Autonomic Neuroscience: Basic and Clinical 178 (2013) 89–95

Contents lists available at ScienceDirect

Autonomic Neuroscience: Basic and Clinical

journal homepage: www.elsevier.com/locate/autneu

Gain and coherence estimates between respiration and heart-rate: Differences between inspiration and expiration

Diogo S. Fonseca [a,*], Alessandro Beda [b], Antonio M.F.L. Miranda de Sá [a], David M. Simpson [c]

[a] Biomedical Engineering Programme, Federal University of Rio de Janeiro, Brazil
[b] Department of Electronic Engineering, Federal University of Minas Gerais, Brazil
[c] Institute of Sound and Vibration Research, University of Southampton, UK

ARTICLE INFO

Article history:
Received 1 November 2012
Received in revised form 7 March 2013
Accepted 27 March 2013

Keywords:
Causal coherence
Heart rate variability
Missing samples
Respiratory sinus arrhythmia

ABSTRACT

The interaction of respiration and heart-rate variability (HRV), leading to respiratory sinus arrhythmia (RSA) and, in the inverse direction, cardioventilatory coupling has been subject of much study and controversy. A parametric linear feedback model can be used to study these interactions. In order to investigate differences between inspiratory and expiratory periods, we propose that models are estimated separately for each period, by finding least mean square estimates only over the desired signal segments. This approach was tested in simulated data and heart-rate and respiratory air flow signals recorded from 25 young healthy adults (13 men and 12 women), at rest, breathing spontaneously through a face mask for 5 min. The results show significant differences ($p < 0.05$) between the estimates of coherence obtained from the whole recording, and the inspiration and expiration periods. Simple and causal coherence from respiration to HRV was higher during inspiration than expiration. The estimates of gain also differed significantly in the high frequency (HF) band (0.15–0.5 Hz) between those obtained from the whole recording, and the inspiratory and expiratory periods. These results indicate that a single linear model fitted to the whole recording neglects potentially important differences between inspiration and expiration, and the current paper shows how such differences can be estimated, without the need to control breathing.

1. Introduction

The autonomic control of the cardiovascular system has been extensively studied by techniques that assess heart rate variability (HRV). Clinical risk evaluation and the relationship between psychological processes and physiological functions have been commonly addressed in these studies (Berntson et al., 1997). However, the evaluation of autonomic cardiovascular control by means of the HRV is still subject of some controversy (Parati et al., 2006; Beda et al., 2007).

HRV is modulated by respiration, a phenomenon called respiratory sinus arrhythmia (RSA), which is responsible for most of the variability of the heart rate (HR). RSA has been used to quantify vagal activity and it has been related to prognosis of cardiovascular health (Camm et al., 1996; Berntson et al., 1997; Parati et al., 2006; Beda et al., 2007). However, not only the autonomic tone influences RSA, but also other factors including differences in breathing parameters between individuals in respiratory frequency, amplitude, and the relative length of inspiration and expiration periods can affect the level of RSA (Brown et al., 1993; Strauss-Blasche et al., 2000; Cammann and Michel, 2002; Yasuma and Hayano, 2004).

In previous studies, paced breathing has often been used to standardize these periods and investigate the effect of their variations (Stark et al., 2000; Grossman et al., 2004). It was noted that rapid inspiration leads to increased RSA (Strauss-Blasche et al., 2000), whereas rapid expiration does not have such an effect. Evidence that baroreflex responsiveness is different between inspiration and expiration (Eckberg, 2003) further reinforces the relevance of considering these two periods separately for investigations of HRV modulation. A protocol in which subjects are breathing spontaneously seems a more desirable approach than paced breathing, for two main reasons: paced breathing leads to physiological repercussions that may confound in the comprehension of RSA (Ritz, 2009); also, it impacts on the ability to carry out other physical or mental challenges at the same time and thus greatly restricts the scenarios that can be investigated.

