Errors in the Estimation of Approximate Entropy and Other Recurrence-Plot-Derived Indices Due to the Finite Resolution of RR Time Series

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Abstract—An analysis of the errors due to the finite resolution of RR time series in the estimation of the approximate entropy (ApEn) is described. The quantification errors in the discrete RR time series produce considerable errors in the ApEn estimation (bias and variance) when the signal variability or the sampling frequency is low. Similar errors can be found in indices related to the quantification of recurrence plots. An easy way to calculate a figure of merit [the signal to resolution of the neighborhood ratio (SRN)] is proposed in order to predict when the bias in the indices could be high. When SRN is close to an integer value, the bias is higher than when near \( n - 1/2 \) or \( n + 1/2 \). Moreover, if SRN is close to an integer value, the lower the bias is, the greater the bias is.

Index Terms—Approximate entropy (ApEn), error, heart rate variability (HRV), recurrence plot, sampling frequency.

I. INTRODUCTION

ANALYSIS of heart rate variability (HRV) has become a clinical research tool to study the modulation that the autonomic nervous system exerts on the cardiovascular system. Traditional HRV analysis includes time-domain and frequency-domain indices computed from the RR time series, which is the time series obtained by measuring the time intervals between successive QRS complexes. Lately, several techniques inspired by the analysis of nonlinear dynamics have been considered. For example, the detrended fluctuation analysis aims to measure the autosimilarity of the time series and approximate entropy (ApEn) quantifies the complexity of the signal. Both techniques share in common that they still work reasonably well with a low number of samples (i.e., 300 samples), unlike other approaches, such as the correlation dimension or the Lyapunov exponents, which require a higher amount of data.

ApEn was first proposed by Pincus in 1991 [1] to measure changes in the complexity of nonlinear systems. The analyzed data came from simulations of deterministic models, such as the logistic or the Henon maps, so the resolution of the time series can be considered as that of the numerical processor and is very high when compared to the usual resolution of actual RR time series. ApEn is becoming a usual tool for characterizing the RR time series [2]–[10], although these time series are characterized by limited resolution.

ApEn is closely related to the quantification of recurrence plots. A recurrence plot shows when a point in the phase space is near (at a distance lower than a certain threshold) to another point [11]. Let us assume that \( RR = RR(1), RR(2), \ldots, RR(N) \) is an RR time series (or any other kind of time series) with length \( N \). The phase space is reconstructed by choosing two parameters: the embedding dimension \( (m) \) and the delay \( (\tau) \) between samples. The choice of \( m \) and \( \tau \) can depend on several criteria (see [12]) although in ApEn computations \( \tau = 1 \) and \( m \) is usually 2 and 3. A point in phase space is defined as

\[
\vec{x}_i = [RR(i), RR(i + \tau), \ldots, RR(i + (m - 1) \tau)]
\]

\( \forall i \in \{1, N - (m - 1) \tau\} \). (1)

A recurrence plot is a bidimensional plot defined by the recurrence matrix

\[
R(i, j) = \begin{cases} 
1, & \text{if } d(\vec{x}_i, \vec{x}_j) \leq \varepsilon \\
0, & \text{if } d(\vec{x}_i, \vec{x}_j) > \varepsilon
\end{cases}
\]

where the distance usually is the Euclidian norm \( (L_2\text{-norm}) \) or the maximum absolute difference between components of the points \( (L_{\infty}\text{-norm}) \), and \( \varepsilon \) is a predefined threshold. The neighborhood of a point \( \vec{x}_i \) is defined as the set of points that complies with \( R(i, j) = 1 \). Because ApEn is commonly computed with the \( L_{\infty}\text{-norm} \), we will use this norm in this paper.

