PCG Signal Analysis using Discrete Wavelet Transform

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Abstract

The Phonocardiogram (PCG) signals are very useful to detect the various diseases related to heart valves. ECG recordings are insufficient to disclose information regarding health of the valves. In this paper discrete wavelet transform (DWT) is used to classify normal and various abnormal heart sound signals without getting into cumbersome process of segmentation or measuring various durations of PCG signals. The proposed method can be easily implemented using electronic stethoscope without the use of ECG recordings. In the proposed method PCG signals are decomposed upto eight level and the variance of detail coefficients obtained at level 5, 6 and 7 are shown to contain classification information to discriminate normal, aortic stenosis, aortic regurgitation, mitral stenosis and mitral regurgitation PCG signals.

Keywords: *PCG, discrete wavelet transform.*

1. Introduction

Cardiovascular diseases are the major cause of death of human beings worldwide. It would be very beneficial if heart diseases are detected at an early stage. Heart sounds can be recorded very easily using electronic stethoscope as it requires minimal equipment. Sometimes this is the only available options for diagnosis in far remote villages in primary health care centres where high end instruments are unavailable and other tools like ECG are difficult in case of infants. Normal heart produces two distinct sounds that are audible often described as S1-S2. S1 is the first heart sound caused by the closure of the mitral and tricuspid valves (atrioventricular (AV) valves) which earlier permitted flow of blood from atria into ventricle, it occurs approximately at the time of QRS complex and just before ventricular systole. S2 is the second heart sound caused by the closing of the semilunar and aortic valves which release blood into the pulmonary and systemic circulation systems (at the end of systole just before the tricuspid and mitral valves reopen), occurs at the end of T wave. S1 contains a series of low-frequency vibrations, and is usually the longest and loudest heart sound. The audible sub-components of S1 are those associated with the closure of each of the two AV-valves. Frequency of S2 is higher than S1, and its duration is shorter. It has aortic and pulmonary sub-components. Murmurs are high-frequency, noise-like sounds that are heard between the two major heart sounds. They can be innocent, but can also indicate certain cardiovascular defects. Murmurs are, generally caused either by improper opening (stenosis) of the valves or by regurgitation which results when the valves don't close completely; or by small opening in the septum. The aim of the proposed work is to develop a method for classification of heart sounds into normal and abnormal sounds so that health of the heart can be checked at home. The PCG signals can be an early indicator to heart problems so before worsening of the problem, a proper diagnosis can be done. Then, the other techniques like Echocardiography could be done to get a better sight of the problem. The proposed method is an early indicator to the problem in order to prevent worsening of the situation. The features were extracted in order to differentiate between normal and various abnormal signals using DWT.

2. Previous Work

The classification of heart sounds is not a new topic; however it is still in a developing stage as far as its embedded applications are concerned. With the use of latest technology, mobile phones can also be used as an electronic stethoscope and the digital phonocardiogram signals can be easily acquired, saved and transmitted to a cardiologist for further analysis. Most of the research in the auscultation field is seen mainly till 1980s but due to other methods like Echocardiography, research trends in PCG decreased, but in past few years it has shown a boost due to improvements in personal computers and signal processing techniques [1-2]. The abrupt frequency changes, the complex and highly non-stationary nature of the heart sound signals make the heart sound signal analysis a tedious job. The FFT and wavelet approaches have been applied to this in various studies and the work of correlating the heart sounds with the heart defects has been done [3-8]. Some related works to this study are as follows:

