On Applying Approximate Entropy to ECG Signals for Knowledge Discovery on the Example of Big Sensor Data

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Abstract. Information entropy as a universal and fascinating statistical concept is helpful for numerous problems in the computational sciences. Approximate entropy (ApEn), introduced by Pincus (1991), can classify complex data in diverse settings. The capability to measure complexity from a relatively small amount of data holds promise for applications of ApEn in a variety of contexts. In this work we apply ApEn to ECG data. The data was acquired through an experiment to evaluate human concentration from 26 individuals. The challenge is to gain knowledge with only small ApEn windows while avoiding modeling artifacts. Our central hypothesis is that for intra subject information (e.g. tendencies, fluctuations) the ApEn window size can be significantly smaller than for inter subject classification. For that purpose we propose the term *truthfulness* to complement the statistical validity of a distribution, and show how truthfulness is able to establish trust in their local properties.

Keywords: Information entropy, ApEn, big data, knowledge discovery, ECG complexity.

1 Introduction and Motivation for Research

Research on heart rate variability (HRV) has attracted considerable attention in the fields of psychology and behavioral medicine. Still, quantification and interpretation of HRV remains a complex issue [1], since the heartbeat period variability is the result of the activity of vasomotor and respiratory centers,

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of baroreflex and chemoreflex closed loop regulation, of cardiovascular reflexes mediated by vagal and sympathetic afferences and of vascular autoregulation [2]. This collection of mechanisms act over various frequencies (similar but not coincident), and contribute to the complexity of the signal [2]. To summarize, Batchinsky et al. [3] state that HRV refers to a collection of methods describing regular periodic oscillations in the heart rate, attributed to the vagal and/or sympathetic branches of the autonomic nervous system.

These findings underline how important it is to recognize the regulatory complexities and organ system interconnections, when drawing conclusions based on heart rate related signals such as the electrocardiogram (ECG).

A promising approach to extract knowledge out of heart rate signals is the heart rate complexity (HRC). It utilizes a statistical approach, with methods derived from nonlinear dynamics. The *structural complexity* of the sampled ECG signal is used to describe the *regulatory complexity* and organ system interconnections [4]. Note that complexity and variability are not necessarily the same [5]. A periodical signal, such as a sinus wave, is variable but not complex. This is a desirable property, since it allows complexity measures to ignore the complicated periodic oscillations to some extend.

One complexity measurement in particular is of high interest to us, which is the Approximate Entropy (ApEn) introduced by Steven Pincus [6] in 1991. ApEn is a statistic quantifying regularity and complexity in a wide variety of relatively short (greater than 100 points) and noisy time series data [7]. The development of ApEn was initially motivated by data length constraints commonly encountered in heart rate, electroencephalography (EEG) and endocrine hormone secretion data sets [8].

In the context of ECG data, ApEn was previously used by Batchinsky et al. [3] to investigate the changes in heart rate complexity in patients undergoing postburn resuscitation. They used ApEn with relatively large windows (> 800 heart beats) of the RRI[1] time series, in order to perform classification of pathological conditions based on the absolute ApEn values. Thus they were aiming at inter-subject classification.

Our ultimate goal is to justify much smaller ApEn windows (< 100 heart beats), to gain intra-subject knowledge (e.g., tendencies and fluctuations) that are consistent for many subjects, without the need for classification based on the absolute ApEn values. To be more specific, we analyzed a number of ApEn distributions out of the *sampled ECG signal* from 26 subjects using ECG data collected while the subjects were submitted to a concentration test [9].

In this paper we investigate the lower bounds for a valid ApEn window size, as well as possible causes for sporadic deviations in small window distributions. For this purpose, we propose the term *truthfulness* to complement the statistical validity of a distribution, in order to establish trust in the window placements, as well as to give an indication for stability of the ApEn distribution.

[1] RRI stands for R-to-R interval and describes the latency between two consecutive R peaks in the ECG. It's inversely proportional to and can be used to derive the heart rate.

