (4). In contrast, steps 4, 5, and 6 verified the behavior of the parameters when introducing noise and trends.

Step 1: To observe the sensitivity of parameters according to the amplitude. The amplitude (A), Equation (4), varied among different values, $A_1 = 0.5$, $A_2 = 0.55$, $A_3 = 1$, $A_4 = 10$, and $A_5 = 15$. For the different amplitudes we considered $f = 3$ Hz, $t \in \{0, 1/f_z, 2/f_z, \ldots, 10\}$, and sampling rate $f_s = 50$ Hz. Fig. 1 shows the artificial signal considering $f = 3$ Hz, $t \in \{0, 1/f_z, 2/f_z, \ldots, 10\}$, $A_1 = 0.5$, and $f_s = 50$ Hz.

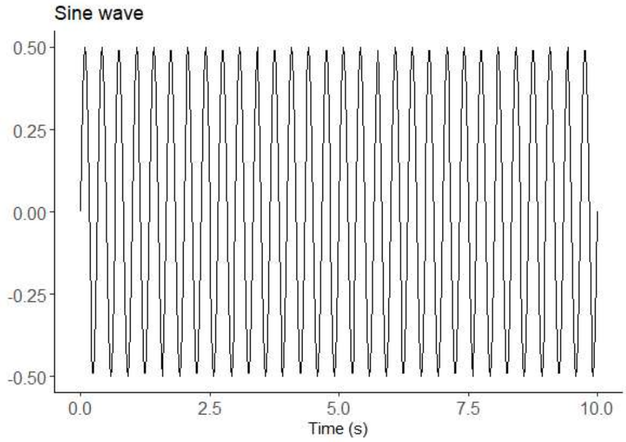

Fig 1: Pure sine wave

Step 2: To observe the sensitivity of parameters according to the frequency. We varied f in (4) among different values: $f_1 = 3$ Hz, $f_2 = 4$ Hz, $f_3 = 5$ Hz, $f_4 = 6$ Hz, and $f_5 = 7$ Hz. For the different frequencies we considered $A = 0.5$, $t \in \{0, 1/f_z, 2/f_z, \ldots, 10\}$, and $f_s = 50$ Hz.

Step 3: To observe the sensitivity of parameters according to the sampling frequency. f_s in (4) was varied among different values: $f_{s1} = 50$ Hz, $f_{s2} = 100$ Hz, $f_{s3} = 150$ Hz, $f_{s4} = 200$ Hz e $f_{s5} = 300$ Hz. For the different frequencies we considered $A = 0.5$, $t \in \{0, 1/f_z, 2/f_z, \ldots, 10\}$, and $f = 3$ Hz.

Step 4: To observe the sensitivity of parameters introducing white noise to the signal obtained from (4). We considered $A = 0.5$, $t \in \{0, 1/f_z, 2/f_z, \ldots, 10\}$, $f_s = 50$ Hz, and $f_1 = 3$ Hz. Fig.2 illustrates a signal with white noise.

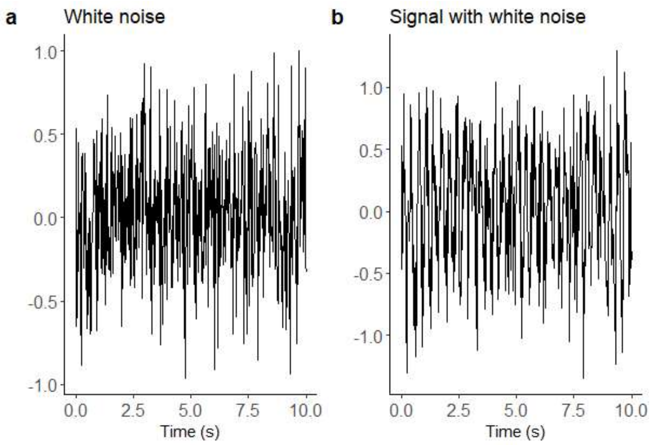

Fig. 2: (a) White noise and (b) a sine wave with white noise

Step 5: To observe the sensitivity of parameters introducing linear trend (5) to the signal obtained from (4). We considered $A = 0.5$, $t \in \{0, 1/f_z, 2/f_z, ..., 10\}$, $f_s = 50$ Hz, and $f_1 = 3$ Hz for the sine wave. For the linear trend we adopted $m = 0.025$, $t \in \{0, 1/f_z, 2/f_z, ..., 10\}$, and $n = 0.025$ as shown in Fig. 3.

