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# Multiscale Analysis of Acceleration and Deceleration of the Instantaneous Heart Rate using Symbolic Dynamics

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*Abstract*—**The multiscale analysis of physiologic time series such as the RR interval time series has revealed that the entropy differs according to the scale. Furthermore, healthy subjects show different characteristics on the different time scales compared to patients. Instead of calculating entropies of the time series, the sequence of acceleration and deceleration of the instantaneous heart rate may also be investigated by means of binary symbolic dynamics. This kind of analysis revealed that the healthy heartbeat series also contains numerous regular binary sequences indicating runs of acceleration or deceleration. Here, we investigate whether this approach yields new information when applied to multiple time scales. We investigate the occurrence of binary patterns of length 8 on different time scales of heart rate series from healthy subjects and patients with congestive heart failure (CHF). Healthy subjects and CHF patients show different occurrences of binary patterns. These occurrences change especially on scales 1 to 5. Healthy subjects show more pronounced changes than CHF patients. At larger scales only gradual changes were observed. In conclusion, the application of binary symbolic dynamics on different scales yields new information, in particular on small scales.**

## I. Introduction

THE variations of the instantaneous heart rate, i.e. heart rate variability (HRV), may be analyzed by various methods e.g. in the time and frequency domain [1]. Another methodological differentiation is to quantify HRV either with methods based on the variance of the time series (e.g. SDNN, variance descriptors of Poincaré plots, spectral measures) or methods based on the complexity of the time series (using e.g. entropy measures or symbolic dynamics) [2]. Furthermore, using appropriate methods (such as detrended fluctuation analysis - DFA) it has been shown that the heart rate time series shows fractal like scaling properties, i.e. similar structures or information appear on different time scales [3]. It has been shown that dissimilarities on multiple time scales can be quantified using e.g. entropies. I.e. each time scale also carries specific information that cannot be obtained on other time scales [4], [5].

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It has been shown that the analysis of symbolic dynamics of the heart rate time series can be used to capture information on short time scales. The instantaneous heart rate can e.g. be symbolized by four different symbols reflecting the closeness of each interbeat interval to the average interbeat interval [6]-[8]. The complexity of such symbolic time series may be analyzed using the Shannon or Renyi entropy [6]. Using this kind of symbolization yields information in the form of frequencies of specific 'words' and forbidden 'words'. This complements measures of spectral analysis in e.g. patients after myocardial infarction [8]. Another approach of symbolization is the division of the full range of cardiac interbeat intervals (minimum interbeat interval to maximum interbeat interval) into several equidistant classes [9]. Classifying this kind of symbolization with respect to the variations (i.e. frequencies of symbolic patterns with 0, 1 or 2 variations of the symbols) also supplements the information found in traditional frequency domain measures [10], [11]. The analysis of graded head-up tilt data showed that the frequencies of specific symbolic patterns may be used to assess sympathetic and parasympathetic modulations of the autonomic nervous system [11].

A further approach is to symbolize the succession of accelerations and decelerations of the instantaneous heart rate with two different symbols. Short binary patterns have been extracted from the symbolized series and Approximate Entropy (ApEn) was utilized to measure of regularity (complexity) of the extracted patterns [12]. Although the heart rate dynamics of healthy subjects is known to show a high degree of complexity [3], regular binary patterns also appear very often [13]. Also, the heart rate dynamics of healthy fetuses show such characteristics as pregnancy progresses [14]. On the contrary, patients with congestive heart failure showed binary patterns characterized by a high level of complexity which is typical for random behaviour. Hence, this approach yields different information when compared to other variance based or complexity based parameters.

The analysis of symbolic dynamics of the heart rate time series was used to investigate dynamical properties on short time scales. In this study we investigate symbolic dynamics of the heart rate time series of healthy subjects and patients with congestive heart failure on different time scales. Accordingly, we combine two different approaches, i.e. multiscale analysis and symbolic dynamics analysis, to test whether this approach also yields relevant information on

different time scales.

## II. METHODS

### A. Subjects

Heartbeat time series from thirty healthy subjects (average age: 29 ± 8 years, 15 female) [15] and fifteen patients with severe CHF (NYHA class III-IV; age range 22-71 years; 'BIDMC congestive heart failure database' taken from the Physionet-database; see http://www.physionet.org [16]) were analyzed. Holter ECGs of the healthy subjects were about 24 hours in duration. The times of the R-peaks served as the basis for further calculations. They had a precision of 1 ms. Data of the CHF group were about 20 hours in duration. We relied on the information provided in the Physionet database. The data in the database (times of the R-peaks and classification of the heartbeats) were taken as provided. The times of the R-peaks had a precision of 4 ms.

