Model of Differentiation between Normal and Abnormal Heart Sounds in Using the Discrete Wavelet Transform

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Abstract—**Today, modern technology has provided more powerful tools to evaluate the information related to heart sounds that traditional tools like stethoscope cannot achieve. One of the most common methods used for listening and tracking the heart sounds is to record them with special devices. The recorded heart sounds is known as PCG (phonocardiogram) signal. It is a particularly useful diagnosis tool since it contains different timings and relative intensities of heart beat sounds which are directly related to heart activity. The objective of this paper we develop a simple model for analysing the PCG signal in order to distinguish between normal and abnormal heart sounds. This analysis is carried out by using discrete wavelet transform. By using the discrete wavelet transform (DWT) the PCG signal is decomposed in to 7 stages. The average standard deviation of the detailed coefficients at each stage is calculated for each signal. The slopes of these curves for each case are obtained by plotting the average standard deviation of the detailed coefficients at each level detail. The analysis of these slopes shown that the discrimination between the normal signals from abnormal is possible**

Index Terms—**heart sounds, phonocardiogram, model, discrimination, level decomposition, average standard deviation, discrete wavelet transform.**

I. Introduction

The heart and during its physiological activity, produces sounds having, large dynamic range and fastly changing low frequency content. Clinician listen to the heart sounds using stethoscope in order to make a diagnosis on heart defects. Heart defects can range from aortic regurgitation and mitral regurgitation to ejection click and systolic murmur. However, the diagnosis of such heart defects with the stethoscope along with human ear present some limitation.

Nowadays, modern technology has provided more powerful tools to evaluate the information related to heart sounds that traditional tools like stethoscope cannot achieve. One of the most common methods used for listening and tracking the heart sounds is to record them with special devices. The recorded heart sounds is known as PCG (phonocardiogram) signal. It is a particularly useful diagnosis tool since it contains different timings and relative intensities of heart beat sounds which are directly related to heart activity. With the improvements of computers power, the PCG signal has digitally been stored, managed, and manipulated for examining its frequency and temporal content. Moreover, the developpement of new digital signal processing techniques, such as a pattern recognition and time-frequency analysis and representation has improved the PCG signal analysis and therefore make it actually as a non-invasive technique in aid to heart activity diagnosis.

To analyse the PCG data, the way of how the PCG signal is generated and its features are correlated to heart activity must be well understood. It is clearly explained in literature how this correlation is established mainly from a timing point of view as is illustrated in Fig. 1.

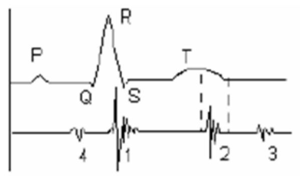


Figure. 1. Correlation between the electrocardiogram (ECG) and the cardiac sounds

As it is shown in Fig. 1 the PCG signal is composed from at most four sounds known as S1, S2, S3, S4. S1 is the first heart sound at the beginning of the depolarization of the ventricle, frequency band and duration are receptively 30-100 Hz and 50-100ms. S2 is the second heart sound and it identified as the sound between closure of the aorta and artery valves of the lungs. Frequency band and duration are respectively 100-200 Hz and 25-50ms. S3 is the third heart sound. It results following the entire filling of the ventricle with blood. It is a diastolic sound. S4 is the fourth heart sound and is generated after the completeness of atriums depolarization. It is also a diastolic sound. The order of the basic heart sounds is chronologically close to each other and they overlap with the heart beat and the murmurs. For defects where the heart beat is high, these

Manuscript received June1, 2013; revised August 1, 2013.

doi: 10.12720/jomb.3.1.5-11

sounds can not easily be separated by the human ear. Therefore, the detection of the heart beat; the heart sounds and their separation on them from each other require expert physicians. On the other hand, in many applications it is desirable to transform a sound waveform into a signal which is more useful than the original. For example in speech processing, the articulation rate can be slowed down to make degraded speech more intelligible. Similarly, in phonocardiography, the heart sounds can be slowed down to improve physician’s capability in recognition and discrimination of dissimilarities resulting from cardiac disorders.