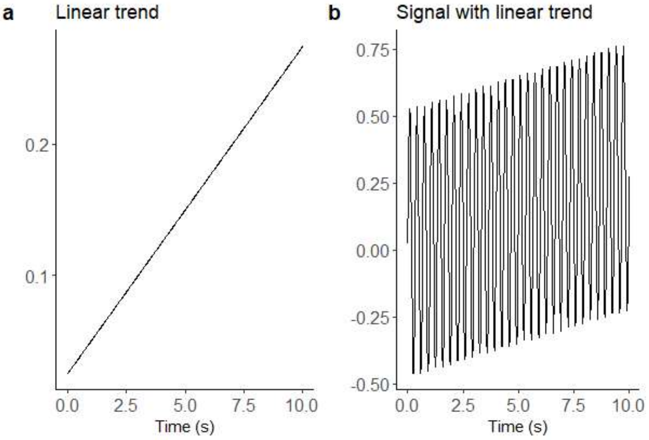

Fig. 3: (a) Linear trend and (b) sine wave with linear trend

Step 6: To observe the sensitivity of parameters introducing nonlinear trend (4) to the signal obtained from (4). We considered $A = 0.5$, $t \in \{0, 1/f_z, 2/f_z, ..., 10\}$, $f_s = 50$ Hz, and $f_1 = 3$ Hz for the pure sine wave. For the nonlinear trend we adopted $A = 1$, $f = 1$ Hz, and $f_s = 50$ Hz, as shown in Fig. 4.

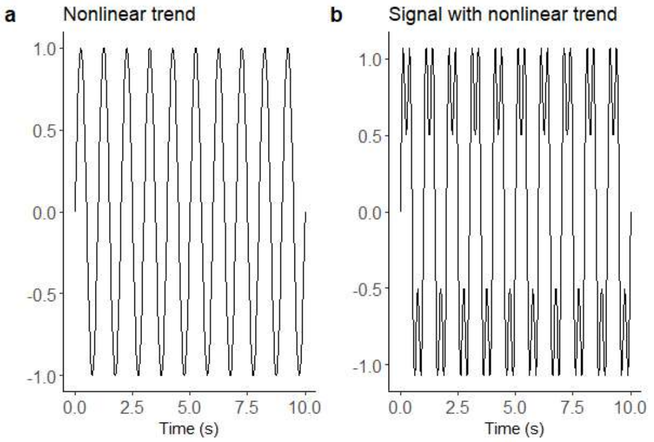

Fig. 4: (a) Nonlinear trend and (b) sine wave with nonlinear trend

III. Results

Steps 1, 2, and 3 focused on evaluating the Hjorth parameters varying some parameters of (4). These parameters of this Equation (4) simulate some fluctuations that may occur in real signals.

Fig. 5 depicts the results obtained from steps 1, 2, and 3.

The results obtained from steps 4, 5, and 6 are presented in Table 1.

Table 1: Sensitivity of Hjorth parameters according to the noise and trends

Type of signal	Activity	Mobility	Complexity
Sine wave	0.125	18.757	1.000
Signal with noise	0.212	46.180	1.774
Signal with linear trend	0.129	18.479	1.015
Signal with nonlinear trend	0.625	10.100	1.581

IV. Discussion

This research proposes to evaluate the behavior Hjorth parameters in artificial controlled experimental scenarios. We simulated six different scenarios and observed the sensitivity of these parameters according to each scenario.

The sine wave was generated for evaluating the behavior of Hjorth parameters in different scenarios. The sine wave has been widely used in several studies that involve biomedical signals due to their similarity with the shape of a sinusoid [9]–[11]. Moreover, its behavior is well established, becoming the analyses simpler and more controlled.

