XVI IMEKO World Congress
Measurement - Supports Science - Improves Technology - Protects Environment ... and Provides Employment - Now and in the Future
Vienna, AUSTRIA, 2000, September 25-28

TIME-FREQUENCY ANALYSIS OF CARDIOVASCULAR SIGNALS

H. Sorsa* and V. Turjanmaa**
*Laboratory of Measurement and Information Technology
Tampere University of Technology, P.O.Box 392, FIN-33101 Tampere, Finland
**Department of Clinical Physiology & Nuclear Medicine
Tampere University Hospital, P.O.Box 2000, FIN-33521 Tampere, Finland

Abstract: Cardiovascular variability signals provide information about the functioning of the autonomous nervous system and other physiological sub-systems. Signals may be measured either as continuous electrocardiogram and blood pressure signals or as so-called beat-to-beat time series of RR-intervals end e.g. systolic and diastolic blood pressure. These signals are typically nonstationary by nature, and joint time-frequency analysis can provide more information than simple time domain methods or spectral analysis. In this paper, some time-frequency methods are compared using signals measured during orthostatic tilt.
Keywords: Joint time-frequency analysis, nonstationary signals, cardiovascular system

1 INTRODUCTION

The rhythm of the heart is continuously modulated by the input from the autonomous nervous system, ANS. The final pace of the heart is defined by the balance between sympathetic (excitatory) and parasympathetic (inhibitory) impulses. The former have a typical response delay of a few seconds, whereas the latter provide faster, nearly immediate response to stimulations [1].

Variations in heart rate and blood pressure originate from different sources, e.g. respiration (respiratory sinus arrhythmia). Analysis of these variations in different situations has been proven useful in understanding cardiovascular regulation and functionality of ANS in normal adults, and adults with congestive heart failure, diabetes, hypertension, and cardiac transplants [2].

There are several methods for testing autonomic function of cardiovascular system. One of these tests is so-called orthostatic tilt. The test begins with the patient resting on a table in supine position. Then the table is rotated to an upright position (passive tilt) or the patient gets up himself (active tilt). Continuous electrocardiography (ECG) and blood pressure are measured during the whole procedure.

The change of position from supine to standing causes significant changes in blood pressure in different parts of the body; gravitational effect causes blood to flow from upper body to the feet. Autonomic cardiovascular regulatory system is needed to prevent arterial blood pressure from collapsing. Functioning of sympathetic and parasympathetic nervous systems can be seen in instantaneous frequency content of the heart rate and blood pressure signals. In supine position, respiratory influences and mainly parasympathetic control at frequencies around 0.15 - 0.4 Hz are dominant. After tilt, the spectral power moves towards lower frequencies (around 0.05 - 0.15 Hz) associated with baroreceptor function and vasomotor activity.

2 METHODS

There are several methods for joint time-frequency signal analysis. In this paper, two of them are compared in analysing the nonstationary signals measured during orthostatic tilt test.

2.1 Wigner-Ville method

The concept of Wigner distribution was originally developed for the area of quantum mechanics by Wigner in 1932 and was introduced for signal analysis by Ville 15 years later. It is now commonly known as the Wigner-Ville distribution (WVD) [3]. Generally, for any complex function x the time-dependent WVD is defined

$$\mathrm{WVD}_x(t,\omega) = \int_{-\infty}^{\infty} x\left(t+\frac{\tau}{2}\right) x^{*}\left(t-\frac{\tau}{2}\right) e^{-j\omega\tau}\, d\tau \tag{1}$$

where $*$ denotes the complex conjugate. WVD maps a one-dimensional function of time into two-dimensional function of time and frequency.

In real applications, evaluation from minus infinite to plus infinite is impossible. To overcome this problem, we can impose a running window $h(\tau)$, such as

$$\mathrm{PWVD}_s(t,\omega) = \int_{-\infty}^{\infty} h(\tau)\, x\left(t+\frac{\tau}{2}\right) x^{*}\left(t-\frac{\tau}{2}\right) e^{-j\omega\tau}\, d\tau \tag{2}$$

which is called the pseudo Wigner-Ville distribution. This windowing operation will result as frequency smoothing in time domain.

