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Research Article

Phonocardiograms Signals Analysis using the Graphical Bispectral Technique

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Abstract

Cardiac or heart sound carries important diagnosis information of several cardiovascular diseases, such as natural or prosthetic valve dysfunction and heart failure. Hence, algorithms are required for the analysis of cardiac sounds for computer-based automatic diagnosis. In the cardiac sound-based analysis, one of the tasks is to classify abnormal cardiac sounds, i.e. murmurs, caused by various cardiac anomalies. We introduce a new feature named system response, chosen to be estimated using bi-spectral technique analysis over Fast Fourier bi-spectrum because of non-stationary and non-Gaussian nature of cardiac sounds. System response feature essentially characterizes the cardiac structure responsible for the production of cardiac sounds, which will be employed later on to automatically classify different types of cardiac murmurs. The cardiac signals analyzed and previously classified will be arranged into three main classes or groups: a group of signals containing neither clicks nor murmurs and having a similar morphology, a second group of signals containing only clicks (reduced murmurs) and a third group containing signals with large murmurs. It has to be noted that all of the heart signals should be part of these three types. The parameters that we are going to define and the graphic representations will help us in this sense to classify the different signals analyzed in one of the mentioned groups.

Keywords: Phonocardiogram; Pathological; Classification; Discrimination; Severity; Graphical; Bi-spectral

Introduction

Analysis of heart sounds by auscultation, based only on the human ear, remains insufficient for a reliable diagnosis of heart disease and for a clinician to be able to obtain all the qualitative and quantitative information of cardiac activity. This information such as the temporal location of heart sounds, the number of their internal components, their frequency content, the importance of diastolic and systolic breaths, can be studied directly on the phonocardiogram signal (PCG) by the use of technical methods. Digital signal processing [1]. The audio recording chain involves a sequence of transformations of the signal: a sensor to convert sound or vibrations to electricity, a pre-amplifier to amplify the signal, a prefilter to avoid aliasing and an analogue to digital converter to convert the signal to the digital form needed to be stored permanently. In the setting of the intelligent stethoscope, this chain is complemented with an analysis step and an information presentation step. Consequently, several auscultation methods of cardiac sounds assisted by computer have been proposed, in particular for the evaluation of murmurs related to cardiovascular diseases such as aortic stenosis [2-4]. The potential of these algorithms is more on a quantitative, precise and objective interpretation of heart sounds [5], improving the process of cardiovascular diagnosis. Beyond this, computer-assisted auscultation allows the detection of pathologies who are unrecognized through a conventional auscultation [6]. Phonocardiography as a non-invasive method is capable of providing clinicians with a complementary tool for graphically recording heart sounds and breaths heard during cardiac auscultation [7]. The phonocardiogram signal confirms and refines the auscultation data by providing additional information on sound activities relating to the chronology of pathological signs during a cardiac revolution, by situating them in relation to normal heart sounds. The cardiac noises and the breaths as being non stationary signals, are located in the range of the low frequencies [10-1000] Hz [8], their treatment in terms of recordings proves to be very important for the diagnosis of various cardiac pathologies. The oldest biomedical signal processing technique is based on the Fourier Transformation (F.F.T). It has shown great promise for many years [9-14]. This technique produces an average spectrum over time. This is suitable for signals whose statistical properties are time invariant (stationary). As the spectral content of physiological signals (PCGs) evolves as a function of time, the temporal averaging techniques of the amplitudes are unable to describe transient and non-stationary phenomena [15]. It is for this purpose that new approaches of Time-Frequency Representations (R.T.F) of signals have been proposed. The short-term Fourier transform (T.F.C.T), was also applied as a time-frequency analysis method. This consists in sliding an analysis window along the signal studied, knowing that the dimensions of this window must be fixed to guarantee the stationary conditions. Unfortunately, these constraints cannot allow good resolution in time and frequency simultaneously [16] the short-term Fourier transform (T.F.C.T) [17] can be proposed to compensate for the lack of information on the time of the Fourier Transform (F.F.T). This method, which can be adapted to non-stationary signals (PCGs signals [18]), is very close to spectral analysis: we define a window of fixed dimensions which will be used as a mask on the signal, and in which we consider that the signal is