The pathological conditions of the cardiovascular system generally cause abnormal murmurs and aberrations in heart sounds before they are reflected as other symptoms [1]. The auscultation technique in which a stethoscope is used to listen the sounds of a body is poorly suited to investigate the heart abnormalities. By analyzing the phonocardiogram (PCG) which is a recording of the acoustical waves produced by mechanical action of the heart by modern digital signal processing technique give more accurate and valuable information about the heart condition. A PCG consist of the two components, the heart sounds and heart murmurs, as acoustic vibrations. The heart sounds are low-frequency transient signals produced by the heart valves. The heart murmurs are noise-like signals caused by the turbulence of blood flow [2]-[4].

The first sound (S1) and the second (S2) cardiac sounds consist respectively of two major majors components. The components of the sound S1 are M1 and T1. M1 is due to closure of the mitral valve and T1 is due to closure of the tricuspid valve. The second Sound S2 is also composed of two components. The component A2 which is due to the cloture of the aortic valve and the component P2 which is due to the closure of the pulmonary valve [5].

Most recent studies aiming at better understanding of the structural content (signal components) of heart sounds perform Time-Frequency Representation (TFR) and analysis such signals considered as transient signals. The studies showed that the new TFR techniques are powerful tools in analysing 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 due to the inherent limitations of the TFR techniques for extracting the basic characteristic of each component contained in these multi component signals [5]-[13].The research concentrated on Short Time Fourier Transform (STFT) analysis and transient chirp modelling of the heart sound as TFR. However, STFT is a useful tool in analysis of non stationary signal such as heart sounds, the problem with the STFT is a compromise in resolution. 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 determine the closure and opening of the heart valve becomes worse.

The wavelet transform has demonstrated the ability to analyze the heart sounds more accurately than other techniques.In traditional cardiac auscultation, murmurs at very low frequencies may not be heard, but can be clearly seen in a spectrogram representation of the sound. Also separation of heart murmurs into innocent and pathological murmur by auscultation is strongly dependent on listener’s experience and training. Software-aided heart sound analysis has improved reliability of diagnosis, by efficient classification of signals.

II. Model Used for PCG Discrimination

A model used for differentiation or discrimination between normal and abnormal heart sounds using the discrete wavelet transform (DWT) can be provide by the block diagram as shown in below Fig. 2:

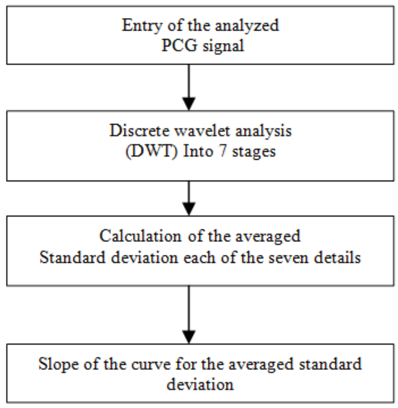


Figure 2. General block diagram of proposed model

In this paper, we are interested in the application of the model for PCG signals analysis using discrete wavelet transforms. The PCG signals we are interested are classified into two groups:

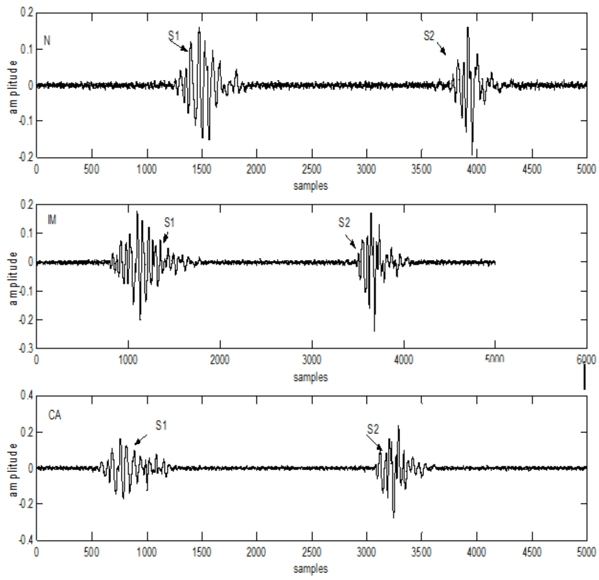


Figure 3. The PCGs signal of the first group (N, IM, CA).