One main deficiency of the WVD is the so-called cross-term interference. For $x(t) = x_1(t) + x_2(t)$, the WVD is

$$\mathrm{WVD}_x(t,\omega) = \mathrm{WVD}_{x1}(t,\omega) + \mathrm{WVD}_{x2}(t,\omega) + 2\,\mathrm{Re}\left\{\mathrm{WVD}_{x1,x2}(t,\omega)\right\} \tag{3}$$

which shows that the WVD of the sum of two signals is not the sum of their respective WVDs. WVD auto-terms are, in general, relatively smooth, but the cross-terms are strongly oscillated. For signals with multiple frequency components this means that their WVD will have undesired cross-term interferences. The effects of these interferences can be reduced by applying a low-pass filter $g(\tau)$:

$$\mathrm{SPWVD}_x(t,\omega) = \int_{-\infty}^{\infty} h(\tau) \int_{-\infty}^{\infty} g(s-t)\, x\left(s+\frac{\tau}{2}\right) x^{*}\left(s-\frac{\tau}{2}\right) ds\, e^{-j\omega\tau}\, d\tau \tag{4}$$

Because the low-pass filter performs a smoothing operation, this is called the smoothed-pseudo WVD. The effect of the smoothing is twofold: it can substantially suppress the cross-terms, but on the other hand smoothing will reduce the resolution of the WVD.

For a finite discrete signal $z(n)$ SPWVD is defined by

$$\mathrm{SPWVD}(n,m) = \frac{1}{2}N \sum_{k=-N+1}^{N-1} |h(k)|^2 \left[\sum_{p=-M+1}^{M-1} g(p) z(n+p+k) \cdot z^{*}(n+p-k)\right] e^{-j2\pi km/N} \tag{5}$$

Here $h(k)$ is a symmetric, normalised window function of length $2N-1$, and $g(p)$ is a time smoothing window of length $2M-1$. The important property of this distribution is that the frequency and time smoothing are independent. If the length of the window $g(p)$ is longer than the local time of stationarity of the signal, it will decrease time resolution and suppress the nonstationary character of the signal.

Real-valued signals have always symmetric spectrum, that is,

$$|S(\omega)|^2 = |S(-\omega)|^2 \tag{6}$$

In this case, only one half of the spectrum contains information, while the other half is redundant. In case of WVD, the negative frequency components also create cross-terms. To reduce the cross-term interference, the concept of analytical signal is introduced. For any real-valued signal $x(t)$, we associate a complex valued signal $x_a(t)$ defined as

$$x_a(t) = x(t) + j\, HT\{x(t)\} \tag{7}$$

where $HT\{x\}$ is the Hilbert transform of x. $x_a(t)$ is called the analytical signal associated to $x(t)$. This definition has a simple interpretation in the frequency domain since X_a is a single-sided Fourier transform where the negative frequency values have been removed, the positive ones have been doubled, and the DC component is kept unchanged. However, the analytical function differs from the original signal in several ways. For instance, the analytical function of a time-limited real-valued signal $x(t)$ is no longer time-limited, because the analytical function is band limited. Although the analytical function has the same positive power spectrum as that of a corresponding real-valued signal, its instantaneous properties may substantially differ from that of the original signal. Because the WVD of the analytical function is smoothed in the time domain, all time domain properties of the WVD of the real signal, such as instantaneous frequency property, are affected.

2.2 Recursive AR method

Spectral analysis based on autoregressive signal modelling is widely used also in cardiovascular signal analysis. For a stationary process $y(t)$ with input $x(t)$ model parameters can be estimated e.g. by using minimum mean-squared error principle, and for stationary data they are assumed to remain constant throughout the process.

With nonstationary signals, however, the model parameters must somehow adapt to the changes is signal. For this purpose, recursive AR algorithms based on e.g. least squares principle have been developed [4,5]. The basic form of the (recursive) AR filter is

$$y(t) = \varphi^T(t)\theta_0(t) + e(t) \tag{8}$$

where the regression vector $\varphi(t)$ contains old values of observed inputs and outputs, $\theta_0(t)$ represents the true description of the system and $e(t)$ is the noise source. The natural prediction is $\hat{y}(t) = \varphi^T(t)\theta(t-1)$ and its gradient with respect to θ becomes exactly $\varphi(t)$.