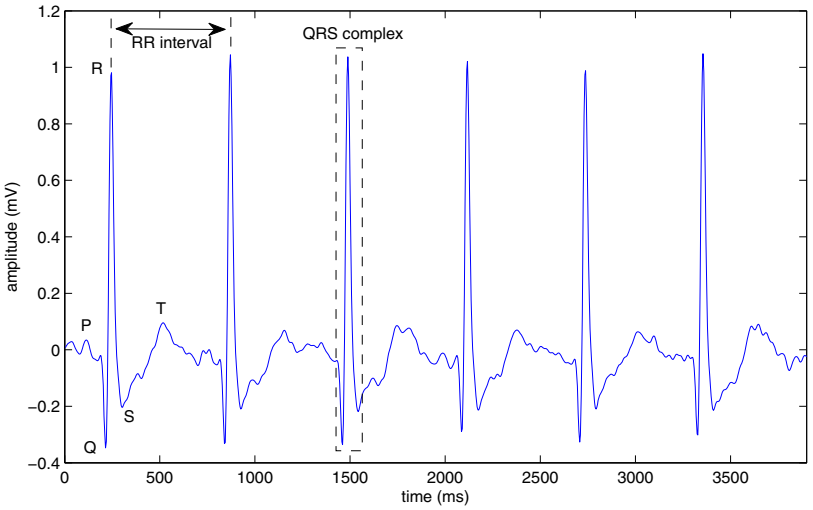

Fig. 1. A typical ECG signal; the first wave is annotated with the typical P-QRS-T complexes. Note that the *RR interval* is not constant (not even for resting subjects), since it oscillates periodically, shortening with inspiration and lengthening with expiration [10].

2 Background

As mentioned before, we make use of the electrocardiogram (ECG). Electrocardiography is an interpretation of the electrical activity of the heart over a period of time. It is a non-invasive procedure, using electrodes attached to the surface of the skin. The recording of the electrical activity is called electrocardiogram, and it is commonly used to measure the heart rate, the regularity of the beats, and characterize properties or injuries in the heart chamber. A clinical assessment of the ECG mostly relies on relatively simple measurements of the intrabeat timings and amplitudes [10].

Figure 1 shows some of the most common attributes analyzed in the ECG signal. The width of the QRS complex is representative of the time the ventricles need to depolarize and is typically lasting between 80 to 120 ms. It is interesting to note, that the lower the heart rate, the wider is the S-T complex [10].

One signal analysis approach commonly applied to ECG time series is frequency domain analysis, and uses the fast Fourier transform (FFT). From the FFT, two key frequency bands of the periodic oscillations in the ECG are typically identified as relevant in the analysis of RRI data, namely high-frequency (HF) power ($0.15 - 0.40$ Hz), and low-frequency (LF) power ($0.04 - 0.15$ Hz) [3]; a frequency range < 0.03 Hz, called very low frequency (VLF) power is also often found in literature.

The RRI indicates the beat-to-beat interval. Each consecutive RRI is of different length, unless the patient is paced. The reason for this is that the RRI oscillates periodically, shortening with inspiration and lengthening with expiration.

This phenomena is called respiratory sinus arrhythmia (RSA) [10]. The term arrhythmia might be misleading to some, since in this case it is not due to a medical condition, but it is a sign of a healthy organism. It occurs at the same frequency as the respiratory rate and has been shown to be a major component of HF [3]. The LF on the other hand is less specific, but has been related to both sympathetic and parasympathetic autonomic activity [11].

Artifacts in the ECG can lead to the spurious quantification of RRIs, which might result in substantial misinterpretation of the data. Results of Berntson and Stowell [12] revealed that even a single artifact, occurring within a 128 s interbeat interval series, can impart substantial spurious variance into all commonly analyzed frequency bands, including that associated with respiratory sinus arrhythmia. They emphasize the importance of artifact awareness for studies of heart period variability [12].

3 Related Work

Approximate Entropy found its way into many fields of application within the medical domain.

Acharya et al. [13] proposed a methodology for the automatic detection of normal, pre-ictal, and ictal conditions from recorded EEG signals. Beside Approximate Entropy, they extracted three additional entropy variations from the EEG signals, namely Sample Entropy (SampEn), Phase Entropy 1 and Phase Entropy 2. They fed those features to seven different classifiers, and were able to show that the Fuzzy classifier was able to differentiate the three classes with an accuracy of 98.1 %.

Hornero et al. [14] performed a complexity analysis of intracranial pressure dynamics during periods of severe intracranial hypertension. For that purpose they analyzed eleven episodes of intracranial hypertension from seven patients. They measured the changes in the intracranial pressure complexity by applying ApEn, as patients progressed from a state of normal intracranial pressure to intracranial hypertension, and found that a decreased complexity of intracranial pressure coincides with periods of intracranial hypertension in brain injury. Their approach is of particular interest to us, because they proposed classification based on ApEn tendencies instead of absolute values.