ApEn is a family of indices defined as

\[
\text{ApEn}(m, k) = \frac{\sum_{i=1}^{N-m+1} \log \left( \frac{N^m(i)}{N-m} \right)}{N-m+1} - \frac{\sum_{i=1}^{N-m} \log \left( \frac{N^{m+1}(i)}{N-m} \right)}{N-m}
\]

(3)

where \( N^m(i) \) is the number of points in the phase space (with \( \tau = 1 \) and embedding dimension \( m \)) that are nearer to \( \vec{x}_i \) than \( k \) times the standard deviation of the time series with \( L_{\infty}\text{-norm} \). In order to compute ApEn, two recurrence plots must be computed with embedding dimensions \( m \) and \( m + 1 \), and a delay of one sample. Then, for each \( i \)

\[
N^m_p(i) = \sum_{j=1}^{N-m+1} R(i, j).
\]

(4)

ApEn is not the only index that exploits features of the recurrence plot. Other indices, such as the recurrence rate or...
percentage of determinism, are computed by summation of rows, columns, or diagonals of the recurrence matrix, and are being applied to the analysis of RR time series [13]. Moreover, other entropies can be obtained from the recurrence plot, such as the Kolmogorov [14] or Rényi entropies [15]. The aim of this paper is to estimate how the resolution of the RR time series affects the computation of the recurrence matrix and the estimation of ApEn.

II. MATERIALS AND METHODS

A. Effect of Finite Resolution of RR Time Series in Recurrence Plot

RR time series always have a limited resolution. If no interpolation or matching template techniques are used, the resolution is that of the sampling period of the ECG in which the QRS complexes have been detected. The standard deviation of the noise in each RR sample associated with the finite resolution can be estimated by manipulating the formula in [16, eq. (5)] as

$$\sigma(RN)_f = \frac{1}{\sqrt{6f_s}}$$

where \(f_s\) is the sampling frequency of the ECG. This noise arises from the difference of two white processes with uniform distribution, so the noise associated with the finite resolution is a colored noise with higher power contents at high frequencies than at low frequencies. Merri et al. [16] characterizes this noise in greater depth.

The main effect of the resolution of the RR time series in the computation of the recurrence plot is that the points on the phase space must lie in discrete positions separated at least by the sampling period (\(T_s\)). Fig. 1 shows an example when considering \(m = 2\) and \(\tau = 1\) (also known as the return map) and compares the return map and recurrence plot of an artificial time series with infinite resolution (obtained from an actual RR time series with \(T_s = 1\) ms) as well as the corresponding time series with \(T_s = 10\) ms. For the description of the rounding method and the creation of infinite-resolution time series, see the next two sections.

Because points in phase space must lie in a lattice, the number of neighbors around a particular point changes in a staircase fashion as \(\varepsilon\) changes. Fig. 2 shows an example of this behavior. The phase space of the example is a return map. We have focused on counting the neighbors of a certain point marked as a circle in the return map. As seen in the figure, each jump in the number of neighbors (solid line) occurs when the threshold \((\varepsilon)\) increases by approximately 8 ms. This is in accordance with the resolution of the time series, which is \(T_s = 7.8\) ms. Fig. 2(d) shows the difference between the number of neighbors when they are obtained from the 128-Hz time series resolution or from the infinite-resolution time series. Just after each jump in the finite-resolution time series, the number of neighbors is overestimated. As the threshold increases, there is no change in the number of neighbors in the finite-resolution time series until the next jump, although this change increases the number of neighbors in the infinite-resolution time series. So, before the next jump, the number of neighbors is underestimated.

![Fig. 1. Example of the consequences of the resolution of the RR time series in the return map \((m = 2, \tau = 1\) beat\) and the recurrence plot for an artificial RR time series. (a) Artificial RR time series with infinite resolution and 300 beats. (b) Return map for the RR time series with infinite resolution. (c) Return map for the RR time series with a resolution of 10 ms. (d) Recurrence plot for the infinite-resolution RR time series from the return map using a radius of the neighborhood of 0.2 times the standard deviation of the time series. The recurrence rate is 29.5%. (e) Recurrence plot for 10-ms resolution RR time series from the return map using a radius of the neighborhood of 0.2 times the standard deviation of the time series. The recurrence rate is 11.3%.](image)

