Nonlinear Schemes for Heart Valve Failure Detection

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Abstract

We provide an signal modality analysis on the heart rate variability (HRV) data, widely studied as an indication of the health status of the heart. The analysis is achieved by using the recently proposed 'delay vector variance' (DVV) method, which rests upon examining the local predictability of a signal in the phase space. A comprehensive analysis of the feasibility of this approach is provided. The simulation results show that the DVV method can be opted for an alternative way to help doctors diagnose the patients with heart disease.

1. Introduction

Heart rate variability (HRV) has long been studied for analysing cardiovascular control from the electrocardiogram (ECG). Detection and analysis on HRV can provide a quantitative and non-invasive method to obtain reliable and reproducible information on the autonomous modulation of heart rate (Malik and Camm, 1990). Many classic 'linear' frequency domain based method have been proposed over the last decade, for instance, those based on spectrum analysis or transfer function for the analysis of HRV data (Signorini, Marchetti and Cerutti, 2001). However, it is natural to question whether such approaches, based solely on the second order statistics, convey enough information to provide fast and reliable detection of aberrant events in HRV. Therefore, methods capable of capturing the change of the dynamics within the processed HRV signals are preferable.

With the emergence of the chaos theory and the method of surrogate data (Schreiber & Schmitz, 2000), nonlinear approaches have just begun their way into the analysis of HRV signals. However, they typically suffer from high computational complexity and lack of straightforward explanation. To this cause, we provide a novel framework for analysing the HRV data, based upon a recently introduced method for signal modality characterisation (Gautama, Mandic & Van Hulle, 2004). This analysis will allow for the detection of aberrant events from HRV data and will provide indication of the extent of such aberrance.

2. Background and 'Delay Vector Variance' Method

By signal nature, we refer to linear, nonlinear, stochastic and deterministic properties of a signal. A linear signal is generated by a linear time-invariant system, driven by white Gaussian noise, measured by a static, monotonic, and possibly nonlinear observation function. Signals that cannot be generated in such a way are considered nonlinear. A signal is considered deterministic if it can be precisely described by a set of equations; otherwise it is considered stochastic.

In some modern machine learning and signal processing applications, especially biomedical and environmental ones, the information about the linear, nonlinear, deterministic or stochastic

nature of a signal conveys important information about the underlying signal generation mechanism. For the sake of simplicity, in this paper, we shall restrict ourselves to the first two properties, and the other two will be studied in the future.

There is one more concept we will constantly refer to in the rest of the manuscript, that is surrogate time series, or 'surrogate' for short. It is non-parametric randomised linear version of the original data which preserves the linear properties of the original data. In the following experiments, we choose the 'iterative amplitude adjusted Fourier transform' (IAAFT) method to generate such surrogates, as it preserves the amplitude distribution of the original signal and yields reliable results (Schreiber & Schmitz, 2000).

There already exist many methods for detecting nonlinearity within a signal. The classic ones include the 'deterministic versus stochastic' (DVS) plots (Casdagli & Weigend, 1991), the Correlation Exponent and 'δ-ε' method (Kaplan, 1994). However, the recently proposed phase-space based 'delay vector variance' (DVV) method (Gautama, Mandic & Van Hulle, 2004), for signal characterisation is more suitable for signal processing application because it examines the nonlinear and deterministic signal behaviour at the same time. The algorithm is summarized below:

- For a given embedding dimension m, generate delay vector (DV): x(k) = [$x_{k-m},...,x_{k-1}$]^T and corresponding target x_k
- The mean, μ_d , and standard deviation, σ_d , are computed over all pair wise Euclidean distances between DVs, ||x(i) – x(j)|| ($i \neq j$)
- The sets $\Omega_k(r_d)$ are generated such that $\Omega_k(r_d)$ = {x(i) | ||x(k) – x(i)|| ≤ r_d }, *i.e.,* sets which consist of all DVs that lie closer to x(k) than a certain distance r_d , taken from the interval [max{0, μ_d - $n_d\sigma_d$ }], where n_d is a parameter controlling the span over which to perform DVV analysis
- For every set $\Omega_k(r_d)$, the variance of the corresponding targets, $\sigma_k^2(r_d)$, is computed. The average over all sets $\Omega_k(r_d)$, normalized by the variance of the time series, σ_k^2 , yields the 'target variance':

$$\sigma^{*2}(r_d) = \frac{\frac{1}{N}\sum_{k=1}^{N}\sigma_k^2(r_d)}{\sigma_x^2} \qquad (2.1)$$

where N denotes the total number of sets $\Omega_k(r_d)$.

