Evaluating MSE Applicability to Short HR Time-Series

Boris Dragojevic and Dusanka Boskovic

Abstract

Multiscale entropy is successfully used to measure dynamical complexity of a finite length time series of different physiological data, including the heart rate. It is shown that the multiscale entropy as a measure can be used to discriminate healthy subjects from subjects with pathological conditions. In this paper we evaluate possibility to apply multiscale entropy to shorter heart rate time series and to evaluate resources needed to implement the algorithm in C, and to assess if it is possible to run the algorithm on a specific DSP platform.

Keywords

MSE • Multiscale entropy • Heart rate

1 Introduction

Multiscale entropy (MSE) is introduced in measuring dynamical complexity of different physiological signals, including the heart rate time series. There are several research papers documenting the success of the MSE in discriminating healthy subjects from subjects with some pathological conditions [1–4]. In this paper we evaluate possibility to apply the MSE to shorter HR time series and also to evaluate resources needed to implement the MSE algorithm in C, in order to assess if it is possible to run the algorithm on a specific DSP platform.

The paper is organized as follows: in the following Section we describe input signals used in the research, followed with the description of the multiscale entropy as a method used to analyze dynamical complexity of the heart rate time series. Our approach and results in applying MSE to short HR time series are presented in the Sect. 3. Conclusions are presented in the Sect. 4.

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2 Methods and Materials

Illustration of the MSE algorithm is done using the following databases of RR interval signals: for healthy patients recordings from the MIT-BIH Normal Sinus Rhythm Database [5]; for congestive heart failure (CHF) patients recordings from the BIDMC Congestive Heart Failure Database [6], and for atrial fibrillation recordings from the MIT-BIH Atrial Fibrillation Database [7]. The illustrative examples of the signals are presented in Fig. 1 and explained in the following section. The signals contain values that are marked as outliers, and their role in the MSE algorithm is explained in the next Sect. 3.

The signal representing the group of healthy subjects is the nsr040 signal from the *Normal Sinus Rhythm RR Interval Database* (*nsr2db*). The signal with marked outliers is shown in Fig. 1a.

The second signal represents the group of signals with Atrial Fibrillation and that's the signal 07162 from the *MIT-BIH Atrial Fibrillation Database* (*afdb*). The signal is shown in Fig. 1b.

The third signal represents Congestive Heart Failure, the signal 11 from the *BIDMC Congestive Heart Failure Databse* (*chfdb*). The signal with marked outliers is shown in Fig. 1c.

2.1 Multiscale Entropy Analysis of Heart Rate Time Series

The MSE algorithm is performed in two stages: coarse graining of the original time series and calculation of Sample Entropy for each time series.

For an original one-dimensional discrete time series given as $\{x_1, \ldots, x_n\}$, consecutive coarse-grained time

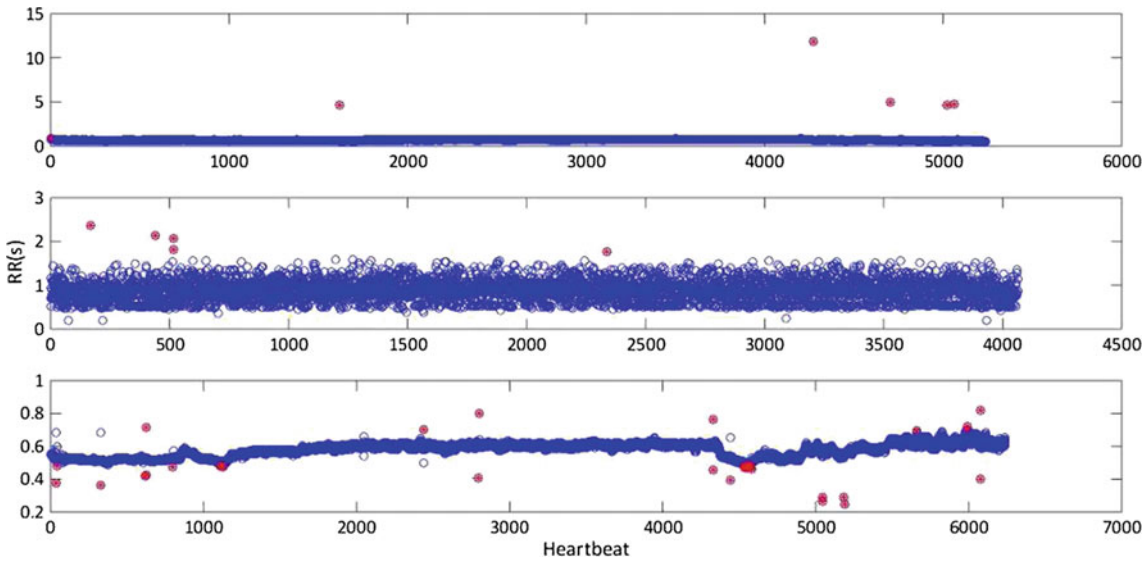

Fig. 1 Input HR time series—with marked outlier values

series are constructed and marked with the corresponding scale factor used in the coarse-graining process. The discrete time series is being modified in a way that group of consecutive data points are averaged and replaced by their mean value. The number of data pointes grouped is referred to as a scale. The coarse-grained time series will have N/τ data points where N is the number of data points in the main time series and τ is the scale factor. The data points in the coarsegrained time series are being calculated according to the Eq. (1).