Muruganantham (2003) derived various features like average power, total power, mean power frequency, median frequency, frequency variance, frequency skewness, frequency kurtosis, and jitter from frequency domain [9]. Shui *et al.* (2004) used wavelet analysis for feature extraction in order to distinguish between normal and aortic stenosis patients. Simultaneous recordings of PCG and ECG were done and ECG acts as a guide to characterize heart sounds [10]. Segaier *et al.* (2005) used STFT (Short Time Fourier Transform) for characterization of systolic murmur [11]. Jiang *et al.* (2006) extracted cardiac sound characteristic waveforms (CSCW) from the cardiac sounds recorded by an electric stethoscope. The diagnostic parameters are [T1, T2, T11, T12] where T1 and T2 are the widths of the first sound S1 and the second sound S2, T11 is the time interval between two abutted S1, which indicates the heart beat rhythm condition and T12 is the time interval between S1 and S2, which is an indicator to express the heart valvular murmurs [12]. Ahlstrom C *et al.* (2005) [13] and Ahlstrom C *et al.* (2006) used tool to be able to investigate how signal content varies over time. Stockwell's TFR formed the basis of this work. Shannon energy was used to measure intensity and a wavelet detail was used to measure intensity in a certain frequency interval. Recurrence points of the first kind, T1, are used to locate S1 and S2 after which S3 is sought in time windows 100-300 ms after the two heart sounds [14]. Noponen *et al.* (2007) combined spectrogram and traditional phonocardiogram to distinguish innocent murmurs from pathological murmurs [15]. Amit *et al.* (2009) worked on the basis of hierarchical clustering, compact data representation in the feature space of cluster distances [16]. Maglogiannisa *et al.* (2009) proposed a diagnosis system using SVM (Support Vector Machine) to classify heart valve disease [17]. Dewangan *et al.* (2016) used variance of 8 detail coefficients along with 4 morphological features to classify different arrhythmias in ECG signals [21].

Most of the previous work used simultaneous ECG recordings and gating and segmentation was done before classification of PCG signal. This process is cumbersome and expensive because it required an additional ECG recorder. The method presented in this paper is simple and cost-efficient as it does not require use of ECG and can be implemented with use of an electronic stethoscope and a PC/laptop.

3. Methodology

3.1 Signal Acquisition

The PCG signal acquisition can be done by an electronic stethoscope. However for this work, the dataset is taken from a clinic trial in hospitals using the digital stethoscope DigiScope®. Four abnormal PCG signals i.e. aortic stenosis (AS), aortic regurgitation (AR), mitral stenosis (MS), mitral regurgitation (MR), along with normal (N) PCG signals each having 30487 samples are taken for analysis.

3.2 Feature Extraction

In this work acquired PCG signals are decomposed upto eight level using DWT. Then variance of details coefficients is calculated. The variance of detail coefficients at level 5, 6 and 7 will form a feature set to classify normal and various abnormal PCG signals.

4. Results

Figure 1 shows the various PCG signals taken for proposed work. Each PCG signal is decomposed upto level eight by selecting ‘db6’ as mother wavelet. Then variance of details coefficients is calculated and is shown in Table 1. One can observe from Table 1 that variance of detail coefficients at level 5, 6 and 7 can be taken as a set of features to classify PCG signals. These values are plotted in Figure 2 to discriminate AS, AR, MS, MR and normal (N) PCG signals.