In the computation of the ApEn, the threshold is proportional to the standard deviation of the time series, so

$$\varepsilon \overset{\Delta}{=} kSDNN$$

where SDNN is the common time-domain index recommended in [17] for the analysis of HRV. Let us define the figure of merit of the RR time series [signal to resolution of the neighborhood ratio (SRN)] in the computation of ApEn (or any other quantification of the recurrence plot) as

$$SRN = SDNN \times f_s \times k = \varepsilon f_s$$

where, for consistency, SDNN is expressed in seconds and \(f_s\) in Hertz.

As seen in Fig. 2, it is expected that the time series with SRN near an integer number will have greater errors than those with SRN near \(n + 1/2\) (\(n \in \mathbb{N}^+\)) because of the underestimation or overestimation of the number of neighbors. It is also expected that the greater the SRN, the lower the error, because the number of new neighbors (those that are included in the counting procedure by a small increase of SDNN, \(k\) or \(f_s\)) will be negligible in comparison with the other neighbors.
3) Differentiation of the $R_{\text{SRN}}$ time series to obtain the $RR_{\text{SRN}}$ time series with finite resolution

$$RR_{\text{SRN}}(i) = R_{\text{SRN}}(i + 1) - R_{\text{SRN}}(i).$$  

The change in SRN is accomplished by changing the SDNN of $RR_{\infty}$. For each $RR_{\text{SRN}}$ time series, ten recurrence plots were obtained with $k$ equal to 0.1, 0.15, 0.2, 0.25, and 0.3, and for embedding dimensions of 2 and 3. The delay was one sample in all the recurrence plots.

In each recurrence plot, the recurrence rate (excluding the line of identity) and percentage of determinism were computed and compared with that of the $RR_{\infty}$ time series [13]. Moreover, ApEn was computed with $m = 2$ and $k = 0.1, 0.15, 0.2, 0.25, 0.3$ for the $RR_{\infty}$ and $RR_{\text{SRN}}$ time series.

C. Errors in ApEn(2,0.2) With Actual RR Time Series

Errors in the indices will depend on the SRN. In this simulation, we have analyzed two free online databases available [19]: the normal sinus rhythm RR-interval database that provides beat annotations obtained from ECGs sampled at 128 Hz, and the Fantasia database whose ECGs are sampled at 250 Hz. The normal sinus rhythm RR-interval database comprises 54 recordings with an approximate duration of 24 h each. For this database, the RR time series were obtained directly from the beat annotations. After artifact correction, a total of 14,915 nonoverlapping RR time series with a duration of 5 min were considered in the study. The Fantasia database has 40 recordings with duration equal to the Fantasia movie (around 120 min). The raw R peak locations were obtained in this database with a Hamilton–Tompkins QRS detector [20]. After this, a cross-correlation procedure was used in order to improve the QRS complex locations by using the first QRS of each ECG as a template. Finally, the RR time series were obtained by digital differentiation of the $R$ time series. After correction of artifacts, as many RR time series as possible with a duration of 5 min were obtained by partitioning the whole RR time series without overlapping. A total of 945 RR time series in the Fantasia database were used in this study.

For each one of these finite-resolution RR time series ($RR_{\text{SRN}}$), ten possible “mother” infinite-resolution RR time series ($RR_{\infty}$) have been created as follows. If the actual RR time series is $RR_{\text{SRN}} = RR_{\text{SRN}}(1), RR_{\text{SRN}}(2), \ldots, RR_{\text{SRN}}(N)$, the procedure has the following steps.

