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Characterization of Entropy Measures Against Data Loss: Application to EEG Records.

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Abstract— **This study is aimed at characterizing three signal entropy measures, Approximate Entropy (ApEn), Sample Entropy (SampEn) and Multiscale Entropy (MSE) over real EEG signals when a number of samples are randomly lost due to, for example, wireless data transmission. The experimental EEG database comprises two main signal groups: control EEGs and epileptic EEGs.**

Results show that both SampEn and ApEn enable a clear distinction between control and epileptic signals, but SampEn shows a more robust performance over a wide range of sample loss ratios. MSE exhibits a poor behavior for ratios over a 40% of sample loss. The EEG non–stationary and random trends are kept even when a great number of samples are discarded. This behavior is similar for all the records within the same group.

I. INTRODUCTION

Biomedical signals such as electroencephalograms (EEG), electrocardiograms (ECG) or heart rate variability (HRV) series, exhibit high non–stationary and non–linear trends. Classical linear signal processing methods are not suitable for their analysis. Noise, artifacts or any other signal outliers may cause these methods to yield misleading results. Linear methods sometimes suffer a lack of robustness when applied to biomedical signals [1], [2]. Another type of methods is necessary when trying to measure the dynamics of the signals. One group of these methods are the non–linear methods, very suitable to assess signal regularity.

Entropy measures are a family of statistics that provide information about the chaotic or deterministic nature of a signal, by quantifying the time–series regularity. In broad terms, they measure the likelihood that runs of patterns that are close, remain close in the next incremental comparison [3]. Among the wide variety of regularity measures, Approximate Entropy (ApEn), Sample Entropy (SampEn) and MultiScale Entropy (MSE) have been successfully used in many biomedical applications [4]–[8]. They have been chosen for the characterization study described in this paper.

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On the other hand, many biosignals are nowadays remotely acquired and wirelessly transmitted to a central communications node. The number of applications that need biosignal transmission is growing up in a very rapid way. For instance, telehealth applications, such as elderly people home monitoring, involves a 24/7 control. Most of data transmission in such applications is carried out in a wireless way (WiFi, Bluetooth, UMTS, GSM, zigbee, or any radio link). This type of transmission can suffer connection loss or interruptions [9] or packet loss [10], due to noise or interferences [11]. In addition, related techniques such as event detection [12], hardware design, energy saving, and data compression [13], [14], among others, may also entail a data loss.

Therefore, it is necessary to study data loss influence on the entropy measures. This loss has not been characterized before, and as wireless data transmission and non-linear methods become more widely used, the application of signal regularity methods to biosignals with missing samples can lead to incorrect conclusions. This paper aims to give an exhaustive characterization of ApEn, SampEn and MSE when EEG signals lose samples randomly.

II. METHODS AND MATERIALS

A. Regularity measures

1) Approximate Entropy (ApEn): ApEn is a regularity measure that quantifies the logarithmic likelihood of a time-series. It can be computed for any time-series and can discriminate a wide variety of signal types [2], [3]. It is considered to be insensitive to infrequent artifacts. It is also robust to noise, as long as the the noise present in the time–series is below a *de facto* threshold established by parameter r. On the other hand, it exhibits a statistical bias due to time–series length (N) and, if a signal-to-noise ratio is below 3 dB, its validity is compromised. A more detailed description of ApEn can be found in [2], [3].

The mathematical definition of ApEn is as follows: Let's consider a time data series $u(n)$ with $n = 0, 1, ..., N-1$. Runs of m consecutive values of $u(n)$, commencing in the i^{th} point can be arranged. We can define these runs as [2]:

$$x(i) = [u(i)u(i+1)...u(i+m-1)] \quad (1)$$

m is an input parameter for the length of the run [2]. In order to find out if the runs are considered similar, a dissimilarity measure is defined as [3]:

$$d(i,j) = d(x(i),x(j)) \\ = \max_k \{|x(i+k-1) - x(j+k-1)|\} \quad k = 1,2...m \tag{2}$$

ApEn is then calculated as a logarithmic likelihood ratio:

$$ApEn(m,r,N) = \Phi^m(r) - \Phi^{m+1}(r) \tag{3}$$

$\Phi^m(r)$ is estimated as follows:

$$\Phi^m(r) = \frac{1}{N-m+1} \sum_{l=1}^{N-m+1} ln\{C_i^m(r)\} \tag{4}$$

and $C_i^m(r)$ represents the number of coincidences, which is obtained as:

$$C_i^m(r) = \frac{1}{N-m+1} \sum_{j=1}^{N-m+1} y(j) \tag{5}$$

$$y(j) = \begin{cases} 1 & d(i,j) \le r \\ 0 & d(i,j) > r \end{cases} \tag{6}$$

r sets the filter level. N is the time-series length and m is the run length. According to (3), larger ApEn values correspond to more irregular signals. Length N should be between 100 and 3000 samples, and r higher than the mean amplitude of the noise present in the signal [3], [15].