The interaction between respiration and HRV has been extensively investigated in previous works (Porta et al., 2012). The objective of this study is to adopt a similar approach, but estimating the transfer function separately for the inspiration and expiration periods. Specifically, we present a method that can provide such separate estimates from the same recording and test for differences in the coupling between respiration and HRV in these two periods on a set of data recorded from healthy adult volunteers at rest, breathing spontaneously.

* Corresponding author. Tel.: +55 21 25628590; fax: +55 21 25628591.
E-mail address: diogo.simoes@peb.ufrj.br (D.S. Fonseca).

1566-0702/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.autneu.2013.03.015

2. Methods

In the following, first the model-based methods for estimating the coherence and gain will be reviewed (based on Porta et al., 2002) followed by a description of how this can be adapted to permit separate estimates during only the inspiratory and expiratory periods.

2.1. Coherence, causal coherence and autoregressive modeling with missing samples

The coherence function expresses the synchrony between the two signals x_1 and x_2, and is defined as:

$$\gamma^2_{1,2} = \frac{|S_{12}(f)|^2}{S_{11}(f)\cdot S_{22}(f)} \quad (1)$$

where $S_{12}(f)$ is the cross-spectrum, and $S_{11}(f)$ and $S_{22}(f)$ are the auto-spectra of the analyzed signals, respectively (Bendat and Piersol, 1986; Baccala and Sameshima, 2001). Initially developed for economic science, the Granger concept of causality aims to assess causality in relationships between the two signals by assessing the contribution the second signal makes to predicting the next sample of the first, over and above the prediction achieved from only previous samples of the latter (Granger, 1969). Applying the Granger causality concept to coherence leads to causal coherence, which aims at quantifying the level at which two signals are functionally connected (Baccala and Sameshima, 2001). Granger causality (Granger, 1969) is probably the most commonly used approach in related studies of the cardiovascular system, (Porta et al., 2002; Faes et al., 2004; Faes and Nollo, 2006), though there are several other alternatives, such as symbolic coupling traces (Wessel et al., 2011) and mixed state analyses (Wiesenfeldt et al., 2001). Granger causality has also previously been used in the context of the cardio-respiratory interactions, for example in Porta et al. (2002), Faes et al. (2004), and Faes and Nollo (2006).

In order to obtain the (Granger) causal coherence, a multivariate AR model is implemented that represents a closed loop model as shown in Fig. 1 (Porta et al., 2002).

This is defined by the following equation system:

$$x_1[t] = \sum_{k=1}^{n} a_{1,1}(k)x_1[t-k] + \sum_{k=1}^{n} a_{1,2}(k)x_2[t-k] + w_1[t] \quad (2)$$

$$x_2[t] = \sum_{k=0}^{n} a_{2,1}(k)x_1[t-k] + \sum_{k=1}^{n} a_{2,2}(k)x_2[t-k] + w_2[t] \quad (3)$$

In our study, x_1 represents the HRV signal and x_2 the respiratory flow signal, w_1 and w_2 are the independent white Gaussian noises, with zero mean and variances of λ_1 and λ_2 respectively, and n is the model order, which is here taken to be equal for all filters. The coefficients of the model are represented by $a_{i,j}(k)$, where i refers to the output and j the input signal, and k is the lag. It should be noted that here $a_{2,1}(0) = 0$ while $a_{1,2}(0) \neq 0$, imposing strict causality only in the $x_2 \rightarrow x_1$ direction but allows for instantaneous effects in the reverse pathway. A linear representation of the causal relationship from x_1 to x_2 is obtained by setting all the $a_{1,2}(k)$ coefficients to zero, and equivalently, to obtain the x_2 to x_1 relationship, the $a_{2,1}(k)$ coefficients are set to zero. This way, feedback effects from the other signal are disregarded and the causal effects are obtained. The auto and cross-spectral density functions can then be calculated, after z-transformation (Porta et al., 2002) as:

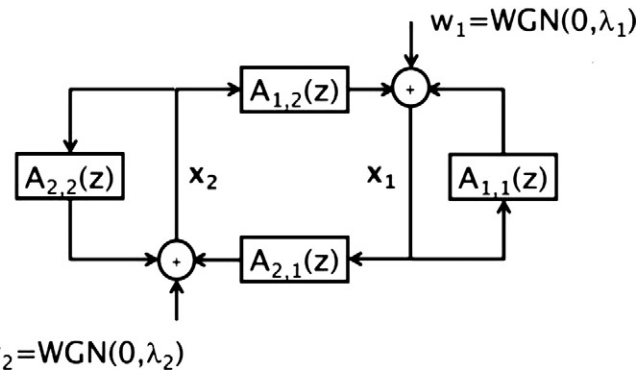

Fig. 1. Closed loop model representation used to model the relationship between HRV and respiration, WGN indicates white Gaussian noise.

$$S_{11}(f) = |\Delta(z)|^2 \cdot \left[\left|1-A_{2,2}(z)\right|^2 \cdot \lambda_1^2 + \left|A_{1,2}(z)\right|^2 \cdot \lambda_2^2\right] \quad (4)$$

$$S_{22}(f) = |\Delta(z)|^2 \cdot \left[\left|A_{2,1}(z)\right|^2 \cdot \lambda_1^2 + \left|1-A_{1,1}(z)\right|^2 \cdot \lambda_2^2\right] \quad (5)$$

$$S_{12}(f) = |\Delta(z)|^2 \cdot \left[\left(1-A_{2,2}(z)\right)\cdot A_{2,1}\left(z^{-1}\right)\cdot \lambda_1^2 + A_{1,2}(z)\cdot\left(1-A_{1,1}\left(z^{-1}\right)\right)\cdot \lambda_2^2\right] \quad (6)$$

where

$$|\Delta(z)|^2 = \left(\left(1-A_{1,1}(z)\right)\cdot\left(1-A_{2,2}(z)\right) - A_{1,2}(z)\cdot A_{2,1}(z)\right)^{-1} \quad (7)$$

and

$$A_{i,j} = \sum_{k=0}^{n} a_{i,j}(k)z^{-k} \quad (8)$$

with $i,j = 1$, and 2 and $z = e^{j\cdot 2\cdot\pi\cdot f/f_s}$, f is the frequency, and f_s the sampling frequency.

The simple (bidirectional) coherence can then be calculated by directly inserting Eqs. (4), (5) and (6) in Eq. (1), and causal coherences in a similar manner after removing the feedback path (Porta et al., 2002):

$$\gamma^2_{i\rightarrow j}(f) = \gamma^2_{i,j}(f)|_{A_{i,j}(z)=0} \quad (9)$$

with $j,i = 1$, and 2 and the gain as

$$G_{i\rightarrow j}(f) = \left|\frac{A_{j,i}(f)}{1-A_{j,j}(f)}\right| \quad (10)$$

with $j,i = 1$, and 2.

In order to calculate the coherence (causal or not) and the gain for only the inspiratory (or expiratory) phase, we now mark all the samples during the expiratory (or inspiratory) phase as 'missing' by replacing them with Not-a-Number (NaN). This leads to signals with gaps (see Fig. 2) and thus parameter estimation methods need to be adapted accordingly. The coefficients of the AR model were estimated by the least squares method applied over the available (remaining) samples (Simpson et al., 2001; Simpson et al., 2005). This may be illustrated for the simple example for a univariate AR model shown in Eq. (11).

$$x[n] = \sum_{i=1}^{M} a_i x[n-i] + \varepsilon[n] \quad (11)$$

and order M = 3, with sample x[4] missing. As shown in Eq. (12), the error ε can only be calculated for samples ε[3], ε[8], ε[9] and ε[10]. In all other lines, either the left side of the equation or the matrix product is NaN, and hence the residual ε[i] is also a NaN. The parameters a_1, a_2, and a_3 are then estimated by minimizing the mean-square