In the field of ECG analysis, Batchinsky et al. [3] recently performed a comprehensive analysis of the ECG and Artificial Neural Networks (ANN) to improve care in the Battlefield Critical Care Environment, by developing new decision support systems that take better advantage of the large data stream available from casualties. For that purpose they analyzed the HRC of 800-beat sections of the RRI time series from 262 patients by several groups of methods, including ApEn and SampEn. They concluded that based on ECG-derived noninvasive vital signs alone, it is possible to identify trauma patients who undergo Life-saving interventions using ANN with a high level of accuracy. Entropy was used to investigate the changes in heart rate complexity in patients undergoing post-burn resuscitation.

4 Methods and Materials

We are concerned with knowledge discovery [15], [16], [17] within ECG signals. For this purpose we model the continuous input signal given by the sensors as $U(t)$. After the digitalization process, the ECG signal $U(t)$ is considered as a discrete time series sampled at different points $t \in T$ over time, and will thus be referred to as ECG time series. Furthermore, to be consistent with Pincus [6], we denote data points of the ECG time series as $u(t)$. Note that the ECG time series we work with are considered *regularly* sampled, which basically means that the used sampling frequency was a constant.

4.1 Approximate Entropy (ApEn)

Approximate Entropy measures the logarithmic likelihood that runs of patterns that are close remain close on next incremental comparisons [6]. We state Pincus' definition [6], [8], for the family of statistics $\mathrm{ApEn}(m, r, N)$, using our previous definition of the ECG time series:

Definition 1. *Fix m, a positive integer and r, a positive real number. Given a regularly sampled time series $U(t)$, a sequence of vectors $\boldsymbol{x}(1), \boldsymbol{x}(2), ..., \boldsymbol{x}(N - m + 1)$ in $\mathbb{R}^m$ is formed, defined by*

$$\boldsymbol{x}(i) = [u(t_i), u(t_{i+1}), ..., u(t_{i+m-1})] \; . \tag{1}$$

Define for each i, $1 \leq i \leq N - m + 1$,

$$C_i^m(r) = \frac{\textit{number of } j \textit{ such that } d[\boldsymbol{x}(i), \boldsymbol{x}(j)] \leq r}{N - m + 1} \, , \tag{2}$$

with $d[\boldsymbol{x}(i), \boldsymbol{x}(j)]$ following Takens' [18] definition of a distance metric

$$d[\boldsymbol{x}(i), \boldsymbol{x}(j)] = \max_{k=1,2,...,m} \left(\left| u\left(t_{i+k-1}\right) - u\left(t_{j+k-1}\right) \right| \right) . \tag{3}$$

Furthermore, define

$$\Phi^m(r) = (N - m + 1)^{-1} \sum_{i=1}^{N-m+1} \log C_i^m(r) \, , \tag{4}$$

*then the **Approximate Entropy** [6] is defined as*

$$\mathrm{ApEn}(m, r, N) = \Phi^m(r) - \Phi^{m+1}(r) \, . \tag{5}$$

4.2 The Idea of Truthfulness

Our goal is to investigate the potential of using smaller ApEn windows (< 100 heart beats) on ECG time series data. With that in mind, we investigated potential pitfalls to ultimately validate a lower bound for heart beat windows. In this preliminary work we tried this without actually needing to interpret the data, but by taking a closer look at the *truthfulness* of the computed ApEn distributions.

We define the terms *ApEn window* and *ApEn distribution* as follows:

Definition 2. *Given a window size N and a time series $U(t)$ containing K data points, we split the time series $U(t)$ into $\lfloor K/N \rfloor$ equally spaced and adjacent parts of size N. Each part, in combination with the computed ApEn value for the part, is referred to as an ApEn window.*

Definition 3. *The sequential collection of all ApEn windows of a given time series $U(t)$ is called the ApEn distribution of the time series $U(t)$.*

With the basic terms defined we state the following definition for an ApEn windows truthfulness:

Definition 4. *The value of an ApEn window within an ApEn distribution is considered truthful for a defined distributional characteristic (e.g. linear or cubic), when sliding the window for an arbitrary amount of data points only influences the value according to the distribution and a specified tolerance.*

Note three things about this definition. First, it is not explicitly specified what rules the distribution follows (e.g. if it's linear or cubic). So we have to define what "according to the ApEn distribution" means. Secondly, this means that a window size of $N = 4$, for example, would cause nearly all windows to be considered truthful, since there is almost no interpolation, however it would not be useful, nor statistically valid. So it is important to note, that truthfulness does not imply usefulness, but the potential to be useful. And last, note that adjacent windows influence the truthfulness of each other. This is not considered to be a problem, since the source of the deviation could as well be between two adjacent windows.