A typical recursive identification algorithm for filter coefficients θ is

$$\hat{\theta}(t) = \hat{\theta}(t-1) + K(t)(y(t) - \hat{y}(t)) \tag{9}$$

Here $\hat{\theta}(t)$ is the parameter estimate at time t, and $y(t)$ is the observed output at time t. The gain $K(t)$ determines in what way the current prediction error $y(t) - \hat{y}(t)$ affects the update of the parameter estimate. It is typically chosen as

$$K(t) = Q(t)\varphi(t) \tag{10}$$

where $\varphi(t)$ is an approximation of the gradient of $\hat{y}(t|\theta)$ (prediction of $y(t)$ according the model described by θ) with respect to θ,

There are several different approaches to choosing the matrix $Q(t)$ that affects both the adaptation gain and the direction in which the updates are made. One approach is to discount old measurements exponentially, so that an observation that is τ samples old carries a weight that is λ^τ of the weight of the most recent observation. This means that at time t, the following function is minimised:

$$\sum_{k=1}^{t} \lambda^{t-k} e^2(k) \tag{11}$$

Here λ is a positive number ≤ 1 (typically 0.97 – 0.995).

This criterion can be minimised exactly with the following choice of $Q(t)$:

$$Q(t) = P(t) = \frac{P(t-1)}{\lambda + \varphi^T(t)P(t-1)\varphi(t)} \tag{12}$$

$$P(t) = \left[P(t-1) - \frac{P(t-1)\varphi(t)\varphi^T(t)P(t-1)}{\lambda + \varphi^T(t)P(t-1)\varphi(t)}\right] / \lambda \tag{13}$$

where $P(t)$ is the inverse weighted autocorrelation matrix of $y(t)$:

$$P^{-1}(t) = R(t) = \sum_{k=1}^{t} b(t,k) y(k) y^{T}(k) \tag{14}$$

where $b(t,k)$ is the weighting function. This algorithm is called the Forgetting Factor (FF) Approach to adaptation. It is also known as recursive least squares, RLS algorithm.

RLS models have some disadvantages. They become unstable if the poles move outside the unit circle during the adaptive process, and poles near unit circle cause extremely sharp and high peaks in spectra. They may also be computationally heavy processes. On the other hand, they converge to optimal solution relatively fast.

3 RESULTS

The data were processed and analysed using MATLAB® [6], System Identification Toolbox [5,7], Time-Frequency Toolbox [8] and ASAPS Toolbox [9]. At first, beat-to-beat time series of RR intervals and systolic and diastolic blood pressure were determined from the continuous ECG and blood pressure signals. These unequally spaced signals were then resampled to 2 Hz sampling frequency using linear interpolation, downsampling and anti-alias filtering. Trend was removed by using 3rd order Chebyshev type II high-pass filter with cut-off frequency of 0.04 Hz. Fig. 1 shows analysed data in its original (unequispaced) form and after resampling and trend removal. Tilt occurs at about 520 seconds from the beginning. Even though the amplitude level transition disappears at trend removal, the change in the frequency content of the signal can still be seen.

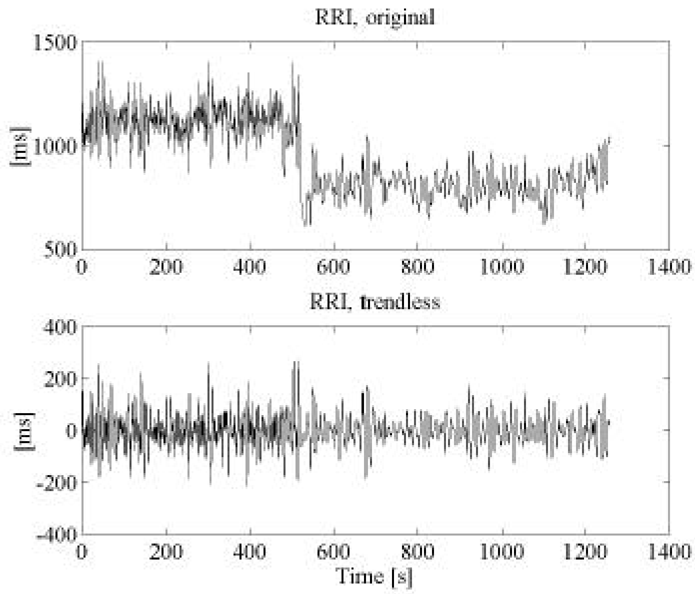

Figure 1. Original and resampled, trendless data.

The time-frequency distribution of the RRI signal were calculated using both SPWVD and recursive AR methods. SPWVD was calculated using Hanning time smoothing window of length 51 samples, and Hanning frequency smoothing window of length 101 samples. Recursive AR model was calculated using model order 15 and forgetting factor 0.995. The results are shown in figs. 2 and 3. In order to increase resolution in picture, the artefactual peaks caused by recursive adaptation in AR model have been removed by median filtering the spectra for plotting.