1) Obtaining the $R$ peak locations time series $R_{\infty} = 0, R_{\infty}(2), \ldots, R_{\infty}(N + 1)$ by cumulated sum of the RR time series so

$$R_{\infty}(i + 1) = \sum_{j=1}^{i} RR_{\infty}(j).$$  

2) Rounding of the $R_{\infty}$ time series to the nearest multiple of $T = 1$ ms. If the RR time series is expressed in milliseconds, then

$$R_{\text{SRN}}(i) = \text{round}(R_{\infty}(i)).$$  

B. Simulation of Fractional Brownian Motion Time Series

We have limited the simulation study to time series with 300 samples with mean 1000 ms. The simulation creates time series with infinite resolution (SRN = $\infty$) from a fractional Brownian motion (fBm) generator [18]. Changing the Hurst exponent of the fBm implies a change in complexity of the signal; consequently, 100 realizations of fBm were done. For these realizations, the ApEn (2, 0.2), a common choice of parameters in chaotic motion (fBm) generator [18]. Changing the Hurst exponent with infinite resolution (SRN $\infty$) and time series to the nearest multiple of $\min = 0.1, 0.15, 0.2, 0.25, 0.3$ and for embedding dimensions of 2 and 3. The delay was one sample in all the recurrence plots.

After correction of artifacts, as many RR time series as possible with a duration of 5 min were obtained by partitioning the whole RR time series without overlapping. A total of 945 RR time series in the Fantasia database were used in this study.

For each one of these finite-resolution RR time series ($RR_{\text{SRN}}$), ten possible “mother” infinite-resolution RR time series ($RR_{\infty}$) have been created as follows. If the actual RR time series is $RR_{\text{SRN}} = RR_{\text{SRN}}(1), RR_{\text{SRN}}(2), \ldots, RR_{\text{SRN}}(N)$, the procedure has the following steps.

1) Obtaining the $R$ peak locations time series $R_{\text{SRN}} = 0, R_{\text{SRN}}(2), \ldots, R_{\text{SRN}}(N + 1)$ by cumulated sum of the RR time series. Thus

$$R_{\text{SRN}}(i + 1) = \sum_{j=1}^{i} RR_{\text{SRN}}(j).$$  

2) Addition of noise to the $R$ peak location

$$R_{\infty}(i) = R_{\infty}(i) + \eta(i)$$  

where $\eta(i)$ is a realization of uniform white noise distributed between $-1/(2f_s)$ and $1/(2f_s)$. 

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Fig. 2. Example of the error caused by the resolution of the RR time series when counting neighbors. (a) Artificial RR time series with infinite resolution. (b) Return map of the 7.81-ms resolution RR time series. The circle indicates the point in the return map that has been considered to compute how the number of neighbors changes with the radius of the neighborhood. The dotted line is the evolution for the infinite-resolution RR time series while the solid line is that of the 7.81-ms resolution RR time series. (c) Difference in the number of neighbors when comparing results for the infinite and the 7.81-ms resolution time series.
Fig. 3. Results for simulated time series with different dynamics. The error is defined as the computed index for the finite-resolution time series minus the computed index for the infinite-resolution time series. (a) Error on the recurrence rate with \( m = 2 \) and \( \tau = 1 \) beat versus SRN. (b) Error on the recurrence rate with \( m = 3 \) and \( \tau = 1 \) beat versus SRN. (c) Error on the determinism with \( m = 2 \) and \( \tau = 1 \) beat versus SRN. (d) Error on ApEn with \( m = 2 \) and \( \tau = 1 \) beat versus SRN.

Fig. 4. Results for the error (defined as in Fig. 3) for the ApEn \((m = 2\) and \(\tau = 1\) beat) in actual RR time series. (a) Mean error versus SRN for the considered 149 15 RR time series of 5 min duration of the normal sinus rhythm database with a 7.81 ms resolution. (b) Standard deviation of the error versus SRN for the considered RR time series of the normal sinus rhythm database. (c) Mean error versus SRN for the considered 945 RR time series of 5 min duration of the Fantasia database with a 4 ms resolution. (d) Standard deviation of the error versus SRN for the considered RR time series of the Fantasia database.

