DISCRIMINATION BETWEEN HEALTHY AND SICK CARDIAC AUTONOMIC NERVOUS SYSTEM BY DETRENDED HEART RATE VARIABILITY ANALYSIS

Y. ASHKENAZY*,†, M. LEWKOWICZ§*, J. LEVITAN§*,§, S. HAVLIN*,†, K. SAERMARK§, H. MOELGAARD§ and P. E. BLOCH THOMSEN‖

*Department of Physics, Bar-Ilan University, Ramat-Gan, Israel
†Gonda Goldschmied Center, Bar-Ilan University, Ramat-Gan, Israel
§Department of Physics, College of Judea and Samaria, Ariel, Israel
‖Department of Cardiology, Aarhus University Hospital, Aarhus, Denmark

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Abstract
Multiresolution Wavelet Transform and Detrended Fluctuation Analysis have recently been proven to be excellent methods in the analysis of Heart Rate Variability and in distinguishing between healthy subjects and patients with various dysfunctions of the cardiac nervous system. We argue that it is possible to obtain a distinction between healthy subjects/patients of at least similar quality by, first, detrending the time-series of RR-intervals by subtracting a running average based on a local window with a length of around 32 data points, then calculating the standard deviation of the detrended time-series. The results presented here indicate that the analysis can be based on very short time-series of RR-data (7–8 minutes), which is a considerable improvement relative to 24-hour Holter recordings.
1. INTRODUCTION

Measurements of Heart Rate (HR) and evaluation of its rhythmicity have been used for a long time as simple clinical indicators. Research from the last decade has indicated that a quantification of the discrete beat-to-beat variability in HR — the heart rate variability (HRV) — might be a possible prognostic indicator of risk associated with a large variety of diseases, behavioral disorders, mortality and also aging. For example, independent of other established risk factors, depressed HRV has been shown to be a powerful predictor of cardiac events after myocardial infarct. It is therefore of great importance to establish a measure of HRV and to classify the HRV of different pathological cases in order to discriminate the healthy HRV profile from that for patients at risk.\(^1\)\(^-\)\(^4\) It is an open question in the literature if one needs long time series (24-hour ECG Holter data series\(^5\)) or if short time-series (ca. 5 minutes\(^6\)) do suffice in producing a reasonably clear separation between healthy and sick individuals. This question is probably tied up with the quality of the ECG recording, i.e. the signal to noise ratio.

In physiological systems, one can recognize different behaviors at different time scales. For example, consecutive heartbeats will occur more or less with the same beat-to-beat interval (the mean HR), which can be defined as a small time scale. Other time scales can be defined by the sleep/wake periods. On these larger time scales, one can identify a different heart rate and a different heart rate variability during the hours of sleep and during working hours. The DFA (Detrended Fluctuation Analysis)\(^7\) and the DWT (Discrete Wavelet Transform)\(^8\)-\(^15\) have been shown to be successful ways of analyzing the HRV. Basically, these methods explore the low and the high frequency behavior of the signal at different time-scales by applying windows of varying lengths. Thus, the DWT was used\(^9\) to analyze data from RR measurements and to calculate the standard deviation of the transformed data. This standard deviation of the Wavelet coefficients serves as a characterization of the HRV during the period of measurement and it was shown that the method discriminates between healthy and sick individuals. Thurner \textit{et al.}\(^9\) observed a complete separation of the two groups for window sizes \(2^4\) and \(2^5\), where the exponent indicates the window scale. Further, this method was used by our group\(^10\) on a different set of data, and the separation mentioned was found to be incomplete (see also Ref. 16). In order to improve the method, a filtering algorithm was constructed and the standard deviation of the filtered time-series now resulted in a complete separation between healthy and sick subjects. We emphasize that the diagnostic virtue of the DFA and DWT methods is apparently due more to the right choice of window size than to the actual method of transformation. Both of the two methods point to a typical time scale of \(2^4\) to \(2^5\) equivalent to a window size of 16 to 32 heartbeats. Thus, in the DFA method,\(^7\) one observes a crossover point for a window size around \(n = 16\) heartbeats where an abrupt change in the slope of their\(^7\) \(F(n)\) versus \(n\) curve occurs.

In this study, we wish to see if the existence of this time scale can be utilized for the analysis of HRV of short-term ECG recordings.