### B. Multiscale analysis

The series $RR_i$ of interbeat intervals serves as the basis for the multiscale analysis. A coarse grained series $y^{(\tau)}$ with a scale factor $\tau$ is constructed as follows [4], [5]:

$$y_j^{(\tau)} = \sum_{i=(j-1)\tau+1}^{j\tau} RR_i, \quad 1 \le j \le N/\tau \qquad (1)$$

The series $y^{(\tau)}$ can be thought of as a moving average covering $\tau$ values that is only calculated at instances $1, \tau+1, 2\tau+1, ..., N/\tau$. Scale factor $\tau = 1$ represents the original series (RR-tachogram). In this study, course grained series were calculated for scale factors $\tau = 1,...,20$. The

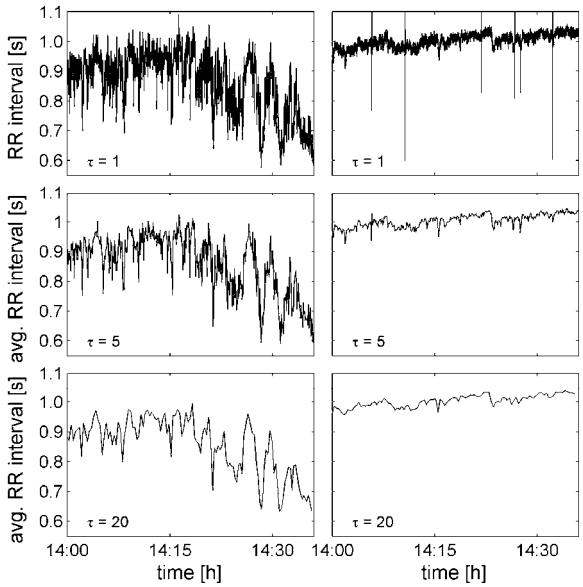


Fig. 1. Examples of coarse grained RR interval series of a healthy subject (left column) and a CHF patient (right column) for scales $\tau = 1$ (top, original series), $\tau = 5$ (middle) and $\tau = 20$ (bottom).

example in Fig. 1 (left) shows the effect of the coarse graining procedure for a RR interval series of a healthy subject. On scale $\tau = 1$ (top diagram, original series) a large amount of short scale variations are visible. On scale $\tau = 20$ (bottom diagram) the large scale variations still exist but the short scale variations have obviously decreased. The length of the coarse grained series is $N/\tau$ according to equation (1).

### C. Construction of symbolic sequences

The series $y^{(\tau)}$ ($i = 1,..., N/\tau$) served as the basis for the calculations. A binary sequence $S_i$ ($i = 2,..., N/\tau$) was created using the differences $\Delta y_i^{(\tau)} = y_i^{(\tau)} - y_{i-1}^{(\tau)}$ between successive values of the series $y^{(\tau)}$ (Fig. 2):

$$S_i = \begin{cases} 0, \; if \;\; \Delta y_i^{(\tau)} \ge 0 \\ 1, \; if \;\; \Delta y_i^{(\tau)} < 0 \end{cases} \qquad (2)$$

Hence, '0' symbolizes a deceleration and '1' an acceleration of the multiscale series $y^{(\tau)}$. In the special case of $\tau = 1$ (RR-tachogram) '0' symbolizes a deceleration and

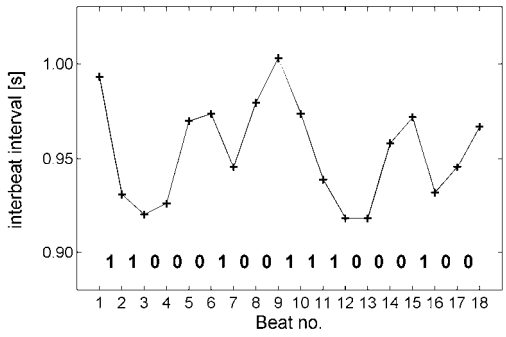


Fig. 2. Example of the construction of the symbolic series $S_i$ for $\tau = 1$, i.e. the RR-tachogram. From the binary sequence each binary pattern of length 8 is analyzed with respect to its regularity.