$$y_j^{(r)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i \tag{1}$$

In the Eq. (1) y_j are the elements of the coarse-grained time series, τ is the scale factor, x_j discrete one-dimensional time series with the length N, while j is the number which is within the interval $1 \leq j \leq \frac{N}{\tau}$. The coarse-grained time series with the scale factor 1 is the original one-dimensional discrete time series.

The second stage in the MSE algorithm is calculation of the Sample Entropy (SE). Sample Entropy is being calculated according to the Eq. (2).

$$sampleEn(m, r, N) = -ln\frac{A^m(r)}{B^m(r)} \tag{2}$$

In the Eq. (2) m presents the pattern length (value between 1 and 10), r is the tolerance and N is the length of the signal. $A(r)$ and $B^m(r)$ are the probabilities that two sequences or time series will match for m and $m + 1$ data point, respectively. The value of the tolerance is within the boundaries 0.1 and 0.2 and mostly it has a value of 0.15.

Time series data may contain outlier values, missed beat detections and artifacts in recording, and may affect SE values because they change the value of parameter r [1]. Prior to the coarse-graining process the outliers are being excluded. The exclusion criteria is based on the value of the median and scaled median for time series.

After the MSE algorithm is calculated, the results are plotted as graph of the values of Sample Entropy according to the scale factors. The results are presented in Fig. 2.

It is possible to see that the Sample Entropy values for the AF and the CHF signals for scale factor 1 and 2 are higher than the value of Sample Entropy for the Healthy signal. The value of Sample Entropy for the AF signal is much higher than for the other two observed signals. How the scale factor raises, the Sample Entropy values for the Healthy signal are also raising. So, somewhere around the scale 10, the Sample Entropy value for the Healthy signal is becoming higher that the values of the SE for the AF and CHF signal.

Using the MSE analysis of the heart rate time series it is possible to conclude that this method can be used to differentiate time series corresponding to healthy and subjects with pathological conditions.

3 MSE for Short Time Series

Resource requirements for the implementation of the MSE algorithm are significant and increase with the time series length. While implementing the MSE algorithm in the MATLAB environment, or in C language for desktop application, the resources as memory availability do not present limitations. Implementation of the algorithm for a

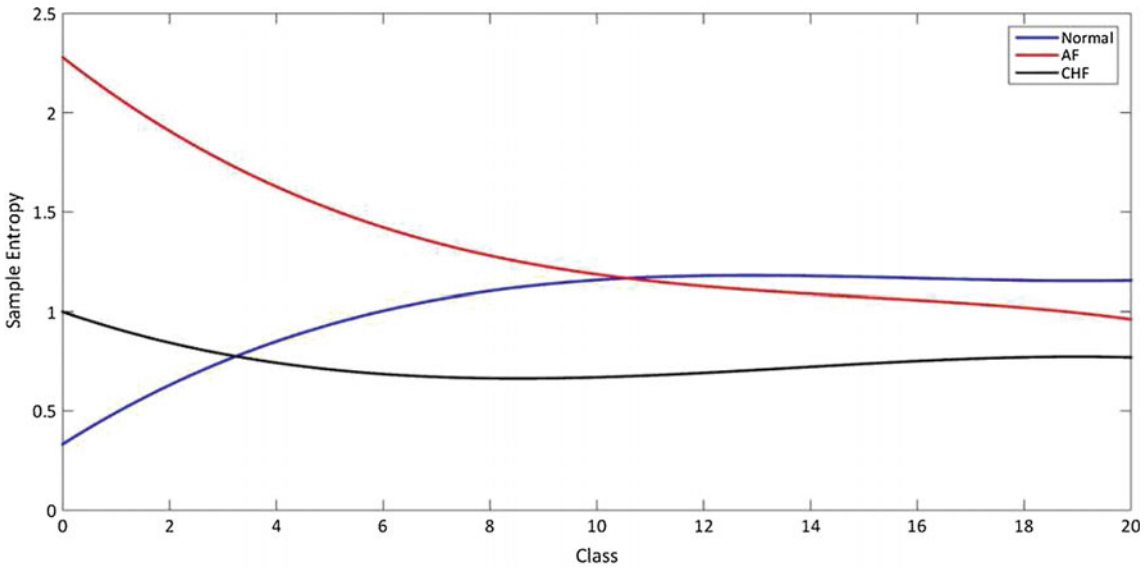

Fig. 2 Results of the MSE analysis applied to the representative HR time series from the following classes: normal sinus rhythm, AF and CHF

target platform with memory size up to 1 MB introduces limitations that prevent accurate execution. Memory size required for the accurate implementation of the MSE algorithm depending on the time series length is presented in Table 1. Target platform is TI DSP platform TMS320C551.

