Expert Systems with Applications 37 (2010) 913–918

Contents lists available at ScienceDirect

Expert Systems with Applications

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

Review

Choice of the wavelet analyzing in the phonocardiogram signal analysis using the discrete and the packet wavelet transform

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ARTICLE INFO

Keywords:
Phonocardiogram
Discrete wavelet transform (DWT)
Packet wavelet transform (PWT)
Multiresolution analysis
Wavelet analyzing
Rebuilding error

ABSTRACT

The phonocardiogram signal (PCG) can be utilized more efficiently by medical doctors when they are displayed visually, rather through a conventional stethoscope. This signal provides clinician with valuable diagnostic and prognostic information. Although the PCG signal analysis by auscultation is convenient as clinical tool, heart sound signals are so complex and non-stationary that they have a great difficulty to analyze in time or frequency domain. We have studied the extraction of features out of heart sounds in time-frequency (TF) domain for recognition of heart sounds through TF analysis. This article highlights the importance of the choice of wavelet analyzing wavelet and its order in the phonocardiogram signal analysis using the two versions of the wavelet transform: the discrete wavelet transform (DWT) and the packet wavelet transform (PWT). This analysis is based on the application of a large number of orthogonal and bi-orthogonal wavelets and whenever you measure the value of the average difference (in absolute value) between the original signal and the synthesis signal obtained by multiresolution analysis (AM). The performance of the discrete wavelet transform (DWT) and the packet wavelet transform (PWT) in the PCG signal analysis are evaluated and discussed in this paper. The results we obtain show the clinical usefulness of our extraction methods for recognition of heart sounds (or PCG signal).

1. Introduction

In normal conditions, the phonocardiogram signal contains two sounds (S1 and S2) for each cardiac cycle. Two other sounds (S3 and S4) with amplitudes definitely less important than the two first (Donant & Bournef, 1981) appear sometimes on the level of the cardiac cycle by the effect of pathology or age (childhood or old age or like precursory signs of any pathology). The sound S1 correspondent to the beginning of the ventricular systole is due to the closure of the atrioventricular valves. This sound is composed of four components including two major internal; the mitral component (M1) associated with the closing of the valve mitral and the component tricuspid (T1) associated with the closing of the valve tricuspid (Obaidat, 1993). The sound S2, marking the end of the ventricular systole and signify the beginning of diastole is composed for its two main components: the aortic component (A2) for the closure of the aortic valve and the pulmonary component (P2) corresponding to the closure of the pulmonary valve (Donant & Bournef, 1981). Valvular pathologies induce considerable modifications on the morphology of the PCG signal (Boudrealt, Boyer, Claude, & Désorey, 2002).

These changes affect the heart sounds S1 and S2 by making changes in terms of duration and amplitude. On the other hand, systolic and diastolic murmurs of different shapes can be added to signal PCG to build a track resulting from a given disease.

The most recent studies aiming at better understanding of the structural content (signal components) of heart sounds perform the time-frequency representation (TFR) of the transient signals. These studies showed that the TFR techniques are powerful tools for the study of the basic mechanism implied in the production of the heart sound components. However, they also showed that their application to the analysis and synthesis of short transient signals like S1 and S2 is a complex and difficult task. This is due to the inherent limitations of the TFR techniques for extracting the basic characteristic of each component contained in these multicomponents signals (Akay, 1997; Xu, Durand, & Pibarot, 2000, 2001).

Most research works concentrated on short time Fourier transform (STFT) analysis and transient chirp modeling of the heart sound as TFR. The STFT is a useful tool in non-stationary signals analysis such as heart sounds. However, it suffers from time-frequency resolution. Indeed, the smaller the window used, the better quickly changing components are picked up, but slowly changing details are not detected very well to investigate exact feature of the signal. If a larger window is used, lower vibrations may be detected, but the localization in time, which is important to

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doi:10.1016/j.eswa.2009.09.036

determine the closure and opening of the heart valve becomes worse. In the analysis of the transient chirp modeling, it has been studied on the analysis and the synthesis of short time portions of the signal.

An alternative way to analyze non-stationary signals such as heart sounds is to expand them onto basis functions created by expanding, contracting, and shifting the considered signal. This is the wavelet transform (WT) designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution at low frequencies. This approach makes sense especially when the signal at hand has frequency component for short durations and low frequency components for long durations, which is the case in most biomedical signals (Debbal and Bereksi-Reguig 2004, 2006).

The rebuilding error between the original signal and the sixth approximation (A6) for the various PCG signals using the DWT and PWT allow you to find that the DWT seems more likely to be used if one wants to have a screening breath without distorting the sound S1 and S2 too much because it presents the weakest errors. The wavelet "db7" is used also here because it emphasizes better the specific characteristics of analyzed PCG signal.