'1' an acceleration of the instantaneous heart rate.

### D. Approximate Entropy (ApEn) of short binary patterns

In this paper, we analyze dynamic properties of binary patterns of length 8 as a tradeoff between shortness of the patterns and sufficient differences of the different patterns. To illustrate the idea, consider the binary patterns 00000000 and 01100010. The former is obviously more regular than the latter. I.e., the succession of 0s and 1s is easy to predict in the first patterns whereas this prediction is more difficult in the latter pattern. Approximate Entropy (ApEn) is an appropriate measure for the quantification of such aspects of binary patterns [12], [17]. For normal time series ApEn calculates the logarithmic frequency that sequences of length $m$ that are close (within a tolerance $r$) remain close (within the same tolerance) in sequences of length $m+1$ [18]. ApEn($m$,$r$) depends on the length $m$ and the tolerance $r$ and it assigns higher numbers to more irregular sequences. For binary patterns (i.e. binary calculations) the tolerance $r$ is set to $r < 1$ and the length $m$ is set to $m = 1$. As a result, a number reflecting the serial irregularity of the succession of 0s and 1s is assigned to each binary pattern $S_i$: the higher

ApEn, the more irregular the binary pattern $S_i$.

Due to redundancies with respect to irregularities of the binary patterns, the $2^8 = 256$ different binary patters are assigned only 17 different values of ApEn. Hence, 17 different pattern sets are created by merging the binary patterns with the same value of ApEn into one set. These 17 pattern sets reflect dynamic properties ranging from regular to irregular [13].

### *E. Statistics*

The relative occurrence of each pattern set (i.e., the relative occurrence of the binary patterns belonging to each pattern set) was calculated for each scale. The results of the binary analysis are presented as medians because some pattern sets showed skewed distributions [13].

Appropriate to this nonparametric presentation, the distributions of patterns of healthy subjects and CHF patients were compared using the Wilcoxon rank sum test. The distributions of different scales were compared in the same manner. $p<0.05$ was considered statistically significant.

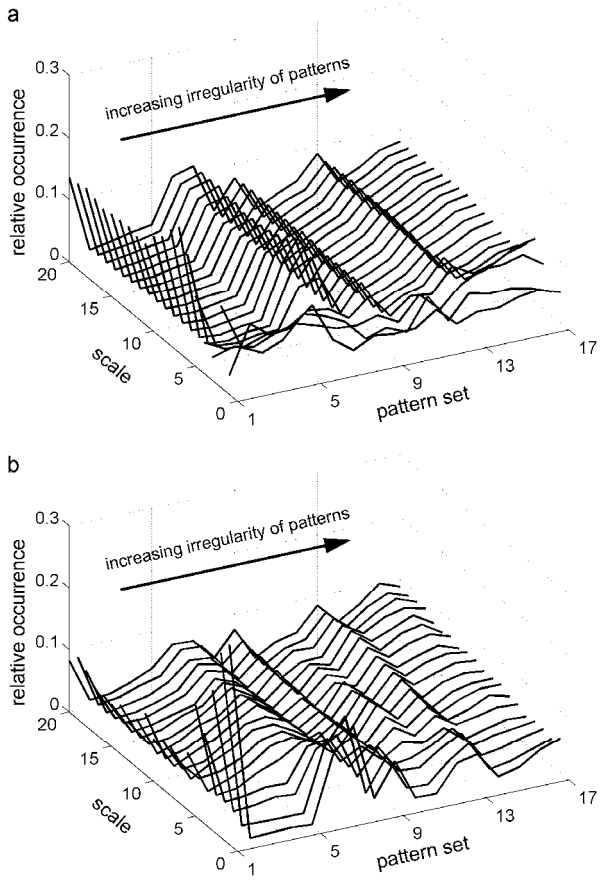


Fig. 3. Relative occurrence of the 17 pattern sets on scales $\tau = 1,\ldots,20$ of (a) healthy subjects and (b) CHF patients. Note that scale $\tau = 1$ represents the results of the original RR interval series. For better visibility the median relative occurrence of pattern sets 1,…,17 is connected with lines for each scale. The pattern sets are arranged with respect to increasing irregularity of the binary patterns in the set.