Based on the definition of the truthfulness of a window, we define truthfulness of a ApEn distribution as follows:

Definition 5. *If all but a negligible amount of ApEn windows within an ApEn distribution are considered truthful, then the ApEn distribution itself is considered to be truthful.*

This is a loose definition, since it is not defined what is considered to be a negligible amount of ApEn windows. However, it enables one to have a tolerance, since in statistic measures there will almost always be outliers. It also enables one to deal with ECG artifacts to some extend, without having to unnecessarily increase the window size, just so that rare artifacts don't cause the distribution to be considered not truthful.

We propose the term truthfulness not as a substitute for statistical validity, e.g. as the term was used by Pincus [8], but as an extension. One does not imply the other. While the statistical validity is concerned with a single ApEn value for a given time series, truthfulness is concerned with multiple ApEn values for a given time series forming an ApEn distribution. In other words, the deviations in the window values do not describe uncertainty of the values, but instability concerning the time dimension.

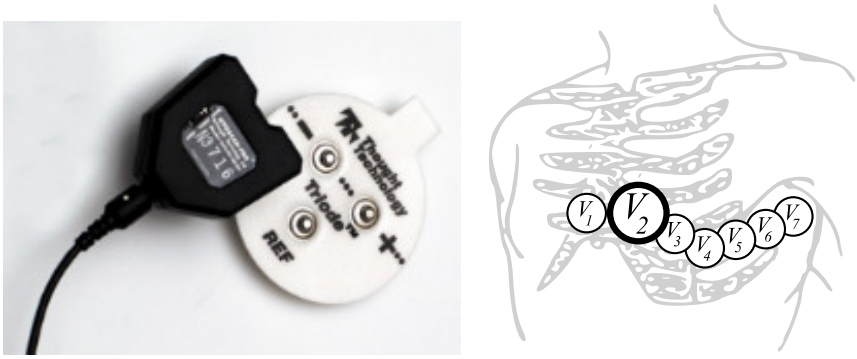

Fig. 2. The left image shows the ECG acquisition sensor. On the right you can see the lead V_2 sensor placement used in the experimental setup.

Our goal is to establish trust in the window placements, as well as to give an indication for stability of the ApEn distribution, and ultimately enabling one to extract knowledge from the properties of an ApEn distribution (e.g. tendencies, fluctuations).

Example 1. If moving some ApEn windows of an ApEn distribution for a negligible amount of data points causes the distribution to decrease over time, when it was increasing before, then the distribution is not considered to be truthful.

4.3 Data Acquisition

For these experiments we used the data of an investigation [9] performed by the co-authors in Lisbon, where 26 volunteering subjects[2] willingly participated in individual sessions (one per subject), during the course of which their ECG signal was recorded. Unlike the conventional acquisitions in a resting position, in each session the subject was asked to complete, on a computer, a task consisting of a concentration test, designed for an average completion time of 10 minutes.

Prior to initiating the task, subjects were equipped with the sensor and placed in front of the computer in a sitting position. No limitations on posture or motion during the activity were imposed, although the task was designed in such way that the subject only used the mouse to interact with the computer. To motivate the subjects commitment to the test, a performance score was computed and assigned to each subject.

For sensor placement the V_2 precordial derivation was chosen, located on the fourth intercostal space in the mid clavicular line, at the right of the sternum (Fig. 2 on the right). Ten-20 conductive paste was used to improve conductivity; for the same purpose, prior to the sensor placement, the selected area was prepared with abrasive gel.

[2] 18 males and 8 females between the ages of 18 and 31 years.

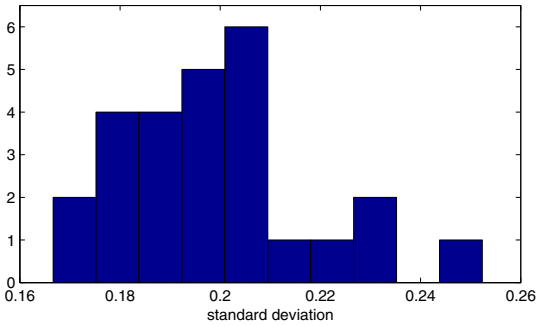

Fig. 3. The histogram of the standard deviation (SD) distribution of all ECG time series, in order to choose a common and valid r as ApEn parameter. The SDs range between 0.16 and 0.25.

