The Ebb and Flow of Heart Rate Variability: Simulation of 24 Hour Heart Rate Time Series Using Time Series Data from Naturally Occurring Phenomena

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Abstract

Current RR time series simulations are distinguishable from real data by automatic algorithms. We hypothesised that RR time series simulations could be improved by using time series data from naturally occurring phenomena. 20 records of annual river flow data for the river Tyne in north eastern England were obtained. Each river flow data record was used to generate a single 24 h simulated RR time series with the property of self similarity. We compared the standard frequency parameters ULF, VLF, LF and HF normalised to the total power, for the simulated RR, with those from physiological data from 20 subjects. The river flow data produced realistic simulations of RR time series with significant differences between physiological and simulated series for VLF only. Time series data from river flow or other naturally occurring phenomena may provide useful components in producing RR time series with more realistic characteristics than current artificially generated data.

1. Introduction

The heart beat exhibits natural variability, apparent as variations in the interval between each heart beat (RR interval). This variability arises from complex physiological interactions brought about, for example, by exercise and breathing. RR time series from healthy subjects exhibit some common characteristics underlying much intersubject variability. Notably, there may be a reduction in heart rate during sleep so that RR increases for a period of hours. Characteristically there are periods of high heart rate due, for example, to exercise. RR is modulated by respiration and a frequency domain analysis of the RR time series exhibits a characteristic increase in power over the respiratory frequency range. Similarly, RR is modulated by THM (Traube-Hering-Mayer) waves, thought to be due to the blood pressure control mechanism, giving an increase in power over a range of frequencies centred around 0.1 Hz. To aid quantification of these and other features of the frequency spectra of heart rate time series, the spectra have been divided into frequency bands: ULF (ultra low frequency, $\leq$ 0.003 Hz); VLF (very low frequency, 0.003-0.04 Hz); LF (low frequency, 0.04-0.15 Hz); HF (high frequency, 0.15-0.4 Hz). Typically, heart rate spectra exhibit a 1/frequency component in ULF and VLF which may relate to hormonal and thermoregulatory mechanisms, and broad peaks in LF and HF corresponding to THM waves and respiratory frequency respectively.[1]

Current simulations of RR time series use artificially generated series, visually appear unnatural and may be distinguished from physiological data by automatic algorithms.[2, 3] Our hypothesis was that time series data from naturally occurring phenomena, such as climate, might be useful in providing more realistic RR time series simulations.

2. Methods

2.1. Data

To test our hypothesis we obtained 20 records of annual river flow data for the river Tyne which flows through the city of Newcastle upon Tyne, UK. These data were available from the National River Flow Archive of the Natural Environment Research Council (http://www.nwl.ac.uk/ih/nrfa/webdata/023001/g.html). We compared our simulated time series with real RR data from 20 subjects without known heart disease randomly chosen from 28 such records provided by PhysioNet for the 2002 Computers in Cardiology Challenge. The river flow data from each year provided the basis of a single simulated 24 h RR time series, so that 20 simulated series were produced in total. For each year, daily values of flow volume were available. Hence, each annual river flow record consisted of 365 sample points. Figure 1a provides an example. The figure shows the daily flow for January through December 1990. Clearly there is greatest flow in the win-

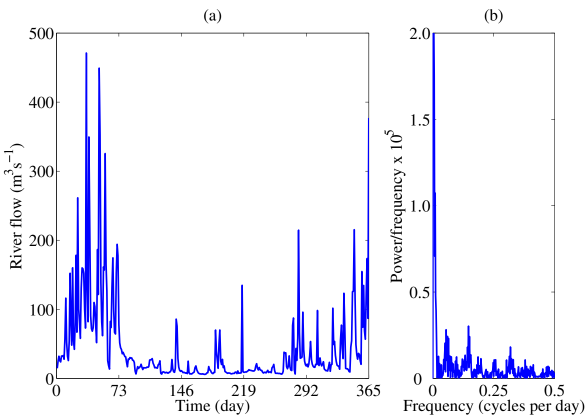

Figure 1. River flow data for 1990: (a) Time series (Jan - Dec), (b) Frequency spectrum.

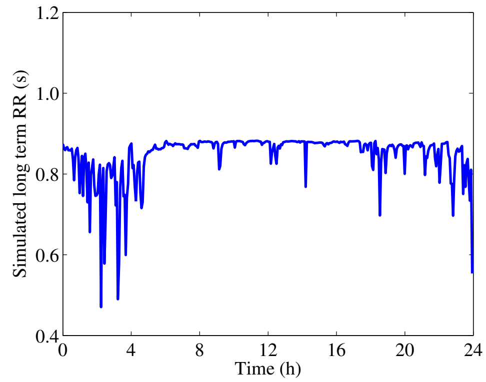

Figure 2. Simulated long term RR (365 sample points).

ter months. The frequency spectrum is shown in figure 1b. Two weekly and weekly cycles of rainfall and/or upriver reservoir management actions are suggested by the peaks at approximately 0.06 and 0.14 cycles per day respectively.

2.2. Simulating the RR time series

Our aim was to use only the river flow data without artificially generated signals to produce the simulated RR time series. From each of the river flow data records an RR time series was generated which exhibited both long and short term variability.