2. THE DETRENDED TIME-SERIES

As mentioned in Sec. 1, both the DFA analysis and the DWT analysis suggest an intrinsic window of scale \(m = 4 - 5\), i.e. a window consisting of 16–32 heartbeats. In this section, we utilize this to perform a detrending in the following way. First, from the time-series of the raw RR-data,\(^a\) a running average is constructed using an interval-length of \(2^m\).\(^b\) Next, the running average is subtracted from the original RR-data time-series. For \(m = 5\), this procedure is illustrated in Fig. 1(a), where the solid curve represents the raw RR-data and the dashed curve represents the running average. The difference between the two curves is denoted by \(r_i\) and is shown in Fig. 1(b). This resultant time-series \(r_i\) is hereby called the detrended time-series (DTS) and represents the fluctuations with respect to the local average. It is hoped that this procedure will at least partly reduce noise and slow oscillations which should not directly affect short-term HRV.\(^1,\)\(^13\)

The standard deviation \(\sigma_d\) of the detrended time-series (DTS), using a detrending window of scale \(m\), includes now only the behavior of relevant small time scales and may thus be considered a measure of the HRV. To evaluate the discriminating capabilities of \(\sigma_d\), we examined RR-data for a group of

\(^a\)An RR interval is the time difference between two consecutive pronounced peaks — the R peaks — of the ECG recording.

\(^b\)In this study we confined ourselves to an interval length of \(2^m\), although any interval length can be chosen.
Fig. 1 (a) Segment of RR-interval data versus beat number (solid curve) and running average based on a local window of 32 heartbeats (broken curve). (b) Detrended curve, i.e., the difference between solid curve and broken curve in the top panel.

Fig. 2 Standard deviation (in seconds) of the detrended series for a group of 33 subjects versus the scale factor of the local window used in the detrending. Healthy subjects, circles; Diabetics, squares; and Heart patients, rhombohedra.

33 subjects (the same data group as in Ref. 10) consisting of 21 healthy subjects, 9 diabetics and 3 heart patients including, one heart-transplanted patient. Thus we calculate $\sigma_d$ for a time-series consisting of $2^{16} = 65,536$ data points, corresponding to approximately 16 hours of measured ECG data, and for the scale values $m = 1 − 12$ for the detrending window. The smallest length of the detrending window is thus 2 and the largest 4,096. The results are shown in Fig. 2, which is analogous to Figs. 2
and 3 in Ref. 10; the latter two figures show, respectively, the standard deviation of the wavelet coefficients and of the filtered time-series. In the present Fig. 2, one notes a clear separation between the group of healthy subjects (circles) on the one hand, and the groups of diabetics (squares) and heart patients (rhombohedra) on the other hand. However, one also notes from this figure that 3 of the diabetics (the 3 topmost) with as much justification could have been included in the group of healthy subjects, thus displacing the separation region for \( \sigma_d \) towards lower values. For systematic reasons, we have chosen the separation region shown in Fig. 2.

In Fig. 2, the largest separation between the healthy subjects and the two other groups is found for the scale \( m = 8-11 \), whereas for the DWT analysis the largest separation was found for the scale \( m = 4-6 \),\(^7\) (see also Ref. 16 for discussion of the dependence of the method) and for the DFA analysis the crossover point for the fractal slope was found for the scale \( m = 4 \).\(^7\)\(^6\) It should be noted, however, that the crossover point in the DFA analysis is not a sharply-defined point, rather the change in fractal slope takes place in a gradual way. On this basis we conclude that the three methods DTS, DWT and DFA yield equivalent estimates for the scale of a characteristic window, and in the following we use the scale \( m = 5 \).\(^c\)

3. ESTIMATION OF INTERVAL LENGTH

In the preceding section, we used an RR-data time-series corresponding to 16 hours of ECG measurements. Clinically, it is of course important to be able to use as short a time-series as possible. In this section, we use the DTS method to examine whether or not short time-series can be used in order to distinguish between the group of healthy subjects and the groups of diabetics and heart patients. Specifically, we choose time-series of lengths 512, 1024, 2048, 4096, 8192 and 16384 data points (RR-intervals). To make sure that all data are collected under similar conditions, we have only used data points from the sleep period starting at the initial time 1 a.m. For the various lengths of the

![Graph](image)

**Fig. 3** The standard deviation (in seconds) of the detrended RR-data time-series versus the length of the time-series analyzed. Symbols: Same as in Fig. 2.