<table>
<thead>
<tr>
<th>( k )</th>
<th>Recurrence Rate ( m=2 ) (%)</th>
<th>Recurrence Rate ( m=3 ) (%)</th>
<th>Determinism ( m=2 ) (%)</th>
<th>ApEn(2,( k ))</th>
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<td>0.25</td>
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<td>22.7 — 78.3</td>
<td>0.70 — 1.31</td>
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<td>0.30</td>
<td>2.61 — 11.1</td>
<td>0.41 — 6.28</td>
<td>28.4 — 83.8</td>
<td>0.59 — 1.34</td>
</tr>
</tbody>
</table>

3) Differentiation of the \( R_\infty \) time series to obtain the \( RR_\infty \) time series with infinite resolution

\[
RR_\infty(i) = R_\infty(i + 1) - R_\infty(i). \tag{13}
\]

With this method, any infinite-resolution RR time series, when rounded as described in the previous section (with a resolution of \( 1/f_s \), in the second step), returns to the finite-resolution RR time series from which it was created.

The ApEn \((2, 0.2)\) has been calculated for each \( RR_\infty \) time series. The difference of the mean of ApEn(2, 0.2) for the ten simulated \( RR_\infty \) with regard to the ApEn(2, 0.2) of the \( RR_{SRN} \) time series as well as the standard deviation of the ten realizations have been computed.

III. RESULTS AND DISCUSSION

Fig. 3 shows the results of the error (index computed with finite resolution minus the index computed with infinite resolution) for the recurrence rate computed with embedding dimensions of 2 and 3, for the percentage of determinism for \( m = 2 \) and for ApEn when dealing with simulated time series. Table I shows the range of simulated indices for the infinite-resolution time series. Fig. 4 shows the error results for the normal sinus rhythm RR-interval and Fantasia databases. Figs. 3 and 4 express the errors with regard to SRN, showing that they decrease with increasing SRN and that they are worse for SRN near an integer. On the other hand, the standard deviation of the error in ApEn \((2, 0.2)\) in Fig. 4 decreases with SRN, and is typically lower than the mean error.

Results show that errors due to the resolution of the time series in ApEn or other indices derived from recurrence plots (percentage of determinism, recurrence rate, sample entropy, etc.) can be very high when certain conditions are met. As Figs. 3 and 4 show, when the SRN is near an integer number, errors can be very high. As an example, in the normal sinus rhythm RR-interval database, the worst scenario for the estimation of ApEn \((2, 0.2)\) occurs when the RR time series has an SDNN near 39 ms (SRN = 1, \( f_s = 128 \) Hz, \( k = 0.2 \) in (7)), or when the SDNN tends to zero. Of course, the RR time series with a standard deviation near 78 ms also deserves special attention, but it depends on the required resolution for the index. If ApEn \((2, k)\) is to be expressed with a significant digit, the maximum admissible error is 0.05. Fig. 3(d) shows that this condition leads to an SRN greater than 10. For the normal sinus rhythm RR-interval database and \( k = 0.2 \), the minimum standard deviation is 391 ms, a condition that it is hardly ever met in actual RR time series. In RR time series with a resolution of 1 ms, this condition relaxes to a SDNN greater than 50 ms. Nevertheless, in stressful or pathological states, it is very common to have a standard deviation lower than this threshold.

The error in ApEn depends on \( k \), the SDNN of the time series, and the sampling frequency of the ECG. Generally, in a clinical or scientific study, the sampling frequency and \( k \) are...
constant parameters, so the changes in error are modulated by the changes in SDNN for different time series. The algorithm described in Section II-C provides a way to estimate if the error in ApEn for a certain RR time series can be high. Moreover, the fact that the error decreases with increasing SRN (although not monotonically) provides an insight into the validity of previously published studies. Table II shows some results from previous studies. The mean SDNN, \( f_s \), and \( k \) are used to compute the average SRN (SRN) while the interval \( \{ (SDNN - \sigma_{SDNN}) f_s, SDNN f_s, k \} \) is used to compute the worst case for SRN (SRNWC) as the minimum integer SRN is contained in it. As can be seen in Table II, some studies can use the RR time series with SRN as low as 1 or 2. Results in Figs. 3 and 4 show that the absolute error in ApEn can be as high as 0.6 for an SRN near 1, or 0.2 for an SRN near 2. Moreover, Table II shows that the mean SRN can be very different among measured groups.

