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Multivariate Analysis for Cardiovascular and Respiratory Signals

Narayanan Srinivasan and S.M. Krishnan

The previous chapters on analysis focused on individual signals like ECG, ABP and HRV signals. It is important to analyse the relationship between cardiovascular and respiratory signals to understand various abnormalities. The current chapter looks at the interaction between cardiovascular and respiratory signals using multivariate analysis. Since the time of the earliest measurements of arterial blood pressure (ABP) and of the electrical activity of the heart (ECG) it was noticed that signals of cardiovascular origin, though almost periodical, were characterized by slight cycle-by-cycle variations (oscillations) in both amplitude and time duration. With the development of ABP recording techniques, it was noticed that wave amplitude variations had different cyclical patterns not only synchronous with breathing activity but also with longer periods of about 10–20 beat duration, which are frequently referred to as Mayer waves [2]. Respiratory system influence is either considered a source of ABP variability inducing a reflex respiratory sinus arrhythmia [3] or a source of a direct modulation of the sinus node [4]. The contributions to cardiovascular variability may be various and change in different experimental conditions [5].

The analysis of biological signals often requires the comparison of multiple recordings which are differently affected by the same oscillation sources [6, 7]. Parametric spectral analysis [8, 9] permits only the recognition and quantification of the oscillatory components in the single signals [1]; on the contrary, multivariate (MV) parametric identification [10–12], provides further information about the casual interactions among the signals [13, 14] and about the cross-spectral patterns [15]. However, studies have been made mostly to the analysis of single-channel signals. Therefore, in order to investigate the interactions between the cardiopulmonary variable signals, a model of multi-channel series that is able to consider multiple inputs simultaneously is needed.

There is a general class of multivariate dynamic adjustment (MDA) models, which includes monovariate autoregressive (AR), multivariate autoregressive (MAR) models. Kalli *et al.* used a black box method to resolve the casual interactions between the cardiovascular variability signals; multivariate autoregressive

(MAR) modelling [16]. The MAR model describes the composition of the signals from each other via linear relationship. As a black-box model, the MAR model requires no presumptions of the system structure. In the model identification, standard techniques, like the multivariate Levinson algorithm [17] can be used.

Spectral analysis which characterizes the frequency content of the measured signals had been performed on the heart rate (or equivalently of heart period) variability [15], and on other cardiovascular signals (mainly arterial pressure). It has revealed the presence of spectral peaks which carry information about the sympathovagal interaction that governs autonomic cardiovascular control [18, 19].

The PSD analysis of the cardiovascular signals seems capable of contributing to the functional investigation into various pathophysiological states (e.g., hypertension, diabetes, etc) [20] or during patient treatment with drugs [15]. Furthermore, studies carried out on both animals and humans clearly indicate the potential importance of this type of analysis for a quantitative evaluation of the role of the autonomic nervous system in the genesis of these rhythms as clearly visible in the spectra (power and frequency of variability components) [1, 9, 13]. Such an approach will improve knowledge of the complex neural mechanisms which will provide an insight into the function of the autonomic nervous system.

In the comprehension of the mechanisms involved in the regulation of the cardiovascular function, the simultaneous observation of ABP and HR variability spectra reveals (under normal conditions) the presence of the 10-sec rhythm(as well as respiratory rhythm) in both the signals [21–23]. Furthermore, animal experiments have indicated that they vary in power under particular experimental conditions, such as pharmacological neural blockade or cardiac pacing, etc [24].

Parametric multivariate analysis of several cardiovascular variability signals is able not only to extract phase, coherence and gain relationships [25,26], but also to assess the casual relationship between two or more signals [27]. The cross spectral analysis of ABP and HR variability signals and the study of the relevant coherence and phase spectra could importantly contribute in the description of the amount of power interchanged between the signals, of the delays by which the rhythms propagate [3, 28, 29] and also of the role of respiration.

The model developed in this chapter is based on the MAR model which is driven by monovariate and uncorrelated autoregressive random inputs. The MAR model is applied to clinical data. The parameters extracted from the developed model are intended for the power spectral analysis and the spectral parameters found may be sensitive enough to differentiate between normal and pathological conditions, particularly for cardiac patients. Indices have been proposed for the detection of cardiac abnormality.

