Method for Generating an Artificial RR Tachogram of a Typical Healthy Human over 24-Hours

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Abstract

An algorithm that generates realistic synthetic 24-hour RR-tachograms by including both cardiovascular interactions and transitions between physiological states is presented. Fluctuations in the beat to beat RR-intervals of a normal healthy human over 24 hours are known to exhibit variability on a number of different time scales. Short range variability due to Mayer waves and RSA are incorporated using a power spectrum with given spectral characteristics described by its low and high frequency components. Longer range fluctuations arising from transitions between physiological states are generated using switching distributions extracted from real data. These physiological states, including sleep states, are specified using RR intervals with different means, variances and trends. This algorithm provides RR tachograms that are similar to those in the MIT-BIH Normal Sinus Rhythm Database. The resulting artificial RR times series generator was submitted for part 1 of the Physionet/Computers in Cardiology Challenge 2002 with entry number 201.

1. Introduction

Beat-to-beat variations of human RR intervals display fluctuations over a number of different time scales ranging from seconds to days. Some of these fluctuations are relatively well understood and arise from (i) the interactions between different physiological control mechanisms such as Respiratory Sinus Arrhythmia (RSA) and Mayer waves, (ii) the amount of physical and mental activity, (iii) the circadian rhythm and (iv) the effects of different sleep stages [1, 2, 3]. This wide range of activity that can be expected in a normal human suggests that the task of classifying normal and abnormal RR records is not straightforward. Nevertheless, the detection of abnormal fluctuations may be used to forewarn of cardiac disease [4].

In this paper, a method for generating artificial RR tachograms which includes fluctuations known to arise in normal healthy humans is presented. By incorporating the fluctuations on short, medium and long time scales the method produces realistic RR intervals over 24 hours. For a healthy human at rest, having a heart rate with approximately constant mean and variance, the power spectrum in the frequency range 0.04 to 0.4 Hz is believed to provide a measure of the activity due to the sympathetic and parasympathetic nerves [1, 5]. A technique for generating data with a prescribed power spectrum, which incorporates both RSA and Mayer waves, provides a means of obtaining a realistic sequence of RR intervals for a given physiological state specified by a particular mean, variance and trend [6]. This technique preserves the fluctuations over short time scales.

The RR tachogram of a healthy human does not reflect a heart rate with constant mean or variance since these physiological states usually change with time. During a 24 hour period, the heart rate tends to jump between different quantised states, relating to different physical and mental activity [1]. Empirical distributions calculated by Bernaola-Galván *et al.* [7] are used to govern the duration and mean heart rate level within each of these states. The transitions between these states typically occur over a much shorter time than that spent in any of the states. The technique for preserving the power spectrum is used as a building block for generating RR intervals both within the states and during transitions. Fluctuations due to both a circadian rhythm (including wake-sleep and sleep-wake transitions) and inter-sleep cycles are added to provide a realistic artificial RR tachogram over 24 hours. Model parameters are initialised using pre-specified distributions so that different seeds produce different RR tachograms.

2. Methods

2.1. Heart rate variability

Analysis of variations in the instantaneous heart rate time series using beat-to-beat RR intervals (the RR tachogram) is known as Heart Rate Variability (HRV) analysis [1, 5].

HRV analysis has been shown to provide an assessment of cardiovascular disease [8]. The heart rate may be increased by slow acting sympathetic activity or decreased by fast acting parasympathetic (vagal) activity. The balance between the effects of the sympathetic and parasympathetic systems, the two opposite acting branches of the autonomic nervous system, is referred to as the sympathovagal balance and is believed to be reflected in the beat-to-beat changes of the cardiac cycle [1]. Spectral analysis of the RR tachogram is typically used to estimate the effect of the sympathetic and parasympathetic modulation of the RR intervals. The two main frequency bands of interest are referred to as the Low-Frequency (LF) band (0.04 to 0.15 Hz) and the High-Frequency (HF) band (0.15 to 0.4 Hz) [5]. Sympathetic tone is believed to influence the LF component whereas both sympathetic and parasympathetic activity have an effect on the HF component [1]. The ratio of the power contained in the LF and HF components has been used as a measure of the sympathovagal balance [1, 5].