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locally stationary, then we shift this window along the signal in order to analyze it entirely [19]. In the theory and practice of time-frequency analysis, the Wigner-Ville Distribution (WVD), applied by Wigner in quantum mechanics in 1932 [20] and subsequently adapted by Ville in 1948 for signal processing [21], plays a fundamental role. It responds appropriately to the improvement of this analysis; however, it remains limited by the problem of interferential terms which generally reduce the readability of a time-frequency diagram and that's in this sense desirable to use it [16,22]. The WVD therefore provides excellent results for mono-component signals but for multicomponent signals, it presents undesirable interference [23]. Many studies have been performed with the goal of providing tools for practical murmur detection and improving the diagnostic accuracy of physicians in small practice settings in time and frequency series. In particular, Ahlstrom et al. [24,25] investigated the issue of feature extraction for systolic heart murmur classification. For more information on the problem of diagnosing systolic heart murmurs see, for instance, McGee [26]. Different methods are used in time and frequency and time-frequency series for feature extraction of heart murmurs, the most important so far has been spectral analysis [27,28]. In order to, achieve a high-resolution result for heart murmurs analysis we used high order spectral methods, such as Bi-spectrum analysis. Considering that the Fourier transform of the second-order cumulant (the auto-correlation function) is known by the Power Spectral Density (PSD). The Bi-spectrum analysis is defined as the Fourier transform of the third cumulant and it is the study of nonlinear interactions. In this paper, we discuss Bi-spectral technique for analyzing heart sounds. The impact of clicks and murmurs as additional components on the Phonocardiogram Signal (PCG) can also be evaluated and quantified by the bi-spectral method. This analysis has given results that can be used in the understanding complementarities of the cardiac functioning through the calculation of graphical representations.

Methodology

Based on clinical data, we could say that all of the PCG signals could be classified into three distinct groups:

- Group 1 (G1): PCG signals having neither click (reduced murmur) nor significant murmur.
- Group 2 (G2): PCG signals with clicks.
- Group 3 (G3): PCG signals without clicks or murmurs.

The objective hoped by this paper is the study of these Phonocardiogram Signals (PCG) presenting a different cardiac severity and try to obtain relevant parameters likely to understand and follow the evolution of the cardiac pathology concerned.

Theoretical notions on the bi-spectral technique

Bi-spectral method analysis is the study of nonlinear interactions [29-34]. It is defined as the Fourier transform of the third cumulant. Considering that the Fourier transform of the second-order cumulant (the auto-correlation function) is known by the Power Spectral Density (PSD). The bi-spectral is defined by equation (1).

$$B(f_1, f_2) = E[X(f_1)X(f_2)X^*(f_1 + f_2)] \quad (1)$$

Where X (f) is the discrete Fourier transform (DFT) of x (nT), X* (nT) is the conjugate of x (nT)

E[.]: is the operator of mathematical expectation. Since the correlation function is an even function, and its FT gives a symmetry spectrum (i.e., the spectrum repeats twice "mirror effect"), we find that the bi-spectrum which represents the FT of the tri-correlation function, repeats itself four times. It is therefore sufficient to calculate the spectrum for the frequencies that lies in the non-redundant region Ω as it is illustrated in Figure 1 [35].

Results

The graphs representations resulting from the application of the bi-spectral technique on the different PCG signals of the three groups can also give us additional information's on the difference in cardiac pathologies (Figures 2-4).

As a result, it is easy to notice that the content increases more and more going from the PCG signals of the group 1 to the PCG signals of group 3. The color is also more accentuated referring to greater amplitude for severe pathological cases. The frequency content (value of f1 and f2) is not the same. It increases when the pathology becomes much more severe.

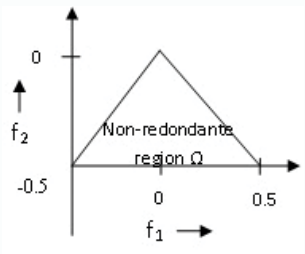

Figure 1: The non-redundant region for the calculation of bi-spectral frequencies.