14.1 Method

The MAR model is a black-box method and thus requires no presumptions of the system structure [27]. The model is able to describe the composition of the signals from one another via linear relationships. A multichannel linear system of m variables is represented as

$$X(k) = -\sum_{i=0}^{p} A(i)X(k-i) + E(k) \tag{14.1}$$

The above equation represents the general MAR model of a stationary discrete time m-variate process where $X(k) \in \mathrm{R^m}$ is the observed (multivariate) measurement signal; and $E(\mathrm{k}) \in \mathrm{R^m}$ is the (multivariate) disturbance signal consisting of m white noise processes with Gaussian probability; k is the sample number; and p is the order of the MAR model. Equation 14.1 may be expressed in the matrix form:

$$\mathrm{A(q)\ X(k) = E(k)} \tag{14.2}$$

where $A(q) \in \mathrm{R^{mxm}}$ and q is the delay operator. A(q) can be represented as

$$A(q) = \mathrm{I_m + A_1 q^{-1} + \ldots\ldots\ldots\ldots + A_p q^{-p}} \tag{14.3}$$

as well as in the matrix form:

$$A(q) = \begin{bmatrix} a_{11}(q) & a_{12}(q) & \cdots & \cdots & a_{1m}(q) \\ a_{21}(q) & a_{22}(q) & \cdots & \cdots & a_{2m}(q) \\ \vdots & \vdots & \ddots & & \vdots \\ \vdots & \vdots & & \ddots & \vdots \\ a_{m1}(q) & a_{m2}(q) & \cdots & \cdots & a_{mm}(q) \end{bmatrix} \tag{14.4}$$

where the entries a_{kj} are polynomials in the delay operator $\mathrm{q^{-1}}$. This polynomial describes how old values of the output number j affect the output number k.

Equation 14.1 shows that the MAR model can be considered as a one-step-ahead prediction model, where the present value of the system output X(k) is a linear combination of the p past values of X(k) and the prediction error E(k). Thus, a MAR model describes a system where all the signals involved explain themselves and each other via certain linear transfer functions defined by A(q). The MAR model is very flexible as it enables interactions between all the involved signals in any direction. Many criteria have been proposed as objective functions for selection of the model order, p. An aid in the determination of the order of the multichannel AR model is the multichannel version of the Akaike AIC criterion [27].

14.2 Multichannel Spectral Analysis

The motivation for parametric models is the ability to achieve better PSD estimators based upon the model than calculated by classical spectral estimators. The goal of multichannel spectral analysis of m channels of data is the estimation of the Hermitian PSD matrix. For a bivariate spectral estimation, the Hermitian matrix P is given as

$$\mathrm{P}\ (f) = \begin{bmatrix} P_{xx} & P_{xy} \\ P_{yx} & P_{yy} \end{bmatrix} \tag{14.5}$$

The diagonal elements are the single channel autospectral densities, P_{xx} and the non-diagonal elements are the cross spectral densities, P_{xy} between the two-channels. The complex dimensionless expression

$$\varphi_{\mathrm{xy}}(f) = \frac{P_{xy}(f)}{\sqrt{P_{xx}(f)P_{yy}(f)}} \tag{14.6}$$

is termed the coherence function which can be described in terms of the magnitude squared coherence known as the k^2 function

$$\mathrm{k}^2 = |\phi_{xy}(f)|^2 = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)} \tag{14.7}$$

The magnitude of k^2 function lies between 0 and 1 and the function may be used to measure, as a function of frequency, the similarity between a pair of signals.

The classical FFT-based methods for estimating the coherence function suffer from an inherent bias towards an over-estimation of the k^2 function. The problem is more pronounced if the averaging process involved in these methods is ignored. For signals of short duration, it is only possible to have limited number of segments for averaging. Therefore, a bias in the k^2 function is inevitable, which results in an over estimation of the degree of coherence between the two channels. As a result, the classical methods for multi-channel spectral estimation are not capable of providing an efficient tool for this purpose. In contrast, parametric methods are known to be capable of estimating the coherence function without introducing bias into the resultant k^2 function.

Indices for abnormality detection

New indices are proposed which are intended for the diagnosis of abnormal state in cardiac patients. Early detection of signals of abnormality is crucial in the assessment of a cardiac patient's condition, as it may indicate the onset of catastrophic physiologic events such as respiratory failure or even leading to sudden cardiac death. Therefore, in such critical cases, a fast and accurate analysis of the simultaneously recorded signals is required in order for prompt action to be taken to save life. The indices proposed here are effective in discriminating between normal and abnormal signals.

These indices are obtained after spectral and cross-spectral analysis by obtaining the fraction of power of the ECG, which is coherent (or not coherent) with respiration (or ABP signal). The total power of the ECG which is coherent with respiration is obtained by multiplying the autospectrum of the ECG by the k^2 function and integrating on the frequency axis. This first index is termed as the ρ.

$$\rho = \Sigma \left(P_{11}{}^{*} \frac{|P_{12}(f)|^2}{P_{11}(f)P_{22}(f)} \right) \tag{14.8}$$

where P_{11} represents the autospectrum of the ECG, P_{22} represents the autospectrum of the respiratory signal and P_{12} is the cross spectrum between the two signals. $\bar{\rho}$ is the power not coherent with respiratory signal obtained by subtracting ρ from the autospectrum of the ECG.