Unlike the standard 12-lead ECG recording setup, which involves six sensors placed on the chest area and six other placed on the limbs, a one-lead surface mount setup was used. Acquisition was performed at a 256 Hz sampling rate using a ProComp2 encoder, and a gain 50 local differential triode (Fig. 2 on the left), with 2 cm inter-electrode spacing, and channel bandwidth of 0.05 – 100 Hz, both from Though Technology Ltd. The acquired signals were filtered using a zero phase forward and reverse 4^{th} order Butterworth filter in the 2 – 30 Hz passing band, which proved to provide adequate results for our application.

5 Experimental Results and Lessons Learned

When choosing values for the ApEn parameters listed in (5), we tried to follow Pincus recommendation. Pincus [8] concluded that for $m = 1$ or $m = 2$, values of r between 0.1 SD (standard deviation) and 0.25 SD of the data produce good statistical validity of ApEn(m, r, N). He also states that ApEn can meaningfully be applied to $N \geq 1000$ data points [8]. However, the term data points is arbitrary, since it's amount depends on the sampling frequency of the signal.

We computed the standard deviation for all 26 ECG time series, as can be seen in Fig. 3, and we decided to use a common r of $r = 0.04$ with $m = 2$ for all ECG time series.

We started with a very small window size of $N = 1590$, which covers about 10 heart beats, in order to amplify possible side effects introduced by small windows. We moved the windows four times (two times to the left and two times to the right) for 30 data points each, which is less than 2 % of the window size and calculated the mean, as well as the SD for each group of five window positions. In order to establish the truthfulness of the ApEn values of the windows, we considered a linear characteristic and a tolerance of 5 % of the distance between consecutive window values.

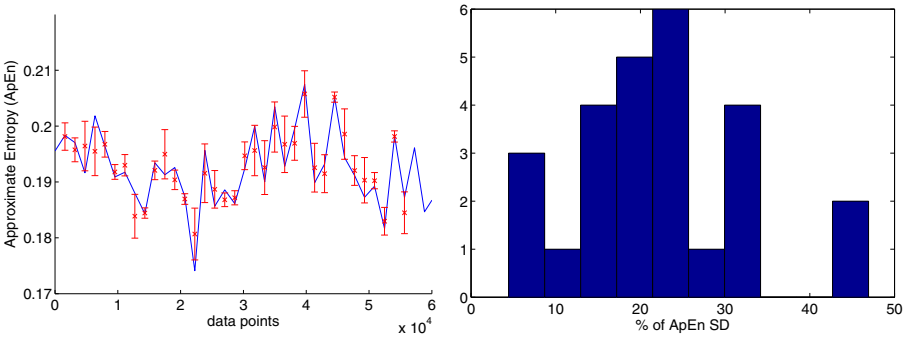

Fig. 4. The impact of the window placement to a window's ApEn value. The left shows part of the ApEn distribution of an ECG time series with the ApEn parameters $m = 2$, $r = 0.04$, $N = 1590$. The red error bars denote the standard deviation around the mean when sliding the windows four times (two times to the left and two times to the right) for 30 data points each, which is less than 2 % of the window size. The right shows that for all 26 ECG time series, the mean SD of all window groups amounts up to 45 % of the SD of its ApEn distribution.

Figure 4 shows, that the SD of the window groups is not necessarily correlated to the distance between consecutive window-values, but seem arbitrary. In fact, the mean SD of all window groups covers between 5 % and 45 % of the SD of its ApEn distribution. This is because the mean SD of all window groups ranges only between $2.4 \cdot 10^3$ and $3.8 \cdot 10^3$. So the impact is stronger for those ApEn distributions that have only a small SD. As expected the window size of $N = 1590$ (10 heart beats) is not considered to be truthful.

Note that the error bars in Fig. 4 do not describe the uncertainty of the concrete window values, but the deviation when slightly sliding the window. This means that for each slide, the underlying data is different, but still closely related in time.

Interestingly, by investigating further with different window sizes ranging between $N = 2000$ and $N = 10000$ data points, we found no notable correlation between the mean SD of all window groups and the SD of the its ApEn distribution.