Sample Entropy value is sensitive to dataset size and relative error in SE algorithm is reduced with larger datasets [8]. In order to get valid results and use them for successful comparison of the MSE values and to classify HR signals accordingly, a large amount of signal samples is required. Large datasets have difficulties to be processed. They require a significant amount of memory and significant preprocessing and processing time. In some cases, the devices or microcontrollers do not have enough memory to store all data produced by coarse-graining from the original dataset.

We explored two approaches to reduce dataset length: using a subset of data, and down-sampling the data. We have evaluated the effects of shortening on the MSE algorithm results. We observed the beginning part of the signals, the first 1000 samples, compared to 4000 samples used for illustration of the MSE in the Sect. 2. The objective is to determine if relevant information are being lost with shortening. We have applied the MSE algorithm not only to selected signals but set of the signals from the databases in our focus: normal sinus rhythm: 5 signals, AF: 20 signals and CHF: 15 signals. Evaluating graphical results of the MSE algorithm for specific signals we have noted that the results are not comparable with the results presented in Fig. 2. Aggregated result for signal sets are presented in Fig. 3.

Aggregated results are presented with mean SE values fitted with a solid line curve, and respective minimal and maximal SE values fitted with a dotted lines. Although we can observe significant overlapping of the SE values from different signal classes, mean SE values are keeping the form of the MSE plot from the Fig. 2.

Table 1 Memory requirements linked to time series length

Time series length (number of samples)	Memory (Bytes)
100	41.728
200	79.872
300	118.272
400	152.320
500	190.464
600	228.608
700	267.008
800	301.824
900	339.456
1000	385.280

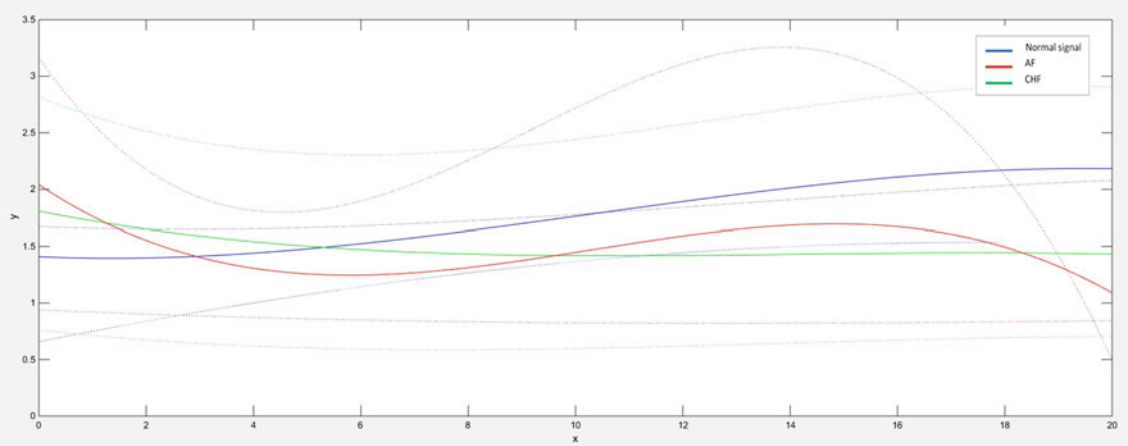

Fig. 3 Results of the MSE analysis applied to the set of HR time series from the following classes: normal sinus rhythm, AF and CHF

We can conclude that shortening of the time series affect success of employing MSE to classify signals. This decrease in sensibility can be compensated with inclusion of additional features that can improve the classification.

Following the analysis of the MSE features in [2] we have calculated the following indicators: area under the MSE curve for scale 1–5 (area 1–5) and 6–20 (area 6–20), value at scale 5, and slope of the MSE curve for scale 1–5 (slope 1–5).

The other approach in shortening the signal: down-sampling, did not provide successful results. Knowing the nature of the MSE algorithm and calculation of the SE values, obtained results are expected due to significant loss of signal dynamics.

4 Conclusion

In this study we have employed the MSE algorithm to normal sinus signals, AF and CHF signals. In order to examine how MSE perform on short time series we have compared results obtained on original time series, and time series created by shortening and down-sampling.

Resulting MSE values are aggregated and maximal, minimal and mean values for each scale are calculated to provide for graphical visualization of the results. For additional comparison of the following MSE parameters were calculated: entropy value of scale 5, the sum of entropy values of scales 1–5 (area 1–5) and 6–20 (area 6–20), and linear-fitted slope of scale 1–5.

The proposed approach demonstrates possibility to employ MSE in discriminating between healthy subjects and subjects with heart problems even for the short time series. The future work will include comparison of the MSE parameters with features of the HR time series obtained by time and frequency analysis methods.

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