$$\bar{\rho} = P_{11} - \rho \tag{14.9}$$

Finally, the percentage of the ρ with respect to the total power of the ECG is tabulated and defined as the Respiration Coherent Index (RCI).

$$\text{RCI}\,(\%) = (\rho / P_{11})^{*}100 \tag{14.10}$$

Similarly, the bivariate spectral analysis is also applied to the ECG-ABP pair. The procedures stated above are repeated to obtain the total power of the ECG which is coherent with ABP. This index is termed as the α

$$\alpha = \Sigma \left(P_{11}{}^{*} \frac{|P_{13}(f)|^2}{P_{11}(f)P_{33}(f)} \right) \tag{14.11}$$

where P_{11} represents the autospectrum of the ECG, P_{33} represents the autospectrum of the ABP and P_{12} is the cross spectrum between the two signals. Then, $\bar{\alpha}$ will be the power not coherent with ABP and is obtained as

$$\bar{\alpha} = P_{11} - \alpha \tag{14.12}$$

Lastly, the Pressure Coherent Index (PCI) is obtained as

$$\text{PCI}\ (\%) = (\alpha / P_{11})^{*}100 \tag{14.13}$$

14.3 Results and Discussion

The three signals ECG, ABP and respiration, which are obtained from the MIT-BIH database are used as inputs into the proposed MAR model. Cross spectrum analysis is performed on the two selected signals via bivariate spectral estimation. The various indices are obtained after spectral and cross spectral analysis of the signals.

14.3.1 ECG and ABP Signal Analysis

Normal Signals: Three consecutive peaks (equivalent to two R-R intervals) of the ECG signal and the corresponding interval in the ABP signal is considered for analysis. Figure 14.1 shows the graph of the coherence (k^2) function. It can be seen that the relatively high values of the coherence function at higher frequencies indicate a strong correlation between the two signals at higher frequencies. However, at low frequencies, the coherence between the two signals is less. In other words, there is greater similarity between the two signals at higher frequencies than at lower frequencies. The total ECG power coherent with ABP is shown in Fig. 14.2. The total power of the ECG is highly coherent to the ABP signal as indicated in Fig. 14.2, ρ and $\overline{\rho}$ values of 1800 and 48 are obtained with a PCI index value of 97.3%.

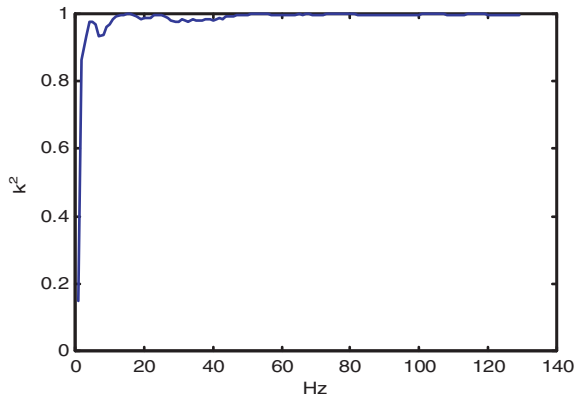

Fig. 14.1. Coherence between normal ECG and ABP signals

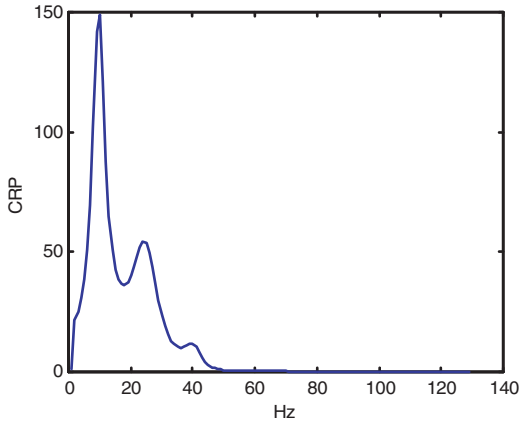

Fig. 14.2. Total power of normal ECG coherent with ABP

Abnormal Signals: Similarly a three peaks interval of the abnormal ECG signal and the corresponding ABP signal is extracted for the power spectrum analysis. Figure 14.3 shows the coherence function after performing cross spectrum analysis between the two signals. Total ECG power coherent with ABP under abnormal condition is shown in Fig. 14.4. The total power of the ECG which is coherent with ABP is much lesser as indicated by the drop in amplitude in the ρ graph.