The first group: group is concerned a normal PCG signal and two others PCG signals of similar morphology without murmur: the innocent murmur and the coarctation of the aorta (Fig. 3)
The Second group: group is concerned with two PCG signals with murmur: the pansystolic and the aortic of the regurgitation (Fig. 4).

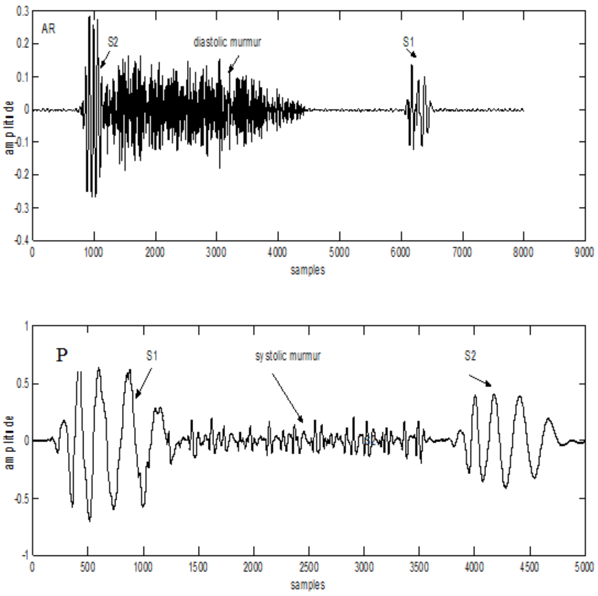


Figure. 4. The PCG signal of the second group (MR, AR)

By using 'Daubechies 7' as mother wavelet the PCG signals are decomposed in to 7 stages. The average standard deviation of the detailed coefficients at each stage (or level detail) is calculated for each signal. The slopes of the curves for each case are obtained by plotting the standard deviation of each level detail. The results we obtain are shown to be able to discriminate between the normal signals from abnormal.

III. Wavelet Transforms

Wavelet transforms have become well known as useful tools for various signal processing applications. The continuous wavelet transform is best suited to signal analysis [14].

Its semi-discrete version (wavelet series WS) and its fully discrete one (the discrete wavelet transform DWT) have been used for signal coding applications, including image compression [15] and various tasks in computer vision [16].

Given a time-varying signal s(t) , wavelet transforms consist of computing coefficients that are inner products of the signal and a family of "wavelets". In a continuous wavelet transforms, the wavelet corresponding to scale "a" and time location "b" is :

$$\Psi(a,b)=\frac{1}{\sqrt{/a/}}\Psi(\frac{t-b}{a}) \qquad (1)$$

where $\Psi(t)$ is the "mother wavelet" which can be thought of as a band-pass function. The factor $\sqrt{/a/}$ is used to ensure energy preservation [12]. There are various ways of discretizing time-scale parameters (b, a), each one yields a different type of wavelet transform.

The continuous wavelet transform (CWT) was originally introduced by G.Grossmann and J.Morlet [17]. Time t and the time-scale parameters vary continuously.

$$\mathrm{CWT}\{s(t);a,b\} = \int s(t)\,\Psi(a,b)^*(t)dt \qquad (2)$$

(the asterisk stands for complex conjugate).

Wavelet series (WS) coefficients are sampled CWT coefficients. Time remains continuous but time-scale parameters (b, a) are sampled on a so-called "dyadic" grid in the time-scale plane (b,a) [18]. A common definition is:

$$C_{jk} = \mathrm{CWT}\{s(t);\, a = 2^{j},\, b = k2^{j}\} \text{with } j, k \in Z \qquad (3)$$

The wavelets are in this case :

$$\Psi_{jk}(t) = 2^{-j/2}\ \Psi(2^{-j}t - k) \qquad (4)$$

The discrete wavelet transform (DWT) has been recognized as a natural wavelet transform for discrete-time signals. Both the time and time-scale parameters are discrete.