As a result of the standardisation of the distance axis, the resulting 'DVV plot' (target variance $\sigma^{*2}(r_d)$) is a function of the standardised distance), are easy to interpret, as illustrated in Figure 1(a) and Figure 1(b). The minimal target variance, e.g., the lowest point of the curve, is a measure for the amount of noise which is present in the time series. The presence of a strong deterministic component will lead to small target variances for small spans. At the extreme right, the DVV plots smoothly converge to unity, as illustrated in Figure 1(a) and 1(b). This is because for maximum spans, all DVs belong to the same set, and the variance of the targets is equal to that of the time series. In the following step, the linear or nonlinear nature of the time series is examined by performing DVV analyses on both the original and 25 of IAAFT surrogate time series. Due to the standardisation of the distance axis, these plots can be conveniently combined within a scatter diagram, where the horizontal axis corresponds to the DVV plot of the original time series, and the vertical to that of the surrogate time series. If the surrogate time series yield DVV plots similar to that of the original time series, as illustrated by Figure 1(a), the DVV scatter diagram coincides with the bisector line, and the original time series is judged to be linear, as shown in Figure 1(c). If not, as illustrated by Figure 1(b), the DVV scatter diagram will deviate from the bisector line and the original time series is judged to be nonlinear, as depicted in Figure 1(d).

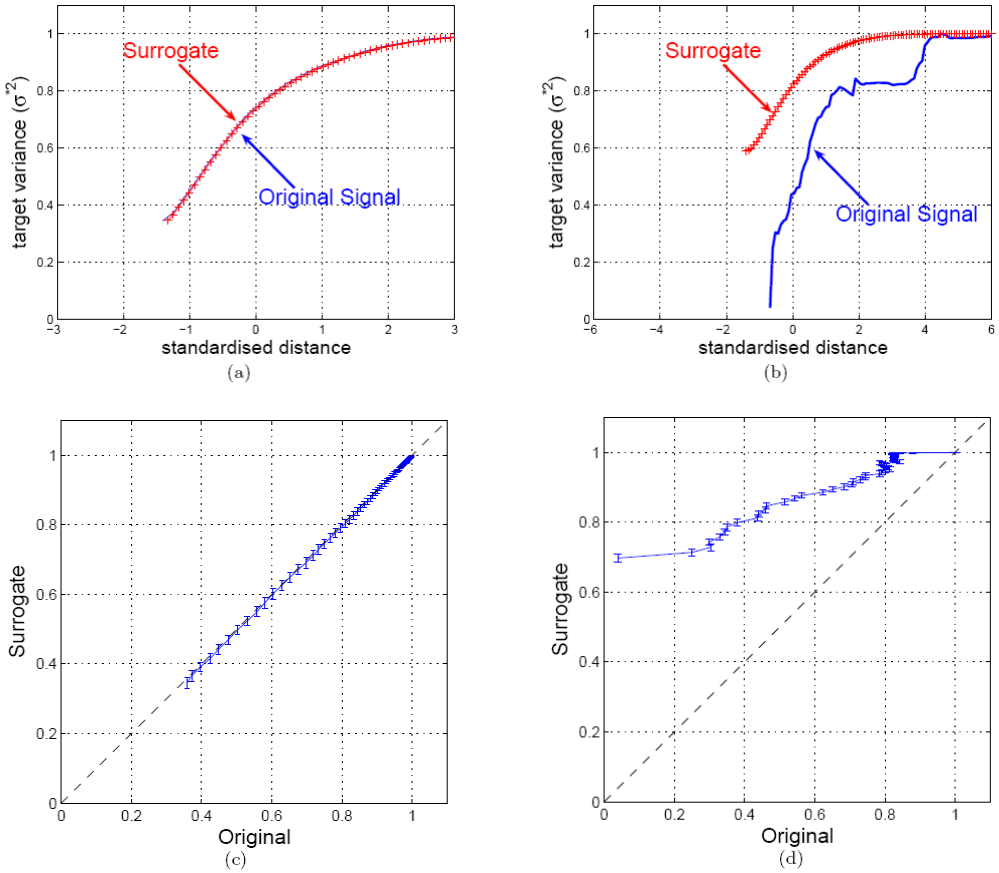

FIGURE 1. Nonlinear and deterministic nature of signals. (a): DVV plot for a linear benchmark signal. (b): DVV plot for a nonlinear benchmark signal. (c): DVV scatter diagram for the linear benchmark signal. (d): DVV scatter diagram for the nonlinear benchmark signal. In (a) and (b), the light line with crosses denotes the DVV plot for the average of 25 IAAFT-based surrogate while the dark solid line denotes that for the original signal. In (c) and (d), error bars denote the standard deviation of the target variances of surrogates.