2) Sample Entropy (SampEn): SampEn measures the conditional probability that two epochs from a time series remain close at the next sampled step [16]. SampEn exhibits relatively consistency under circumstances where ApEn does not, since it does not count for self–matches and it is largely independent of the record length (N). SampEn presents a reduced bias for short records [1]. The algorithm to compute SampEn is simpler than that of ApEn. Given a time–series $u(n)$ with $n = 0,1,...,N-1$, input vectors should be constructed as shown in (1). SampEn is defined as the natural logarithm of the likelihood ratio [1], [16] according to:

$$SampEn(m,r,N) = ln(\Phi^m(r)) - ln(\Phi^{m+1}(r)) \tag{7}$$

Although the same notation is used in (3), (4) and (5) they should not count for self-matches. Therefore their new expressions are:

$$\Phi^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} C_i^m(r) \tag{8}$$

$$C_i^m(r) = \frac{1}{N-m-1} \sum_{\substack{j=1 \\ j \neq i}}^{N-m} y(j) \tag{9}$$

where $y(j)$ is computed as given in (6).

3) MultiScale Entropy (MSE): MSE computes SampEn over a modified version of the original time–serie. MSE enables the resolution of regularity on larger scales. To estimate MSE, a coarser grained time-series, $w^{(M)}(n)$, is obtained from the original one $u(i)$, according to [17]:

$$w^{(M)}(n) = \frac{1}{M} \sum_{n=(j-1)M}^{jM} u(n) \qquad 1 \le j \le \frac{N}{M} \tag{10}$$

then SampEn is estimated as in (7) over the coarse grained series defined in (10).

B. EEG Database

This database [8] consists of 5 groups: Data A, B, C, D, and E. Each group contains 100 signals of 20s duration, sampled at a rate of 173.61 Hz. The first two groups (Data A and Data B) are control patients , while the other three groups (Data C, D and E) contain signal segments corresponding to patients suffering from epilepsy. Data C and D contain signal segments between interictal epochs, recorded on both hippocampal formations (left and right). Data E contains only ictal events.

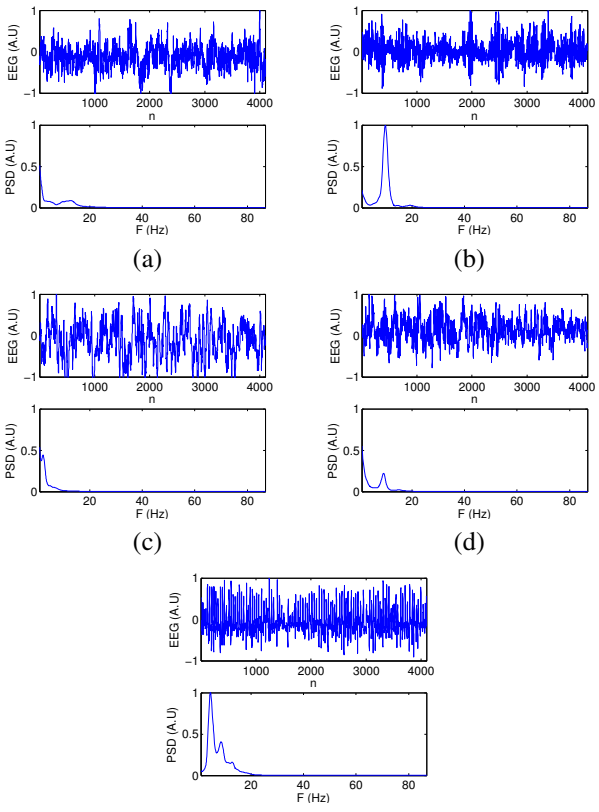

Fig. 1. EEG and PSD for one signal of each group. (a) Data A, control subjects with open eyes. (b) Data B, control subjects with closed eyes. (c) Data C, epileptic subjects, interictal events. (d) Data D, epileptic subjects, interictal events. (e) Data E, epileptic subjects, ictal events.