This study approached six different scenarios, which allow us understanding better the sensitivity of Hjorth parameters. These scenarios were depicted in steps 1, 2, 3, 4, 5, and 6 in the methods section. For Step 1, which varied the amplitude, we observed that only the activity was sensitive to this variation (Fig. 5-a). This result corroborates Hjorth's definition. For step 2, we varied the parameter of frequency. According to Fig. 5-b, the mobility followed the variation of frequency as described by Hjorth [1]. M. Mouzé-Amady and F. Horwat found similar results [2]. From step 3, we concluded that variation of the number of samples (Fig. 5-c) does not affect the Hjorth parameters.

In steps 4, 5, and 6 the sine wave (Fig. 1) was distorted by adding noise and trends. There are different sources from the noise in biomedical signals, for instance, noises from physiological variability, electronic, and environmental interference [12].

In order to understand the sensitivity of the Hjorth parameters to the noise, we introduced white noise in the signal (Fig. 2). The graph shown in Fig. 2-b allowed to observe that the amplitude, frequency, and shape of the signal were modified—these distortions reflected in the three Hjorth parameters (Table 1).

Also, the trends may distort the signal. Linear and nonlinear trends may originate from experimental protocol, acquisition process, and electronic devices. They are widely present in biomedical data [13]. Step 5 introduced a linear trend in a signal (Fig. 3 – b). The Linear trend provided small changes in the signal (Table 1). However, it does not mean that the Hjorth parameters are not sensitive to linear trends. Maybe adopting higher parameters on (5) may become the Hjorth parameters more sensitives to the linear trend. In contrast, the nonlinear trend (Fig. 4) modified the signal's amplitude, frequency, and shape. In Table 1, we can see that all Hjorth parameters were sensitive to the nonlinear trend.

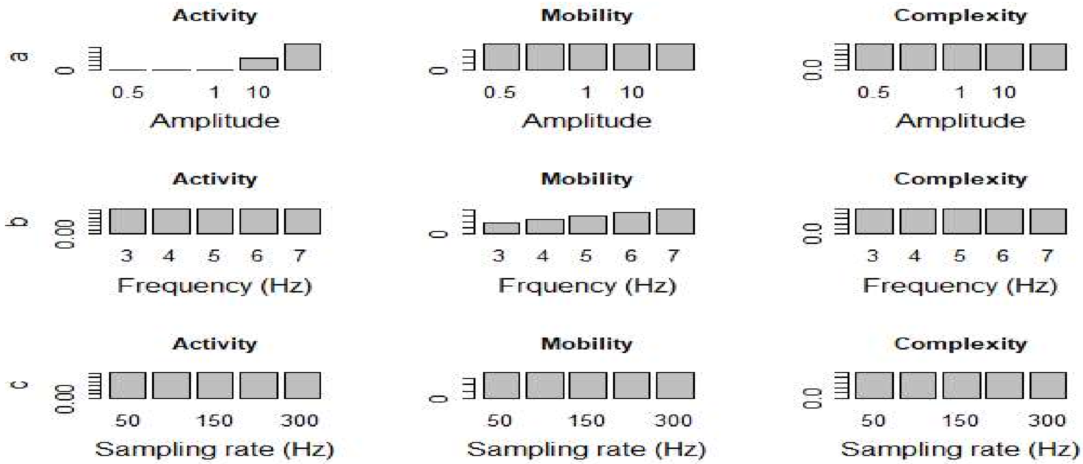

Figure 5: Sensitivity of Hjorth parameters from variations in amplitude (a), frequency (b), and sampling frequency (c)

V. Conclusion

The different controlled experimental scenarios used in this study to assess the Hjorth parameters had a key role in understanding these parameters better. The results presented may support other further studies for employing properly of these parameters. More studies are needed to extend the knowledge about the parameters. As future work, we suggest including more realistic signals.

Acknowledgment

The present work was carried out with the support of the National Council for Scientific and Technological Development (CNPq), Coordination for the Improvement of Higher Education Personnel (CAPES – Program CAPES/DFATD-88887.159028/2017-00, Program CAPES/COFECUB-88881.370894/2019-01) and the Foundation for Research Support of the State of Minas Gerais (FAPEMIG). A. O. Andrade is fellow of CNPq, Brazil (304818/2018-6).

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