The purpose of this work is to try to find the optimal analyzing wavelet but also using a breakdown based on packet wavelet transform (PWT). Thus, the analyzing wavelet chosen in this case will be one that reflects the best results (minimal error) and the best features of the PCG signal (the clear distinction of both internal components of the sounds S1 and S2). It will calculate the error (called also rebuilding error: RE) between the original signal and the sixth approximation (A6) taken as a synthesis signal for the various PCG signals used with the respective implementation of the DWT and PWT using the analyzing wavelet found.

2. Wavelet transform

The wavelet transform makes it possible to apply a multiresolution analysis to the studied signal. This analysis, which it would be advisable to call time-scale, uses a very wide range of scales to analyze the signal. On the basis of a quite localized function, in the time-scale plan, one associates the family of wavelets to him $\psi_{a,b}(t)$ generated by translations and dilations of $\psi(t)$:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \cdot \psi\left(\frac{t-b}{a}\right) \quad a > 0,\ b \in R. \tag{1}$$

The wavelets are of constant shape but variable size proportional to the expansion parameter "a" (variable scale). The wavelet transformation is also interpreted as a filtering process signal analyzed by a band pass filter bandwidth variable; it is the parameter "a", which sets the value of this band (Flandrin, 1998). This means that any energy signal can be written as a linear combination of wavelets $\psi_{a,b}(t)$ and that the coefficients of this combination of wavelets are the scalar products $\int s(t) \cdot \psi(\acute{e}chelle, position, t\})dt$, s (t) being the studied signal. These scalar products measure, in a certain direction, the fluctuations of the signal $s(t)$ around the point "b" on the scale "a". The continuous wavelet transform is thus defined by the calculation of the coefficients:

$$C(a,b) = \frac{1}{\sqrt{2}} \int_{-\infty}^{+\infty} s(t) \cdot \psi^*\left(\frac{t-b}{a}\right) \cdot dt. \tag{2}$$

The parameter "a" is a factor of scale, inversely proportional to the frequency. The time-scale representation is not a limitation of the wavelet transform, but it is another way to approach the analysis of the signal by a combination of informed frequency and time. It is noteworthy that the duration of the wavelet is directly proportional to the scale of parameter "a". In its formulation, the wavelet transform can be interpreted as an analysis with bench of constant overpressure filters. In such a bench, each filter (band pass) can result from a single gauge by a dilation or compression in frequency. The transformation into wavelet can also be regarded as a process of decomposition of the signal in approximations and details. The signal of origin $s(t)$ crosses two complementary, high-pass and low-pass filters, and emerges as two signals: respectively, the signal of approximations A and the signal of details D (Mallat, 1989) as shown in Fig. 1.

3. Multiresolution analysis by DWT

The wavelet transform of a signal s is the family $C(a,b)$ coefficients of wavelet, which depends on the two parameters "a" and "b". According to the needs for the analysis of the signal s, the parameters (a,b) can be used continuously (CWT) or discrete (DWT). The basic principle of the DWT is to separate the signal in two components, one representing the general signal, the other representing its details. The general allure of a function is represented by its low frequencies, the details by its high frequencies. To separate the two, we need a pair of filters: a low-pass filter to get the general (also called approximation or average), and a high-pass filter to estimate its details, that is to say the elements which vary rapidly. In order not to lose information, these two filters must of course be frequencies eliminated by one must be retained by another. It is said that the two filters are a pair of mirrors quadrature filters. The use of DWT as a filter at several levels (multiresolution) helps find the best level of decomposition. The high-frequency information is generally represented in the first levels of decomposition d1...d4, while levels of decomposition d5...d8 show the low frequency information. Please note that only approximation signals are again broken down. The details signals from the high-pass filtering are left behind at every step (Fig. 2a).

4. Multiresolution analysis by PWT

Compared to the decomposition by the DWT (Fig. 2a), the PWT provides a richer decomposition (Isar, Cubitchi, & Nafornita, 2002; Fig. 2b), since even the detail signals from the high-pass filtering are also broken again contrary to the DWT or they are left aside at every step. Thus, each level of decomposition presents different information.

5. Choice of the analyzing wavelet

The analysis of the choice of the wavelet analyzing (mother wavelet) will be carried out on the basis of test of several wavelets analyzing. This will be done on the study of the error existing between the original signal (normal case) and the synthesis signal (signal after reconstruction). In this direction, a parameter of error characterizes the rebuilding (or synthesis). The error that will be calculated each time in the continuation of the analysis is given by the following expression:

$$\varepsilon_{ermoy} = \frac{\sum_{i=1}^{N} |S_{oi} - S_{ri}|}{N} \tag{3}$$

with S_o is the original signal; S_{oi} is the sample of S_o; S_r: is the synthesis signal; and S_{ri} is the sample of S_r.

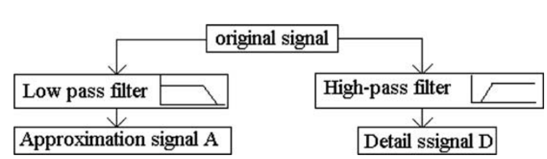

Fig. 1. Decomposition of the signal s in approximations "A" and details "D".