## III. Results

The results with respect to the relative occurrence of the pattern sets for the different scales are shown in Fig. 3. For the healthy subjects the most pronounced changes occur within scales 1 to 5 (Fig. 3a). The pattern sets 2 to 5 containing regular binary patterns occur most frequently on scale 1. The occurrence decreases with increasing scale ($p<0.001$, scale 1 vs. scale 5). At the same time pattern set 1 (binary patterns with alternations, i.e. 01010101), and pattern sets in the medium range of regularity (sets 6 to 10) occur more often ($p<0.001$, scale 1 vs. scale 5). Pattern sets with high irregularity (sets 11 to 17) also change in occurrence (except pattern sets 14 and 15, $p<0.001$ for the other pattern sets, scale 1 vs. scale 5). Qualitatively, the appearance of pattern sets seems to be reversed at large scales compared to scale 1.

The CHF patients also show changes in the occurrence of the pattern sets between scale 1 and 5 (Fig. 3b). However, these changes are less pronounced compared to the healthy subjects. The occurrence of pattern set 1 and pattern sets in the medium rang decreases ($p<0.05$, scale 1 vs. scale 5; pattern set 8: n.s.) whereas the occurrence of pattern sets 2 to 5 increases ($p<0.01$, scale 1 vs. scale 5). For the pattern sets with high irregularity only pattern sets 11, 12, 14 and 15 show a change of occurrence ($p<0.05$, scale 1 vs. scale 5).

The appearance of pattern sets for CHF patients on scale 1 seems to resemble the occurrence of pattern sets in healthy subjects on larger scales (≥5). However, a quantitative comparison shows that all pattern sets (except pattern sets 6, 9 and 12) occur differently comparing scale 1 (CHF patients vs. healthy subjects, scale 5). Similar results are obtained for larger scales.

## IV. Discussion

The human organism exhibits variations and oscillations on different time scales [19]. Multiscale analysis is an appropriate approach to investigate physiologic time series on different time scales [4], [5]. In this study, using symbolic dynamics, we investigated whether the sequence of acceleration and deceleration of the instantaneous heart rate also carries relevant information on different time scales.

In healthy subjects the most pronounced changes of the occurrence of binary patterns were observed between scale 1 (original time series) and scale 5. From scale 5 to scale 20 only gradual changes occur. Hence, the coarse graining procedure shows large variations with respect to symbolic dynamics analysis only on small scales whereas coarse graining on large scales seems to result in similar dynamics from the point of view of symbolic dynamis. Interestingly, the occurrence of pattern sets that occur often clearly decreases whereas pattern sets that occur less often clearly increase. Hence, the occurrence of the pattern sets an large scales seems to be reversed compared to scale 1. This result indicates that most of the relevant information is carried on

scales 1 to 5. Hence, this kind of symbolic analysis captures mainly short-term information. This is consistent with the initial aim of this approach to symbolic analysis: to investigate dynamical aspects on short time scales [13].

CHF patients also show differences in the occurrence of the pattern sets with respect to the different scales. Again, most pronounced changes appear form scale 1 to scale 5. However, compared to the healthy subjects the changes of occurrence on these scales do not reverse the distribution. Instead, the distribution seems to flatten gradually.

Interestingly, the distribution of the occurrence of pattern sets of healthy subjects at larger scales (≥5) seems to qualitatively resemble the distribution of the occurrence of pattern sets of CHF patients at scale 1 (although the quantitative analysis reveals clear differences in the actual numbers). Hence, healthy subjects at larger scales and CHF patients at scale 1 seem to be close to the distribution of pattern sets that is obtained from randomized heart rate series [13]. As a consequence, the procedure for the generation of the coarse grained time series influences the sequence of acceleration and deceleration in such a way that it produces random like behavior when analyzed with binary symbolic dynamics reflecting acceleration and deceleration of the instantaneous heart rate.

It has to be noted that the procedure used to generate the coarse grained time series is closely linked to a moving average calculation. Keeping in mind that a moving average acts like a low pass filter, it is obvious that this procedure generates time series that lack high frequency characteristics at larges scales (cf. Fig. 1). The effect of different filter characteristics on the distribution of the occurrence of the pattern sets needs to be investigated.

In conclusion, the analysis of binary symbolic dynamics reflecting acceleration and deceleration of the instantaneous heart rate also carries relevant information on coarse grained series with scales >1. However, the main information is obtained on scales 1 to 5 because this kind of analysis captures mainly dynamical aspects on short time scales. It needs to be shown whether the procedure for the generation of coarse grained time series affects the results. Furthermore, physiological implications have to be elucidated.

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