Respiratory Sinus Arrhythmia (RSA) [9, 10] is the name given to the oscillation in the RR tachogram due to parasympathetic activity which is synchronous with the respiratory cycle. The RSA oscillation manifests itself as a peak in the HF band of the spectrum. For example, 15 breaths per minute corresponds to a 4 second oscillation with a peak in the power spectrum at 0.25 Hz. An additional 10 second oscillation, due to Mayer waves [2], often gives rise to a second peak found in the LF band of the power spectrum at approximately 0.1 Hz.

2.2. Short time scales

Following [6], the effects of both RSA and Mayer waves in the power spectrum $S(f)$ of the RR intervals are incorporated by generating RR intervals which have a bimodal power spectrum consisting of the sum of two Gaussian distributions, $S(f) = S_1(f) + S_2(f)$, given by

$$S_i(f) = \frac{\sigma_i^2}{\sqrt{2\pi c_i^2}} \exp\left[-\frac{(f - f_i)^2}{2c_i^2}\right] \quad (1)$$

with means f_i and standard deviations c_i for $i = 1, 2$. Power in the LF and HF bands are given by σ_1^2 and σ_2^2 respectively whereas the variance equals the total area $\sigma^2 = \sigma_1^2 + \sigma_2^2$, yielding an LF/HF ratio $\gamma = \sigma_1^2/\sigma_2^2$. An example of the power spectrum $S(f)$ given by $f_1 = 0.1$, $f_2 = 0.25$, $c_1 = 0.01$, $c_2 = 0.01$ and $\gamma = 0.5$ is shown in Fig. 1.

A RR interval time series with power spectrum $S(f)$ is generated by taking the inverse Fourier transform of a sequence of complex numbers with amplitudes $\sqrt{S(f)}$ and phases which are randomly distributed between 0 and 2π radians. By multiplying this time series by an appropriate scaling constant and adding an offset value, the resulting time series can be given any required mean
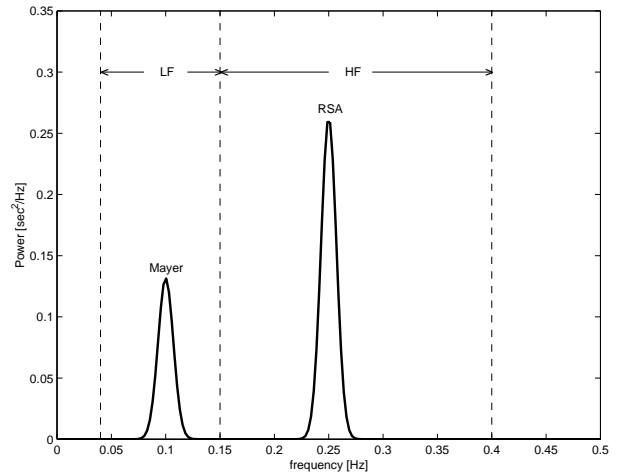

Figure 1. Power spectrum $S(f)$ of the RR interval process with a LF/HF ratio of $\gamma = 0.5$.

and variance. In addition, trends are used to simulate the effect of increasing and decreasing heart rate throughout a particular physiological state.

For a given physiological state of RR intervals, a number of operating parameters must be specified, such as the mean and standard deviation of the RR intervals along with the trend throughout the state. The mean of the RR intervals in a particular state is specified according to whether the state is in the wake or sleep stage. These stages are described in more detail in the following sections. The standard deviation of the RR intervals for a particular state is given by $\sigma_{RR} \sim U(0.01, 0.02)$ seconds and the trend is given by $\beta_{RR} \sim U(-A_\beta, A_\beta)$ where $A_\beta \sim U(1, 1.25)$ seconds and $U(a, b)$ denotes a uniform distribution on the interval $[a, b]$. The shape of the power spectrum is specified by the relative contributions of the two modes comprising the LF and HF bands given by the LF/HF ratio which is uniformly distributed according to $\gamma \sim U(0.5, 8.0)$.