2.2.1. Simulating long term RR variability

Inverting the river flow data and scaling both time and amplitude axes provides a time series that exhibits long and medium term variability characteristics similar to those expected of RR time series over the 24 h period. Figure 2 illustrates this and is derived from the river flow data shown in figure 1. The characteristic slowing of heart rate or increase in RR during sleep is expressed by the corresponding fall in summer river flow. Periods of high heart rate or short RR, for example due to exercise, are expressed by periods of high flow volume. Translating the 365 sample points into a 24 h period provides a sampling interval of approximately 4 minutes (24*60/365). This resolution is adequate for simulating the medium to long term changes in heart rate but is not sufficient resolution for the short term variability which occurs on a beat to beat basis.

2.2.2. Simulating short term (beat to beat) RR variability

Realistic simulation required beat to beat RR variability to be simulated. To achieve this using only the river flow data we used the property of self similarity. Self similarity is a property of many natural processes where features of the process exhibit similar characteristics at different time scales.[4] This was achieved by repeatedly concatenating sections of random interval from the long term RR signal (see figure 3). Additionally, the concatenated sections were randomly amplitude scaled. A further consideration was the frequency characteristics of the simulated signal. Compressing the river flow data into a shorter time interval had the beneficial effect of translating the spectra of the river flow data to frequencies more typical for RR data. By assuming a sampling rate of 5 Hz for the compressed river flow data, so that the 365 samples of each annual record of river flow compressed into 73 s, the simulated heart rate time series exhibited frequency characteristics similar to those from physiological data. In real heart rate data, a sample point occurs at each heart beat. This interval is of course variable but would be around 1 s for a subject at rest. It was necessary to decimate the short term RR sections to give a sample interval of 1 s.

2.2.3. Combining the long/medium and short term RR variability signals

The RR time series for each river flow record was derived by combining the long and short term variability signals. For each of the 365 samples comprising the long term RR signal, 18 sections of short term RR signal of variable length and amplitude were generated and combined with the long term signal using the formula

$$RR = LT(i) + \frac{j}{18}(LT(i+1) - LT(i)) + ST, \;\; j = 1:18$$

where RR is a section of simulated RR time series, $LT(i)$ is the i^{th} long term RR sample and ST is a short term RR section. 18 sections of variable length short term RR signal for each sample of the long term RR signal were

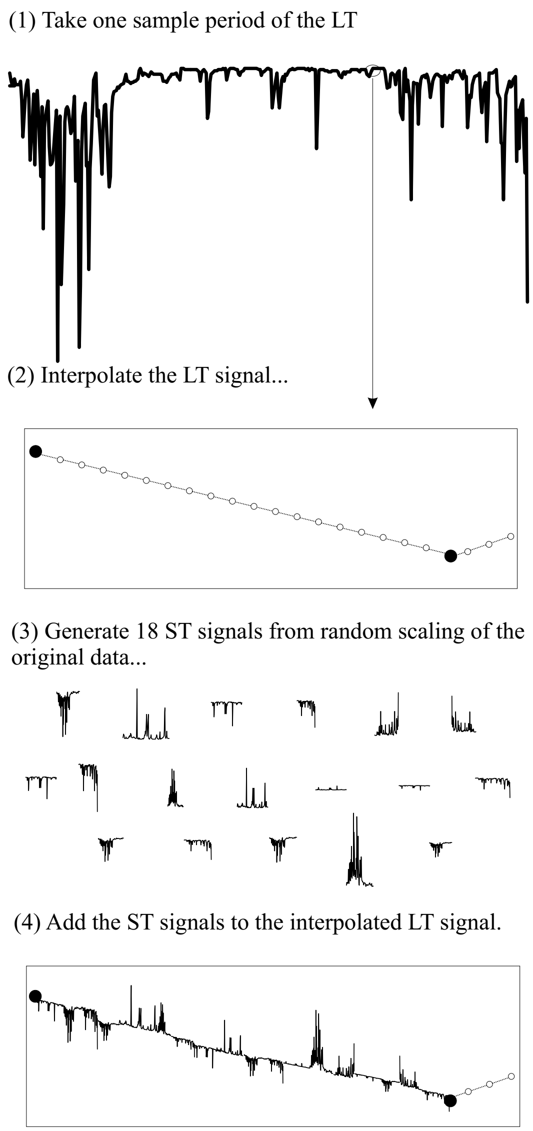

Figure 3. Method of combining the long term (LT) and short term (ST) RR signals.

found to be sufficient for generating simulations of approximately 24 h duration. Figure 3 illustrates the formation of the RR time series.

The resultant signal was scaled so that the simulated RR had a maximum between 1.0 to 1.2 s and a minimum between 0.4 and 0.6 s. These were assigned randomly for each simulation to achieve sufficient variability between individual simulations necessary for inter-subject variability. The values are typical physiological ranges for healthy subjects.

2.3. Assessing the simulated RR signals

We compared the standard frequency parameters ULF, VLF, LF and HF normalised to the total power, for the simulated RR, with those from the physiological RR time series using the Student's *t*-test.