In the normal signals, the total power coherent with ABP is very much higher as indicated by the PCI index (97.3%). However, in the abnormal signals the total power coherent with ABP is much lower, at only 46.9%. Therefore, it can be concluded that the percentage of the autospectrum of the ECG which is coherent with ABP decreases as the signals go into abnormality

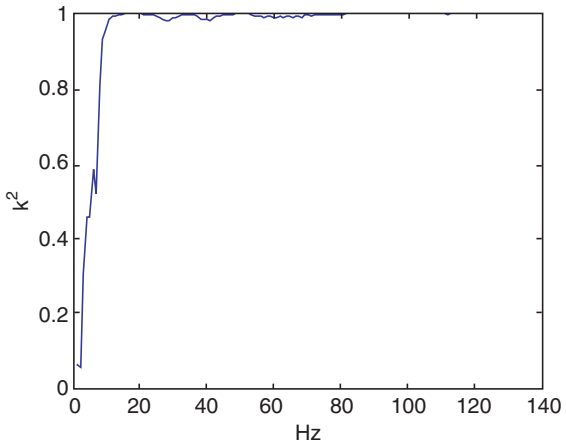

Fig. 14.3. Coherence between abnormal ECG and ABP signals

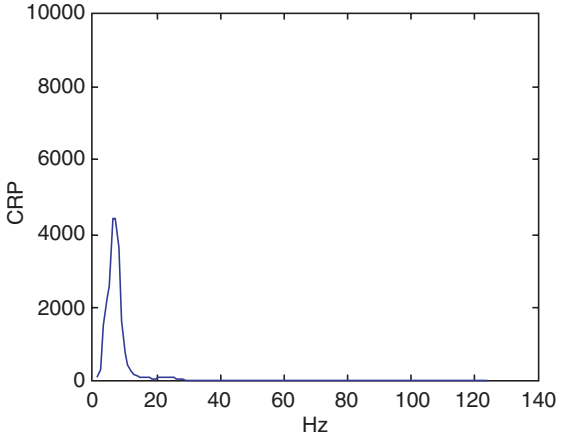

Fig. 14.4. Coherence between abnormal ECG and ABP signals

and increases during normal state. Hence the PCI index can also constitute a quantitative mean for discriminating between normal and abnormal signals in stable and unstable condition of the patient.

The above analysis is then performed on a range of data which is obtained from a cardiac patient whose initial condition was stable but became unstable at the end due to cardiac problem resulting in respiratory failure. The range of PCI index for the signals under stable condition is between 90% and 97%.

The line graph is also obtained for the PCI index for transition period from stable to unstable condition. There is a drop in the PCI index from above 90% for normal stable signals to below 80% when the signals go into abnormality. When the patient is in total unstable condition, the range of PCI index is smaller than that of the RCI index for abnormal signals.

14.3.2 ECG and Respiratory Signal Analysis

Three consecutive peaks (equivalent to two R-R intervals) of the ECG signal and the corresponding interval in the respiratory signal is considered for analysis each time. In this case also, the graph of the k^2 function shows there is greater similarity between the two signals at higher frequencies than at lower frequencies.

Analysis similar to the one done previously for ABP signals has been made and similar results have been obtained. In the normal signals, the total power coherent with respiration is very much higher as indicated by the RCI index (96%). However, in the abnormal signals the total power coherent with respiration is very low, at only 35%. Therefore, it can be concluded that the percentage of the autospectrum of the ECG which is coherent with respiration decreases as the signals go into abnormality and increases during normal state. Hence the RCI index can constitute a quantitative measure for discriminating between normal and abnormal signals.

The above analysis is then performed on a range of data from a cardiac patient whose initial condition was stable but became unstable towards the end. The range of RCI index for the signals under stable condition is between 90% and 97%. In the transition period, there is a drop in the RCI index from above 90% for normal stable signals to below 80% when the signals go into abnormality. When the condition of the patient further deteriorates, the RCI index falls from a high of 90% to a low of 2%.

14.4 Conclusion

ECG, blood pressure and respiratory signals can provide important information on the pathophysiology of the cardiovascular regulatory mechanisms. Spectral and cross-spectral analysis of these signals gives quantitative information which can be of potential interest in clinical studies. This has been done in this chapter using a methodology based upon multivariate autoregressive

identification and parametric power spectral density estimation. Autospectra and coherence, which completely characterize the physiological relations between the signals in terms of exchanging powers and statistically consistent phase relations, has been used to obtain useful indices. These indices, called respiration coherence index and ABP coherence index, have been found very useful in differentiating normal signals from abnormal ones and they act as a fast and convenient tool for the purpose. The indices proposed have the advantage of being automatically calculated on the PC in an ICU setup. Results on a few test cases show that the multivariate autoregressive model developed is able to differentiate accurately the condition of a patient in an ICU changing from stable to unstable condition.

It is known that various systems involved in the generation of ECG, ABP and respiration are interrelated and hence one can expect a good coherence between these signals under normal conditions. The results obtained here indicate that this coherence is somehow reduced when the condition of body becomes abnormal. It will be interest to study the mechanisms leading to such a decrease in coherence.

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