Signals were cut from a continuous multichannel EEG recording after visual inspection for artifacts (muscle activity, eye movement, etc.) and band–pass filtered [0.53, 40] Hz [8].

Fig. 1 shows an EEG signal segment and its corresponding power spectral density (PSD) for one signal of each group.

C. Simulations

Simulations were done using the MatLa$\langle c \rangle$ environment. The sample loss was implemented by removing a number of samples equal to a percentage previously established. The samples to be removed were selected by a random distribution. Sample loss percentage began at 0%, increasing in steps of 5%, up to 90%. One hundred random realizations were considered for each percentage, taking the mean values for the regularity measures. The parameters were configured as follows: m was set to 2 and r was set to $0.15\sigma_u$, where σ_u was the original time–series standard deviation.

D. Evaluation

Two types of analysis were done. The first one studied how the regularity measure(RM) evolved with sample loss for each group of signals in terms of median ($\tilde{\mu}$) and Median Absolute Deviation (MAD). The second analysis calculated the correlation coefficient (CC) of the regularity measures after the sample removal with respect to the original signal regularity value, so as to establish the robustness of the measure. The correlation coefficient is computed as follows:

$$CC = \left| \frac{\sum_{i=1}^{N_s-1} (RM - \mu_{RM})(RM_r - \mu_{RM_r})}{\sqrt{\sum_{i=0}^{N_s-1} (RM - \mu_{RM})^2} \sqrt{\sum_{i=0}^{N_s-1} (RM_r - \mu_{RM_r})^2}} \right| \quad (11)$$

RM and RM$_r$ are the vectors containing the regularity measures from the original and modified time–series of each data set. μ_{RM} and μ_{RM_r} are their respective mean RM values for data set. N$_s$ is the number of signals on each dataset.

The work described in [11] states that if CC is higher than 0.8–0.9, results are still valid to be used in clinical diagnosis.

III. RESULTS

Scale 1 MSE corresponds to SampEn, so this case was not considered for MSE. Scales ranged initially from 2 to 10, but results for scales higher than 3 were not robust enough in terms of class differentiation when the sample removal ratio was higher than 15%. Thus, results are only shown for ApEn, SampEn, and scales 2 and 3 of MSE.

Fig. 2 shows the median RM and their MAD for the 100 signals present in each data group. For each signal, a mean RM is taken from 100 random realizations. Fig. 2.(a) and Fig. 2.(b), show that ApEn and SampEn allow a better separation between control data (groups A and B) and epileptic data (groups C,D and E), even for an 80% of sample loss. MSE (see Fig. 2.(c) and Fig. 2.(d)) only allows a segmentation between main groups when sample loss ratio is below 40%. It can also be seen that even though regularity values change, the separation between control and epileptic subjects remains present for a high range of sample loss ratio (only for ApEn and SampEn).

Fig. 3 shows the CC versus the sample loss ratio. This figure enables to assess the robustness of the RM against data loss. SampEn appears to be the most robust one, as its

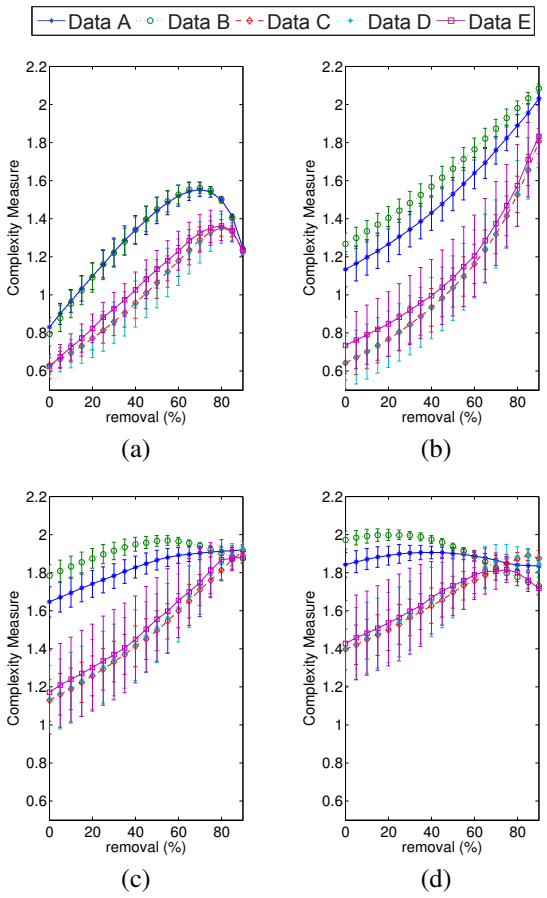

Fig. 2. RM ($\tilde{\mu} \pm MAD$) for each data set vs. sample removal ratio (%). (a) ApEn, (b) SampEn, (c) MSE scale 2, (d) MSE scale 3.