2.3. Wake stages

Circadian activity leads to an approximately sinusoidal variation in baseline activity throughout the day. This variation corresponds to a high heart rate during the wake stage and a decrease in heart rate during the sleep stage. During the wake stage, the mean RR interval used for initialising each physiological state beginning at time t in seconds is given by

$$\mu_{RR} = \hat{\mu}_{RR} + A_{RR}\sin[\pi + (2\pi/T_c)t] + 0.2A_{RR}r \quad (2)$$

where the underlying mean is $\hat{\mu}_{RR} \sim U(0.7, 1)$ seconds, $A_{RR} \sim U(0.075, 2.075)$ seconds, the circadian period is given by $T_c \sim N(24, 1)$ hours and $r \sim N(0, 1)$ where

$N(a, b)$ denotes a normal distribution with mean a and standard deviation b.

2.4. Sleep stages

The sleep period exhibits an intricate, yet approximately regular structure. After an initial drop in heart rate, a human will typically cycle through stages of deep and light sleep with a period of about 90 to 110 minutes. The transitions between these sleep stages are marked by changes in the baseline heart rate and HRV, reflecting state changes in the model. The starting sleep time T_s and sleep duration interval T_d are given by $T_s \sim U(14, 16)$ hours and $T_d \sim U(6, 8)$ hours. During the sleep stage, the mean RR interval for a state beginning at time t in seconds is given by

$$\mu_{RR} = \hat{\mu}_{RR} + \frac{1}{2}B_{RR}\left[1 + \sin\left(2\pi t/T_s\right)\right] \qquad (3)$$

where $B_{RR} \sim U(0.1, 0.2)$ seconds, $\hat{\mu}_{RR} \sim U(0.7, 1)$ seconds and the period of the sleep cycle is $T_s = 100$ minutes. This implies that the RR intervals undergo sinusoidal fluctuations with a minimum RR interval of $\hat{\mu}_{RR}$ and a maximum of $\hat{\mu}_{RR} + B_{RR}$.

2.5. State transitions

The size of transitions between different mean heart rates, ΔRR, are replicated using a distribution with a similar shape to that found from empirical observations [7],

$$\Delta RR = 0.5 A_{\Delta RR}(1 + e^r/10)u/|u| \qquad (4)$$

where $A_{\Delta RR} \sim U(0.03, 0.13)$ and r and u are normal and uniform distributions with $r \sim N(0, 1)$ and $u \sim U(0, 1)$.

The length of each transition between states is $\tau_{trans} \sim U(5, 30)$. RR intervals during each transition are generated by using a V-shaped bridge to span between the first and last RR interval of the neighbouring states. The V-shaped bridge gives the effect of under-shooting when the control mechanism adjusts to a new level of RR interval and was found to be present during a number of transitions between states for RR intervals from the MIT-BIH Normal Sinus Rhythm Data Base (NSRDB) [11] hosted at the Physionet web-site [12]. The short range variability produced by the power spectrum is superimposed on this V-shape to mimic the effect of RSA and Mayer waves during the transition.

2.6. Duration of states

Using the empirical power-law distribution estimated by Bernaola-Galván *et al.* [7], the length of time τ spent in a given state is governed by a power law distribution with

$$\tau = (u/\alpha)^{-\beta} \qquad (5)$$

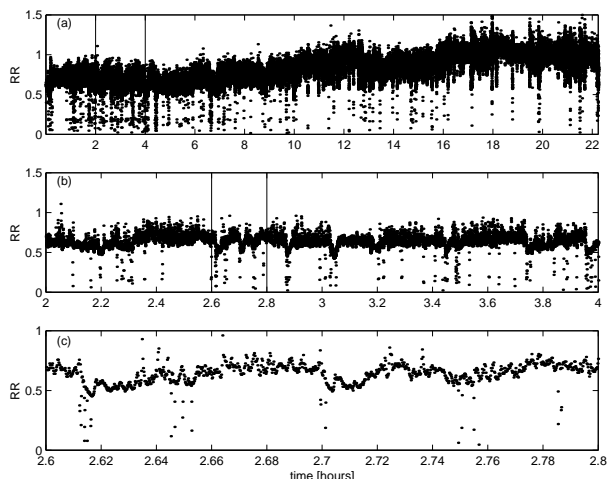where $\alpha = 5466.8$, $\beta = 2.2$ and $u \sim U(0, 1)$.