The discretization process partially depends upon the algorithm chosen to perform the transformation. The $C_{j,k}$ could be well approximated by digital filter banks. By using Mallat's [19] remarkable fast pyramid algorithms which involve use of low-pass and high-pass filters.

The Mallat algorithm is in fact a classical scheme known in the signal processing community as two-channel subband coder. The original signal S, passes through two complementary filters and emerges as two signals: signal approximation "A" and signal detail "D". The approximation is the high scale, low-frequency components of the signal. The details are the low scale, high-frequency components. The filtering process, at its most basic levels, look like this.

IV. Results and Discussion

Software is developed and implemented. This is related to using to the analysis DWT (discrete wavelet transform) of the two groups of PCG signals already above described (see Table I).

TABLE I: Phonocardiogram Signal Used

Type of the PCG	Normal	Innocent murmur	Coarctation of the aorta	Pana systolic	Aortic of the Regurgitation
Abbreviation	N	IM	CA	PAS	AR
Frequency sampling (Hz)	8012	8012	8012	8012	8012

The analysis of PCG signals using wavelet transforms has shown that it is important to find out the appropriate wavelet. The study carried out on different types of orthogonal and bio-orthogonal wavelet at different levels using the standard deviation, and the error of rebuilding ε_{or} between synthesized signal and the original signal used as a discrimination parameter has shown that db7 can be used in PCG signal analysis. In fact its morphology and duration can highly be correlated to the different sounds in the PCG. In this case the original PCG signal is decomposed over seven levels and the seventh detail of decomposition is considered as the synthesised signal. According to the results we obtain, the error ε_{or} can be considered as an important parameter in the classification of PCG signals. In fact, these results showed that the variation of this parameter is very sensible to the added murmur intensity in the PCG signals.

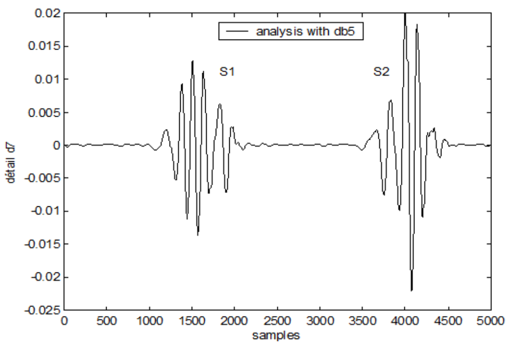
The error ε_{or} is given by :

$$\varepsilon_{or} = \frac{\sum_{i=1}^{N} \left| s_{o_i} - s_{r_i} \right|}{N} \qquad (5)$$

where s_{oi} : sample of the original signal s_o ; and s_{ri} : sample of the synthesized signal s_r .

A. Analysis of the PCG Signals of the First Group

For example the two internals components of the sound S1 (M1 and T1) and the two components A2 and P2 of the sound S2 are clearly distinguished in Fig. 5b which “db7” is used as mother wavelet



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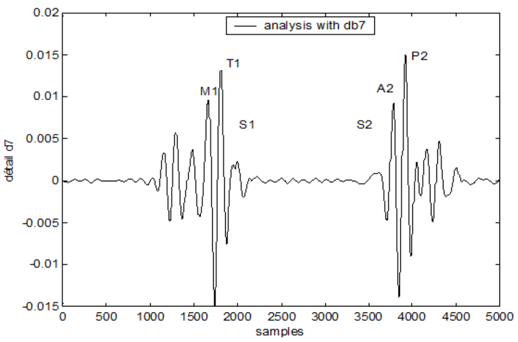