\(^c\)The maximum separation depends on the size of the interval; we have found that \( m = 5 \) offers the optimal scale for small interval lengths.
4. DAILY VARIATION OF HRV

We next study the daily variation of the standard deviation of the detrended 24-hour ECG time-series. The full data series was divided into smaller segments and in agreement with the conclusion of the preceding section, we chose a segment length of 512 measurements, not including artefacts. Although the daily variation was calculated for all 33 subjects (the same group as in Ref. 10), we display only 9 representative results here. Thus in Fig. 4, we show 3 healthy subjects [top panel, (a)], 3 diabetics [middle panel, (b)] and 3 heart patients [lower panel, (c)] and in all cases \( \sigma_d \) is plotted versus the time position of the data segment. From Fig. 4, one notes, first, that the average value (across 24 hours) of \( \sigma_d \) is far smaller for the heart patients than for the healthy subjects, whereas the diabetics form a more varied population: one (central recording) clearly similar to recordings for heart patients, one (middle panel, third recording) reminiscent of recordings for healthy patients and one (middle panel, first recording) appears to be an

![Graph](image)

**Fig. 4** The daily variation of the standard deviation, calculated for data segments of length 512, versus the time location for the segment. Three representative recordings for each of the groups (a) Healthy subjects, (b) Diabetics and (c) Heart patients. Again the standard deviation was calculated for the detrended time-series and the scale \( m = 5 \), i.e. 32 heartbeats, was used in the detrending procedure.
Fig. 5 Histograms for the daily variation of the standard deviation (segment length and scale $m$ as in Fig. 4) shown for the three groups: Healthy subjects (circles), Diabetics (squares) and Heart patients (rhombohedra).

Fig. 6 (a) The group average of the standard deviation (parameters as in Fig. 4) versus the time location for the data segment. Healthy subjects, circles; Diabetics, squares; Heart patients, rhombohedra. (b) Same as (a), but with the standard deviation across the group indicated by vertical bars.

in-between case. Secondly, the fluctuation of $\sigma_d$ during the 24 hours of observation appears to follow the same pattern as just described. We illustrate the above features in two other ways. In Fig. 5, we show the histogram for the daily (24 hours) variation of $\sigma_d$ for the three groups: 21 healthy subjects (circles), 9 diabetics (squares) and 3 heart patients (rhombohedra). For the healthy
subjects, the maximum of the histogram, i.e. the most probable value of $\sigma_d$, is well separated from the maximum of the two other histograms and there is very little overlap with the histogram for the heart patients but some overlap with the histogram for the diabetics group. The histograms thus clearly distinguish between healthy and sick subjects, but the statistics are too poor to distinguish between the two patient groups. Finally, in Fig. 6(b), we show the group average of $\sigma_d$ for each of the three groups versus the time position for the relevant data segment. In Fig. 6(b), we have shown the standard deviation (across the group) of the group average of $\sigma_d$. From Fig. 6(a), it follows that the healthy group is separated from the heart patient group by a factor of around 4 in the average of $\sigma_d$, a conclusion supported by the standard deviations shown in Fig. 6(b). It is also tempting to draw the conclusion that the diabetics group is separated from the heart patient group by 25–50%, but the standard deviations shown in the bottom panel do not allow for a definite conclusion. It also appears from Fig. 6 that the group average value of $\sigma_d$ is larger during the sleep period, for the healthy group and also partly for the diabetics group (see also Ref. 17). For the healthy group, the difference between the sleep and wake period is around 0.01 s.

5. CONCLUSION

In this paper, we have focused on the standard deviation $\sigma_d$ of detrended RR-data time-series using a detrending window with a length $2^n$ measurements of RR-data, this value being indicated by results from DWT and DFA analyses (see Refs. 7 and 10). Our results suggest that even a short time-series of 512 data points, i.e. 7–8 minutes of measurements, suffices to distinguish between healthy subjects and patients (heart disease, diabetics). The same kind of analysis can of course be performed on the raw, not detrended data.4 We have done so, but found that using detrended data series was more successful. We note that even if the length of the RR-data time-series would have to be increased to, say, 2048 measurements corresponding to approximately half an hour of ECG measurements, this would still from a clinical point of view represent a substantial advantage relative to 24 hours of ECG measurements.

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