CC does not decay below 0.8 even though the 80% of the samples are lost. ApEn (see Fig. 3) seems to be slightly less stable, particularly for control data. Finally, MSE shows little robustness when sample loss ratio increases over 50%.

IV. DISCUSSION

From the description of the database [8], it was expected to have at least 2 main groups, control subjects (data A and B) and epileptic subjects (data C,D and E). It would be optimal to discriminate also among data groups C, D and E, as the first two contain interictal events while E contains only ictal events. However, given the small regularity dissimilarity among those groups, more realistic results to expect were a small variation of the regularity measures when increasing sample loss rate, and at least a clear separation between control and epilectic data groups.

These results can be observed in Fig. 2. ApEn and SampEn set a clear boundary between control patients (A and B) and epileptic patients (C,D and E), for almost the whole range of the sample loss ratio evaluated. Thus, it can be stated that these measures are able to make a clear distinction between these two groups even when the 80% of the samples are lost, regardless of the regularity value changes along with the sample loss ratio.

On the contrary, MSE does not exhibit such desirable properties. When the scale increases, the sample loss percentage

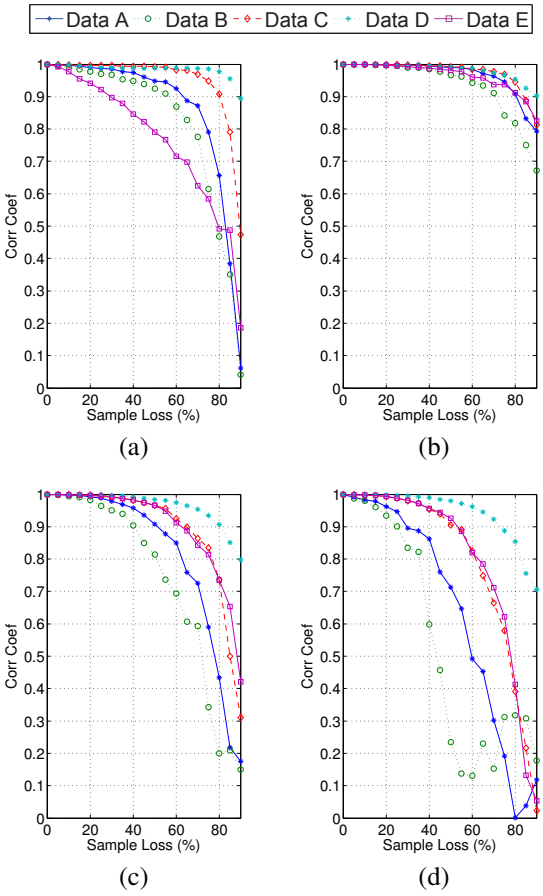

Fig. 3. CC versus sample loss ratio (%) for each data set and RM considered. (a) ApEn, (b) SampEn, (c) MSE scale 2, (d) MSE scale 3.

where the separation becomes blurred is lower, 60% for scale 2 and 40% for scale 3. If this measure is used to characterize only control patients (groups A and B), a separation between open eyes and closed eyes EEG's can be observed.

A robustness study in terms of the cross correlation coefficients (CC) was also performed. The corresponding results are graphically shown in Fig. 3. As long as the CC is over 0.8–0.9 [11], data suffice for a clinical diagnosis [11]. SampEn is preferred in terms of robustness as for all data groups as CC is over 0.8 for sample loss ratios up to 80%. MSE loses the robustness of the measure, earlier for larger scales, making it not reliable when the sample loss is above 40%.

V. CONCLUSION

A. Conclusions

In this paper, a characterization of 3 different signal regularity measures over EEG signals when the time-series data suffer of sample loss was presented. SampEn proved to be more robust in terms of CC value variation and in terms of group discrimination up to sample loss ratios of 80%. MSE demonstrated to be useful when looking for differences within a main group. EEGs showed a non-stationary trend which remained almost unaltered when some samples were not considered.

B. Future Work

A deeper characterization of these and additional regularity measures is being carried out. Some more studies like how interpolation or decimation affects the regularity measure, how these measures vary with the sample frequency, are under development. Parameterization also needs to be investigated, so as to establish how m and r affect the discriminating power of the regularity measures.

VI. ACKNOWLEDGMENT

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