3. Results

Figure 4 shows two examples each of simulated and physiological RR time series and their associated frequency spectra. The simulated data are shown in the top two panels and the physiological data in the bottom two panels. The most notable difference was that most of the variability in the simulated signal lay below the mean level giving a 'flat top' appearance to the plots. In the physiological data variability lay both above and below the mean level. In the frequency domain the simulated data exhibited 'respiratory' peaks very similar to the physiological data. The ULF, VLF, LF and HF ratios for all physiological and simulated data are given in table 1. These indicate there is good agreement for the frequency content of the signals. The exception was that the simulated data lacked sufficient power in the VLF band which is usually characterised by the 1/frequency component.

Table 1. Mean (sd) of frequency parameters for physiological and simulated data.

	Physiological	Simulated	p
ULF	0.82 (0.06)	0.84 (0.03)	NS
VLF	0.10 (0.03)	0.07 (0.02)	< 0.0008
LF	0.04 (0.02)	0.04 (0.01)	NS
HF	0.03 (0.02)	0.04 (0.01)	NS

4. Discussion and conclusions

We have investigated a novel approach to simulating RR time series using climatic data. We chose river flow data because it appeared to have long term variability characteristics similar to physiological RR time series and because of the availability of many data records. The simulations exhibited reasonable time and frequency domain characteristics but lacked sufficient variability in RR interval and had too narrow a spectrum of 1/frequency component in the VLF band. Further work is need to enhance our algorithm, but we hope to have inspired a new approach to the problem of RR time series simulation and predict that other naturally occurring phenomena could be used to generate RR time series perhaps indistinguishable from real data. This approach may be extended to simulation of other physiological phenomena and may be particularly beneficial where there is a better understanding of the underlying

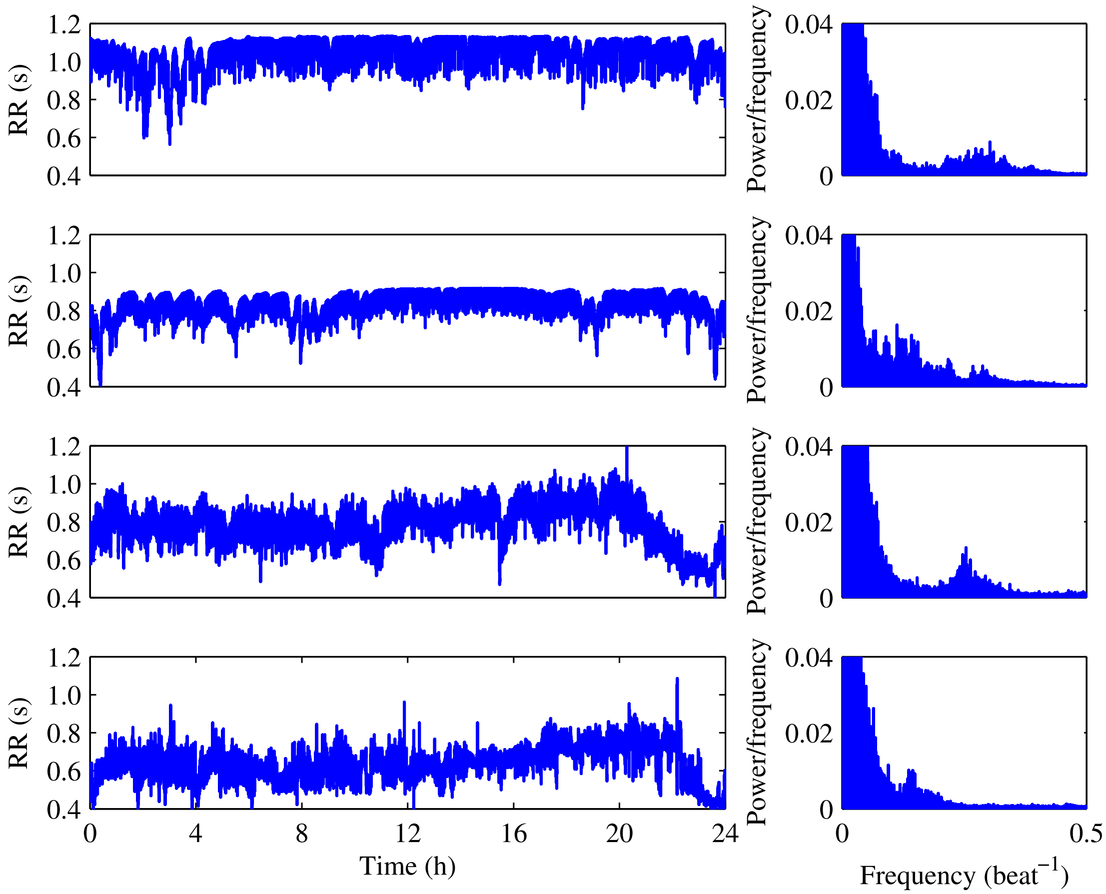

Figure 4. Simulated (top 2 panels) and physiological (bottom 2 panels) RR time series and associated frequency spectra.

processes of the natural phenomena compared to the physiological process.

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