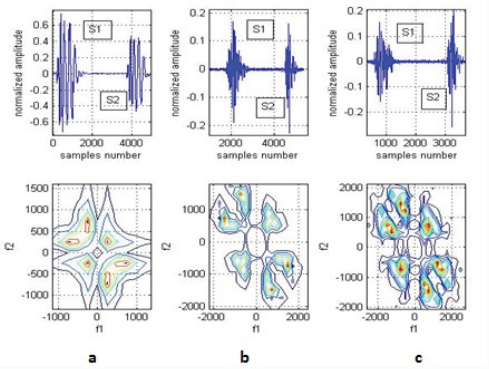

Figure 2: Bi-spectral graphic representation of the group 1 PCG signals (a) the signal (N), (b) the signal (IM), (c) the signal (coa).

Conclusion

As a conclusion, we can say that the results obtained by the application of the bi-spectral technique in the analysis of cardiac pathologies on the Phonocardiograms (PCG) signals which translate the cardiac acoustic activity of the heart seems very satisfactory.

This satisfaction was made possible by the establishment of relevant parameters which made it possible to discriminate (differentiate) between the PCG signals of the three pre-established groups before starting our analysis. These parameters can therefore not only make a distinction between the cardiac pathologies of the PCG signals of the three groups but allows too the possibility of following the evolution of the same pathology in the event of its targeted study.

In addition, the graphic plots obtained for the PCG signals of the three groups made it possible to quickly discern this discrimination.

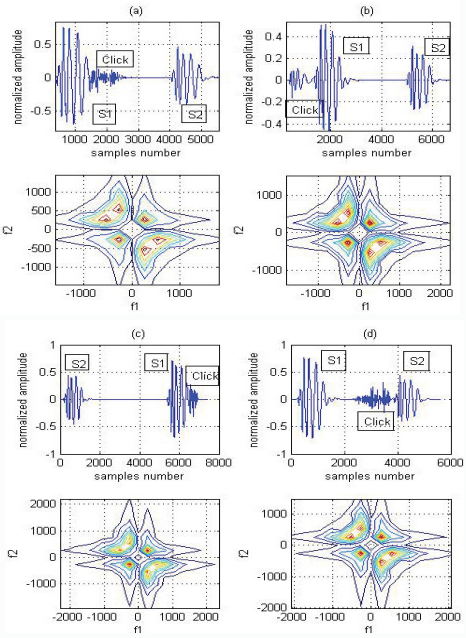

Figure 3: Bi-spectral graphic representation of the group 2 PCG signals (a) the signal (Eas), (b) the signal (AG).

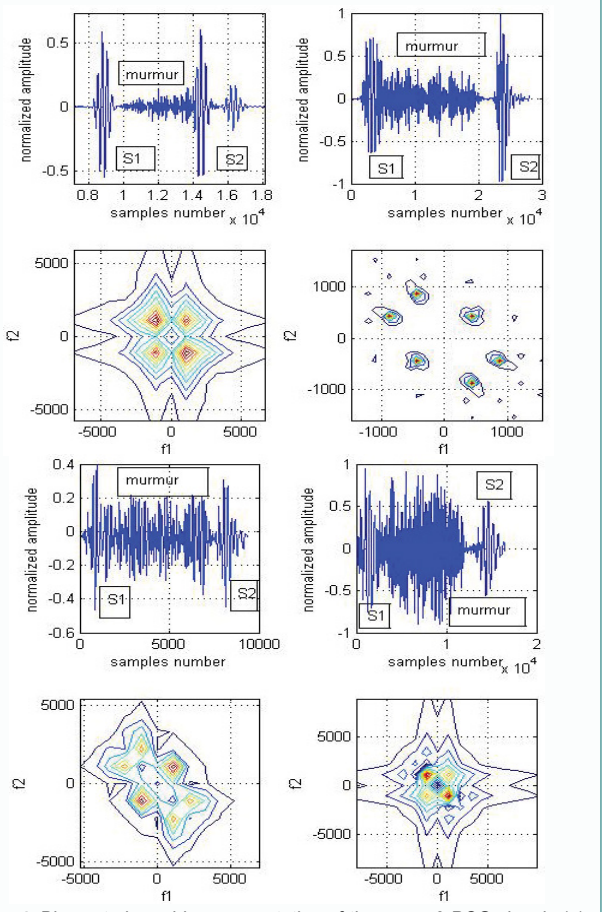

Figure 4: Bi-spectral graphic representation of the group 3 PCG signals (a) the signal (PS), (b) the signal (Ar), (c) the signal (Tr), (d) the signal (As).

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