In both distributions it is seen that the spectral power moves towards lower frequencies after tilt, as can be expected. However, in the SPWVD model the spectral power is distributed into wider frequency band. This is due to the smoothing effects both in time and frequency domain. As it can be seen in Fig. 3, WVD can also get negative values. This may cause problems in analysing the instantaneous frequency properties of the distribution.

Figs. 4 and 5 show the behaviour of the two time-frequency distributions around the tilt point (at about 520 s). In AR model, there can be seen a momentary increase in spectral power at about 0.1 Hz, which is typical frequency for vasomotor activity. After about 15 seconds of standing, the power of this frequency component starts increasing again. In SPWVD the transition can be seen as the decreasing power in the higher frequencies. There is no obvious increase in 0.1 Hz component at tilt; instead, the power decreases smoothly and starts increasing again at the same point as in AR model.

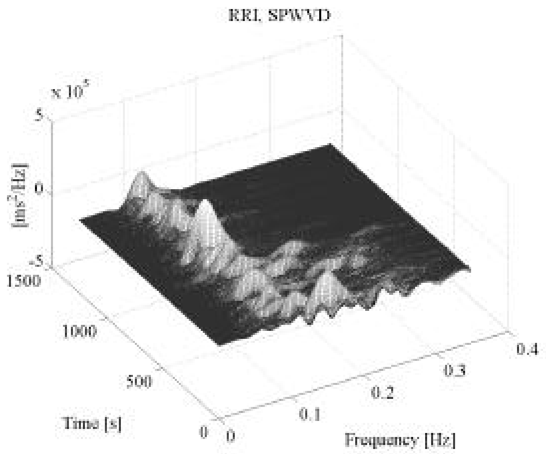

Figure 2. SPWVD of RRI signal.

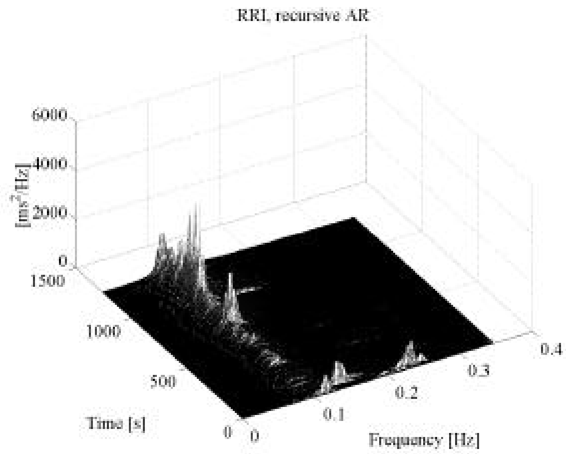

Figure 3. Recursive AR spectra of RRI signal.

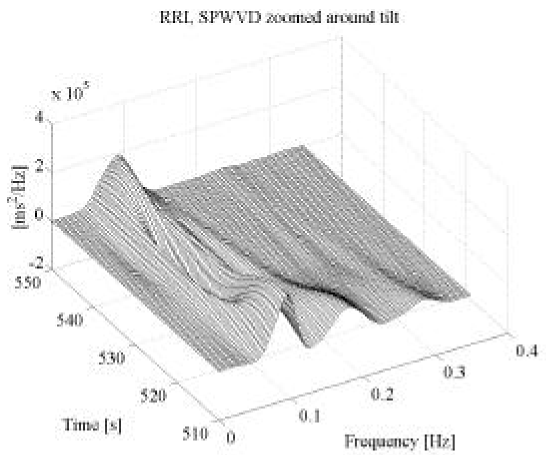

Figure 4. SPWVD around tilt point.

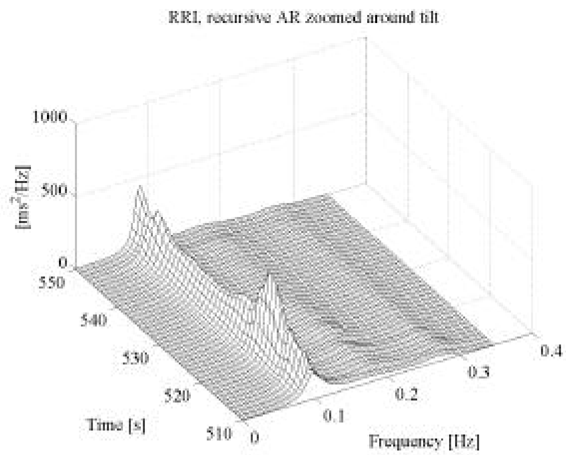

Figure 5. AR spectra around tilt point.