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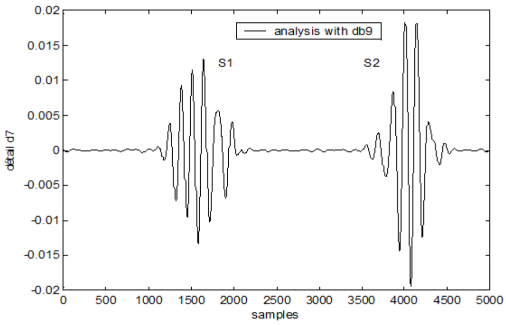
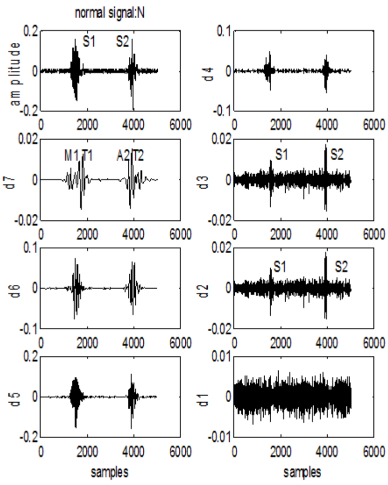


c

Figure 5. Discrete wavelet transform analysis of one cycle of the normal Phonocardiogram signal with: a) the mother wavelet “db5”; b) the mother wavelet “db7”; c) the mother wavelet “db9”.

In Fig. 5a and Fig. 5c where db5 and db9 are used as mother wavelet these components are not clearly depicted.signals at corresponding levels of decomposition, although originally they got similar morphology. If the detail d7 in figure 6a reveals clearly the two internal components of the first sound S1 (M1 and T1) and those of the second sound S2 (A2 and P2), the detail d7 in figure 6b, on the other hand, does reveal several components; at least three significant. This is very significant for the establishment of a medical diagnosis.



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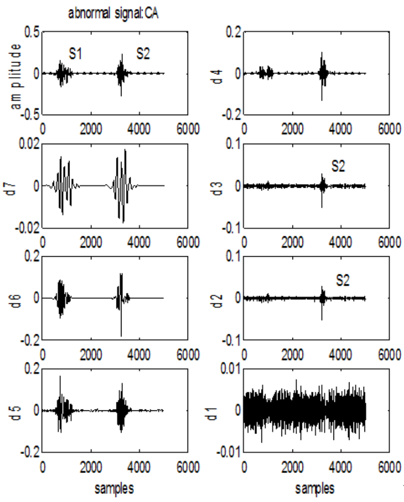


b

Figure 6: Discrete wavelet transform application of a) the normal PCG(N) , b) the coarctation of the aorta (CA).

Fig. 6 illustrates the results of the analysis of two PCG signals of this first group (N and CA). Es it illustrated, they are some difference between these

Also the details d2 and d3 of the figure 6b reveal only the sound S2 (S1 is being almost completely filtered) the corresponding details in Figure 5a reveal the sound S2 as well as S1.

The calculation of the average standard deviation at each detail level (d1 at d7) revealed visible differences between these three PCG signals of this first group. The average standard deviation is represented across each detail level (d1 at d7) for each PCG signal (N, IM, CA). The curve is given in Fig. 7.

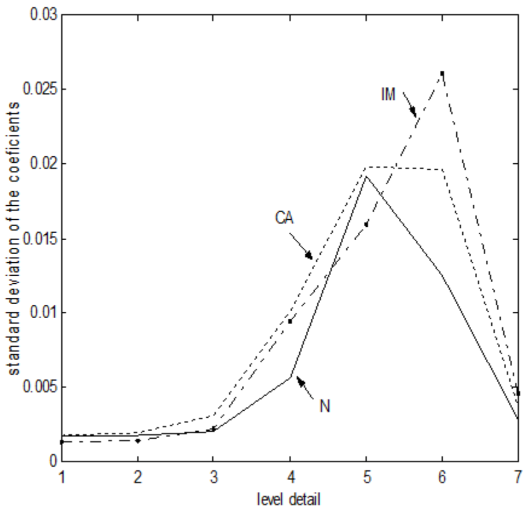
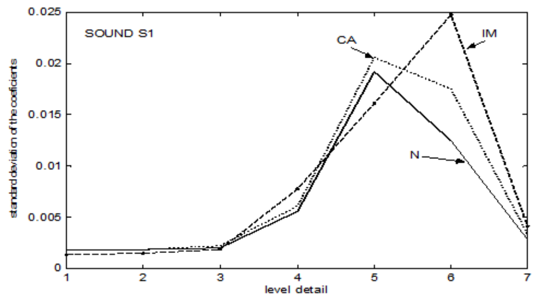