Some authors claim that the recurrence plot analysis can be used with nonstationary time series as well as with stationary signals \([21], [22]\) in order to track state changes or characterize the degree of complexity of the system under analysis. Although the stationarity issue of the time series has not been treated by most authors when applying ApEn to the RR time series, it must be stressed that the mathematical sense of entropy only has meaning when dealing with stationary time series. The presence of nonstationarity in the time series can affect the estimation of ApEn or other related indices. As an example, Fig. 5 shows how a trend modifies the errors in the estimation of ApEn (2, 0.2). Fig. 5(a) shows a simulated RR time series, which is a realization of white Gaussian noise with no trend. Fig. 5(c) shows the same realization, but with a superimposed linear trend. Fig. 5(b) and (d) shows the evolution of the error in ApEn(2,0.2) for both time series by changing the SRN. Both evolutions have the same pattern, although the errors are not equal because the ApEn(2, 0.2) of both time series are different (1.09 for the stationary time series as compared to 1.14 for the nonstationary time series).

Although most of the studies of ApEn in HRV work directly with the RR time series, some authors \([23], [24]\) use the resampled RR time series in order to work with an evenly sampled time series. Fig. 6 shows the effect of the cubic spline resampling procedure at 2 Hz and how the errors behave in a different fashion. Fig. 6(a) shows a RR_{\infty} time series obtained from a RR time series sampled at 1 kHz with ApEn (2, 0.2) = 1.033 and with an SRN = 7.40. The obtained RR_{\infty} has ApEn (2, 0.2) = 1.068. Fig. 6(b) shows RR_{\infty} resampled at 2 Hz and how the errors behave in a different fashion. The ApEn (2, 0.2) for RR_{\infty} is 0.938 due to the smoothing of the interpolation. Fig. 6(c) shows the return map for RR_{SRN} obtained from RR_{\infty} when resampled at 100 Hz, and Fig. 6(d) the return map for RR_{SRN} (the resampled version at 2 Hz of RR_{SRN}). One of the effects of the resampling procedure is to blur the return map. Finally, Fig. 6(e) and (f) shows the evolution of ApEn (2, 0.2) for RR_{SRN} and RR_{SRN} against SRN. The ApEn (2, 0.2) for RR_{SRN} evolves as in the previous sections, with the error reducing as SRN increases, but higher when SRN approaches an integer. However, the evolution of ApEn (2, 0.2) for RR_{SRN} is different. The error (compared to the solid line, the ApEn (2, 0.2) of RR_{\infty}) reduces more monotonically as SRN increases. On the other hand, the resampling procedure introduces a bias in the computation of ApEn (difference between the solid and dashed line). This bias depends on the resampling frequency (i.e., the ApEn (2, 0.2) of the RR_{\infty} is 0.694 when resampled at 3 Hz).

Finally, the effect of noise on recurrence plots has been studied previously \([25]\) taking into consideration that the observational noise is not correlated with the signal. These investigations show that the error can be minimized by choosing a convenient size of the neighborhood or by improving the resolution of the time series. Unfortunately, in ApEn computations,
the neighborhood size is conditioned by $k$ and SDNN, and the resolution is determined by the sampling frequency.

IV. CONCLUSION

The finite resolution of RR time series can create very high errors when estimating the ApEn or other indices related to the quantification of recurrence plots. These errors are particularly significant when the product of the threshold of the recurrence plot and the inverse of the resolution is low and approaches an integer number (especially 0 or 1). Thus, the results of indices such as ApEn when applied to time series with low finite resolution or low standard deviation should be regarded with caution.

REFERENCES


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