The ability of these two methods to follow the change in the frequency content of the signal can be compared by calculating the instantaneous central frequency, ICF, which is defined as first order moment or centre of gravity in frequency for spectrum:

$$\mathrm{ICF} = \frac{\sum_i f_i P_i}{\sum_i P_i} \tag{15}$$

where f is frequency and P is spectral power at that frequency. Fig. 6 shows that for AR model the ICF change is rather smooth and it drops at tilt as expected. The high ICF peak at the beginning is caused by the transient effects of the recursive AR algorithm. For SPWVD the trend in ICF is similar, but there is much more variation than in AR model. The instantaneous frequency properties of the signal are clearly affected by the use of analytical function instead of the real-valued signal.

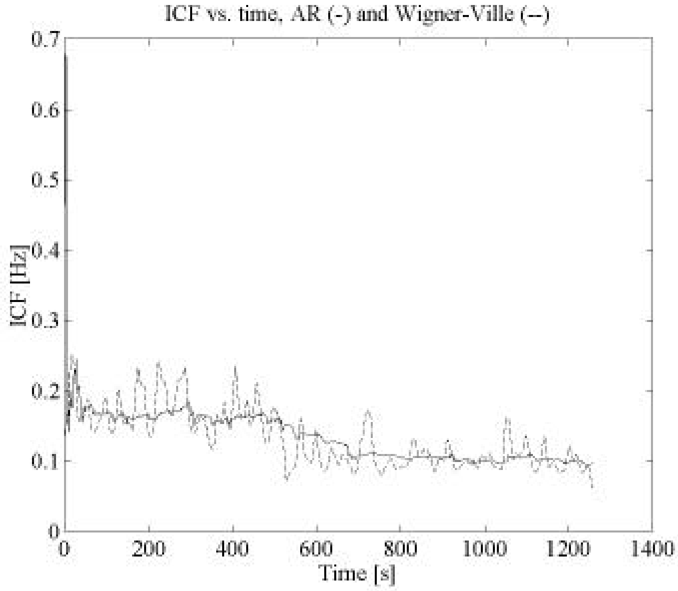

Figure 6. ICF of AR spectra and SPWVD distributions.

4 CONCLUSIONS

Both the recursive AR model and Wigner-Ville distribution are highly sensitive to the properties of analysed data and selection of model parameters. The analysis has to compromise between time and frequency resolution, instantaneous model properties and computational burden. With suitable parameters, both of the investigated methods are capable of modelling the nonstationary process. Finding those parameters, however, may be very time consuming and tedious process for each signal under investigation. More research is needed to find a way to reduce the effect of the signal properties to the selection of parameters, and to determine most suitable parameters more easily.

REFERENCES

[1] D.L. Eckberg, Respiratory Sinus Arrhythmia and Other Human Cardiovascular Neural Periodicities, in: C. Lenfant, A. Pack, J.A. Dempsey (eds.), *Regulation of Breathing, 2nd Edition*, Marcel-Dekker, New York, 1995, p. 669-740.
[2] M.Di Rienzo et al. (eds.), *Computer Analysis of Cardiovascular Signals*, IOS Press, Amsterdam, 1995, 315 p.
[3] S. Quian, D. Chen, *Joint Time-Frequency Analysis: Methods and Applications*, Prentice-Hall PTR, 1996, 302 p.
[4] B. Widrow, S. Stearns, *Adaptive Signal Processing*, Prentice-Hall Inc., 1985, 474 p.
[5] L. Ljung, *System Identification: Theory for the User*, Prentice-Hall Inc., 1987, 519 p.
[6] http://www.mathworks.com/products/matlab/
[7] http://www.mathworks.com/products/sysid/
[8] http://www-syntim.inria.fr/fractales/Software/TFTB/tftb.html
[9] H. Sorsa, Signal analysis and processing tool for physiological signals, in: J. Halttunen (ed.), *XIV IMEKO WORLD CONGRESS. New Measurements-Challenges and Visions. Vol. VII. Topic 10, 13. Proceedings* (Tampere, 1-6. June 1997), Tampere, Finland, 1997, p. 113-127.

AUTHOR: M.Sc.(Tech.) Heli SORSA, Tampere University of Technology, Laboratory of Measurement and Information Technology, P.O.Box 392, FIN-33101 Tampere, Finland, Phone Int. + 358 3 3653 573, Fax Int. + 358 3 3652 171, E-mail: lyyti@mit.tut.fi