Figure 2. RR intervals from record 16265 of NSRDB: (a) 22 hours, (b) 2 hours and (c) 12 minutes. Vertical lines in panels (a) and (b) indicate the regions which are blown up and shown in panels (b) and (c).

2.7. Ectopy and artefact

An analysis of ectopic beat and artefact incidence in an accompanying paper [13] is used to provide an algorithm for generating realistic ectopy and artefact. Ectopic beats are added with an independent probability of one per hour. Artefacts are added with a probability proportional to the mean heart rate within a physiological state and increased for state transition periods. The frequency of artefacts in relation to state changes may also be used to classify real (normal) and artificial RR interval time series [13].

3. Results

The Computers in Cardiology Challenge 2002 suggested that the RR generator models should be constructed to replicate RR interval recordings found in NSRDB [11, 12]. An example of one such recording (labelled 16265 in NSRDB) is shown in Fig. 2. This illustrates the circadian rhythm (Fig. 2a), various levels of physiological activity reflected by fluctuating RR intervals with different means, variances and trends (Fig. 2b) and modulation of the RR intervals due to RSA and Mayer waves (Fig. 2c).

The model used for generating artificial RR tachograms, entry number 201 in event 1 of the Computers in Cardiology Challenge 2002, was used to simulate two long records of RR intervals. These two records are labelled 19 and 31 in the database of recordings used for the classification competition (event 1). The time series of RR intervals for entry 19 is shown in Fig. 3. The artificial tachogram (Fig. 3) replicates most of the characteristics of the real human RR tachogram (Fig. 2), including the
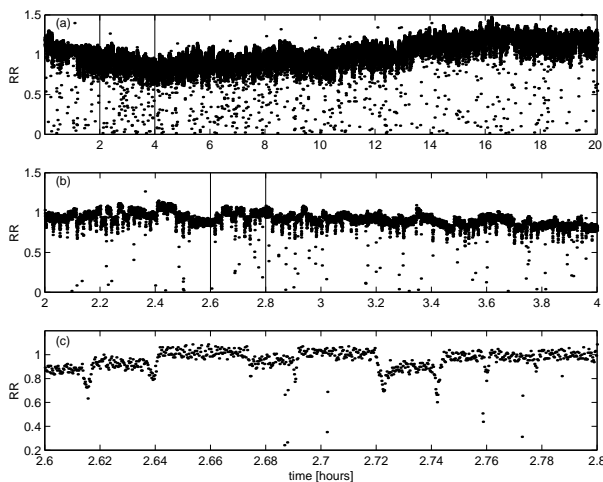
Figure 3. Simulation of RR intervals corresponding to entry (a) 19 in the Computers in Cardiology Challenge 2002: (a) 20 hours, (b) 2 hours and (c) 12 minutes. Vertical lines in panels (a) and (b) indicate the regions which are blown up and shown in panels (b) and (c).

circadian rhythm (Fig. 3a), switching between different states (Fig. 3b) and activity over short time scales due to RSA and Mayer waves (Fig.3c).

4. Conclusion

A new model for generating realistic RR intervals has been presented. This model provides a building block for incorporating low frequency variability related to the interactions of the control mechanisms due to the sympathetic and parasympathetic nerves. In this way, both RSA and Mayer waves, which often yield spectral components at approximately 0.25 Hz and 0.1 Hz respectively are preserved. The ratio between the low frequency and high frequency components is modelled stochastically. Fluctuations with longer time scales (on the order of minutes) due to state transitions are modelled by allowing the RR intervals to have different means, variances and trends. The duration of these states are given by a power-law distribution. Variability on time scales of the order of hours, such as the circadian rhythm and sleep stages are modelled by a combination of deterministic sinusoids and stochastic noise.

While the overall model is relatively complex, it summarises many of the important physiological control mechanisms that influence heart rate over 24 hours. Each of the model's parameters has a very clear physiological meaning, suggesting that if the model is tuned to replicate a particular human RR tachogram, it may be possible to use the derived parameter values to facilitate medical classifications and diagnosis.

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