Figure. 7. Representation of the variation of the standard deviation of the detailed coefficients , during one cycle, for the cases N, IM and CA.

Such a representation, as it is noted, provides us with much more differences between PCG signals that illustrated in Fig. 6.



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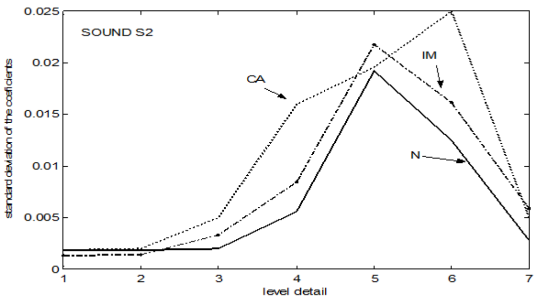


b

Figure 8: Representation of the variation of the standard deviation of the detailed coefficients of the cases N, IM and CA for a) the sound S1 and b) the sound S2.

Fig. 8a and Fig. 8b, relating to respectively the cardiac sounds S1 and S2, gives a more appreciable representation of the average variation of the standard deviation of the details d1 to d7 of the PCG signals “N,” “IM” and “CA”.

One notices according to these figures that the signal “CA” seems to have a variation more accentuated compared to the signal “N” than the signal “IM”. This demarcation is perceived better on the second sound (S2) than the first sound (S1).

This variation very accentuated according to the analysis of S2 than that of S1, concerning the signal “CA” can be explained by the higher number of internal components in S2 for this signal. Fig. 9 represents the analysis of the signal S2 by the continuous wavelet transform (CWT). This illustration confirms this result [11] while revealing an additional component “C” in the case of the signal “CA”. Such component does not exist in the case of the signals “N” and “IM”.

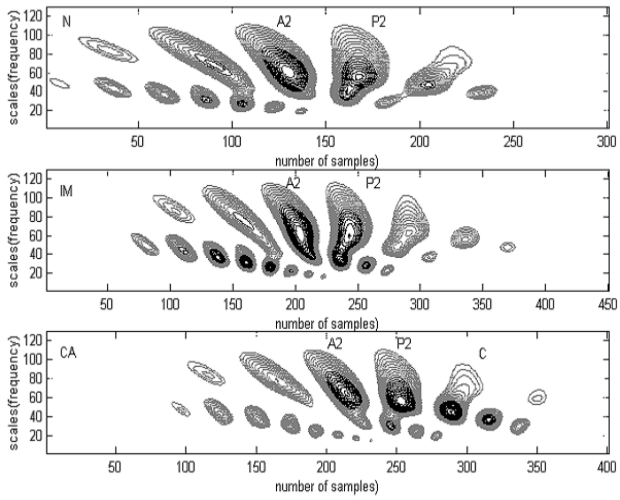
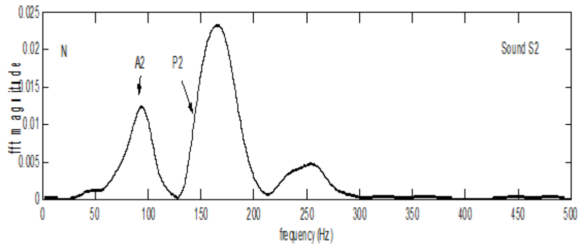


Figure 9: Continuous wavelet transform (CWT) application of the N, IM and PCG cases for the sound S2.

These results can also be illustrated by Fourier transform (TF) analysis of the second sound (Fig. 10c) in which one still notices the exisence of this component “C” concerning the signal “CA” [8],[10].