3. Experiment Results

In this section, we set out to perform the DVV analysis on the HRV data, (provided by Dr. Massimo Griselli from Royal Brompton Hospital). The data contains HRV recording for a healthy human and for an ill patient before and shortly after the heart operation.

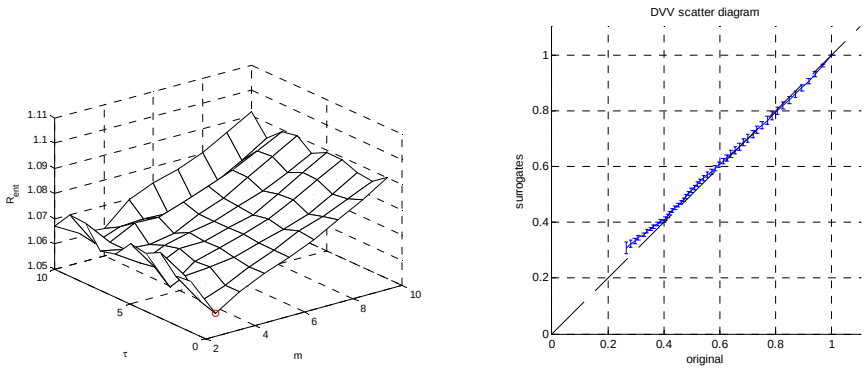

FIGURE 2. Differential-entropy based method (Left) and DVV scatter diagram for the HRV of the healthy human.

To choose the optimal embedding parameters, *e.g.*, the embedding dimension (m) and the time lag (τ), for the DVV method, we opted for the differential-entropy based method (Gautama, Mandic and Van Hulle, 2003), which yields m = 3 and τ = 1, indicated as an open circle in the left diagram in Figure 2. Based on this, we obtained the DVV scatter diagram for the HRV data for a healthy human, as illustrated in the right diagram in Figure 2. From the Figure, the DVV scatter diagram almost coincided with bisector line, indicating its linear nature. This is in consistent with previous established results (Poon and Merrill, 1997).

Next we perform the similar analysis on the data obtained for the ill patient before and after heart operation. The differential entropy method yields m = 5 and τ = 1 for these two signals. From Figure 3, the left diagram denotes the DVV scatter diagram before the heart operation whereas the right one denotes that after operation. By comparing two diagrams in Figure 3, it can been seen that the operation was successful, judging from the fact that the DVV scatter diagram for the HRV data after the heart operation began to approach the bisector line. Since the HRV data in right diagram of Figure 3 was recorded shortly after the operation when the patient has not fully recovered yet, the DVV scatter diagram can be expected to be more biased towards the bisector line, *e.g.*, more linear if future data is available.

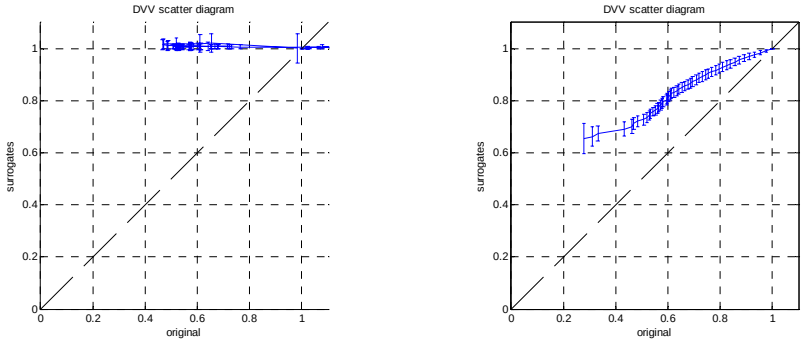

FIGURE 3. DVV scatter diagram for the HRV of the patient before heart operation (left) and after operation (right).

3. Conclusion

We have utilised the 'delay vector variance' (DVV) method and have performed an analysis on the HRV data for both the healthy human being and the patient having heart disease. It has been shown that the DVV method is able to provide an alternative way to help diagnose the status of patients with heart disease.

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