Those findings strongly suggest that something is introducing deviations, that could for simplicity be described as noise, to the ApEn distributions. We expected it might be the influence of an additional QRS complex in every other window, since the amount of QRS complexes per window oscillates for ± 1 QRS complexes. We fabricated scenarios, where moving the window would result from covering exactly 10 - to covering exactly 11 QRS complexes. We found that the QRS complex has an influence, but even for a small window size only covering 10 QRS complexes it's only around 8 % of the mean SD of all window groups of its ApEn distribution. That means, that the majority of the source lies somewhere else.

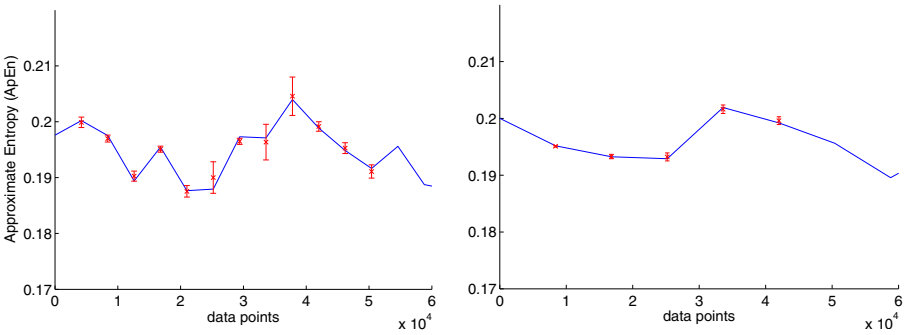

Fig. 5. The impact of the window placement to a window's ApEn value for larger N. The left shows part of the ApEn distribution of the same time series used in Fig. 4, with an ApEn window size of $N = 4200$ and the right with an ApEn window size of $N = 8400$. The red error bars denote the standard deviation around the mean when sliding the windows four times (two times to the left and two times to the right) for 2 % of its corresponding window size.

We now suspect, that the source of this "noise" might be the influence of the lower frequency bands when using very small windows, since a window would only contain parts of an oscillation period. The oscillation period ranges between 2.5 s and 35 s, which for us would be 640 - to 9000 data points, or 4 - to 50 heart beats. That, in turn, could cause ApEn to treat this influence as arbitrary complexity, because it has too few information available to recognize those as patterns.

We computed the ApEn distributions for larger windows, such as $N = 4200$ ($\sim$20 heart beats) and $N = 8400$ ($\sim$40 heart beats) to see how the deviation changes. Figure 5 shows parts of the resulting ApEn distributions of the same ECG time series. Increasing the window size results in an increased stability of the distribution and that in turn causes more windows to be considered truthful.

It is interesting to note, that if there is a window size that establishes the truthfulness for the ApEn distribution of one ECG time series, it does not imply that the window size is able to establish the truthfulness for the ApEn distribution of another ECG time series. This means that the lower bounds for truthfulness can be different, depending on the ECG time series.

Our results indicate that for the 26 ECG time series we have available, a window size of $N = 18000$, which is about 100 heart beats or approximately 70 seconds, is enough to establish the truthfulness for all corresponding ApEn distributions. Note that we considered a linear characteristic and chose a tolerance of 5 % of the distance between consecutive window values.

6 Conclusion and Future Research

We pointed out, that knowledge discovery within ApEn distributions of ECG time series has to overcome a lot of obstacles. We showed that the complex nature

of an ECG signal renders it difficult to establish trust in the fluctuations of their ApEn distributions. For that purpose we introduced the term *truthfulness* as a complement to the statistical validity of the ApEn windows and to give an indication for stability of the ApEn distribution.

We believe that it is possible to validate intra subject information (e.g. tendencies, and fluctuations) with only small ApEn windows, while avoiding modeling artifacts, in order to gain knowledge of the underlying ECG time series. Our hypothesis is that this can be done with a higher resolution than usually applied for inter subject classification based on absolute values, if the truthfulness of the ApEn distribution can be established.

For future work, it would be interesting to investigate alternatives to the distribution assembling, e.g it would be interesting to use distances between windows that are smaller than the window size itself. This would result in the values of the windows being closely related to its neighbors, since they partially describe the same data, but we think this might enable one to have higher resolution of the distributions to some extend, while still being able to establish their truthfulness.

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