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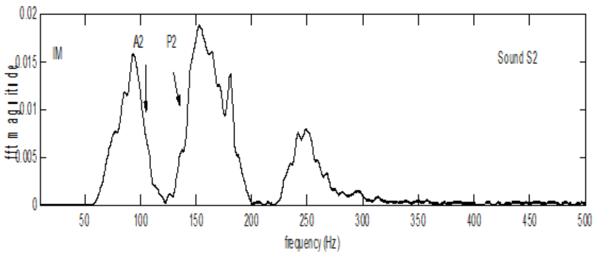

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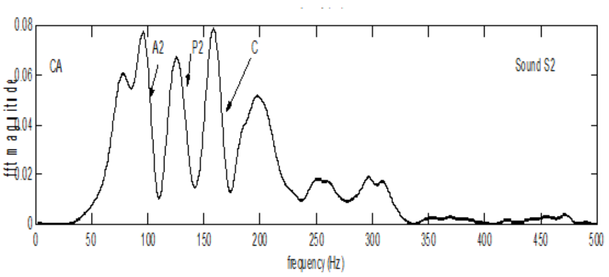

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Figure. 10. The Fast Fourier transform (FT) application of the second cardiac sound S2 for : a) The normal PCG signal (N); b)The innocent murmur signal (IM); c) The coarctation of the aorta signal (CA).

B. *Analysis of the PCG Signals of the Second Group.*

We can also use this method of the average standard deviation of the coefficients representing the details obtained by the use of the discrete wavelet transform to analyze the two PCG signals of the second group: AR and PAS.

As it is illustrated in Fig. 11 the variation of the average standard deviation according to DWT level decomposition is completely different from the normal case (Fig. 7).

The use of this technique in the analysis of the PCG signals having murmurs can provide us with additional information.

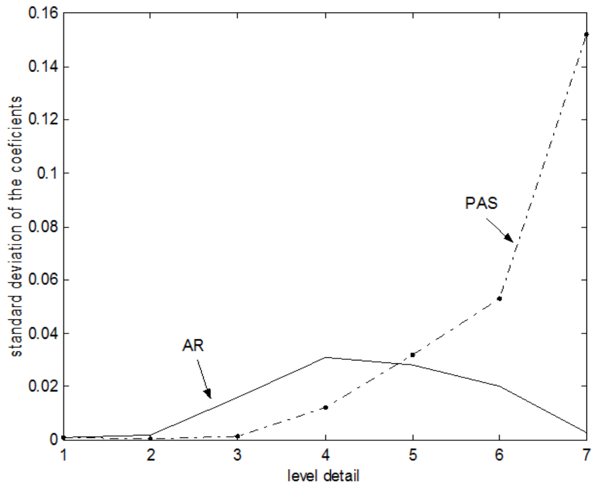

Figure. 11. Representation of the variation of the standard deviation of the detailed coefficients of the panasystolic (PAS) and the aortic regurgitation (AR).

Indeed the variation of the average standard deviation in this case is rather increasing with increases level decomposition d1 at d7 with the systolic type (PAS) signal and decreasing with increased level decomposition d1 at d7 for the diastolic type (AR) signal.

V. Conclusion

The results we obtained using the analysis of standard deviation variation according to each level of DWT decomposition show that discrimination between normal and abnormal phonocardiogram signals is possible. In fact, it is shown that the average standard deviation variation may increase or decrease with increased level of decomposition d1 at d7 according to the nature of PCG signals under study.

Five different signals: the normal signal, the innocent murmur, the aortic of the coarctation, the aortic regurgitation and the pansystolic case, have been analysed and the average standard deviation according to each level of DWT decomposition studied to confirm this results.

The difference between PCG signals of similar morphology have been found without any difficulties.

This result can provide more features and characteristics of the PCG signals. This will help physicians to obtain qualitative and quantitative measurements of the time-frequency characteristics of the PCG signals and consequently aid to diagnosis. Normal and pathological signals have been considered to give some idea of the generality of the evaluation.

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