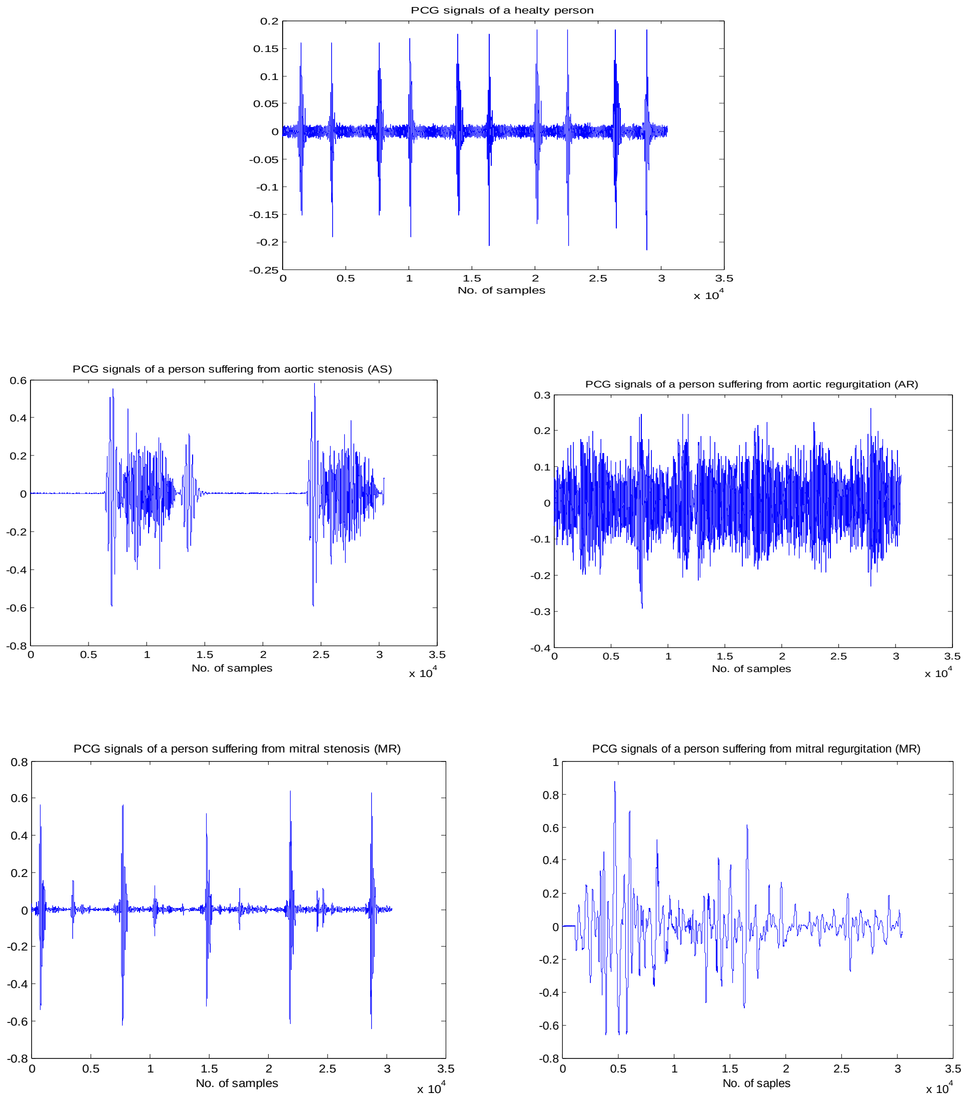
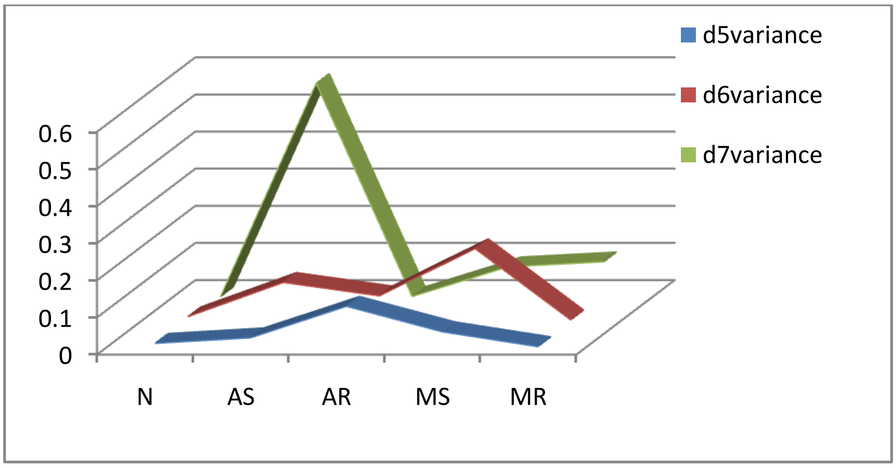


Figure 1. N, AS, AR, MS and MR PCG signals

Table 1: Features Extracted for Classification

Variance of detail coefficients	Normal	Aortic Stenosis	Aortic Regurgitation	Mitral Stenosis	Mitral Regurgitation
$d1_{variance}$	6.98E-06	4.97E-08	2.04E-06	1.56E-09	7.98E-10
$d2_{variance}$	1.32E-05	9.51E-08	5.33E-06	4.88E-07	3.16E-08
$d3_{variance}$	3.53E-05	1.12E-06	6.25E-05	2.55E-05	7.89E-06
$d4_{variance}$	8.49E-04	4.06E-04	0.006	4.82E-04	5.41E-05
$d5_{variance}$	0.0101	0.0252	0.11	0.0413	0.0011
$d6_{variance}$	0.0147	0.1073	0.0712	0.1983	0.0057
$d7_{variance}$	0.0017	0.577	0.0022	0.0823	0.0958
$d8_{variance}$	3.04E-05	0.8519	8.49E-04	0.0012	1.8891



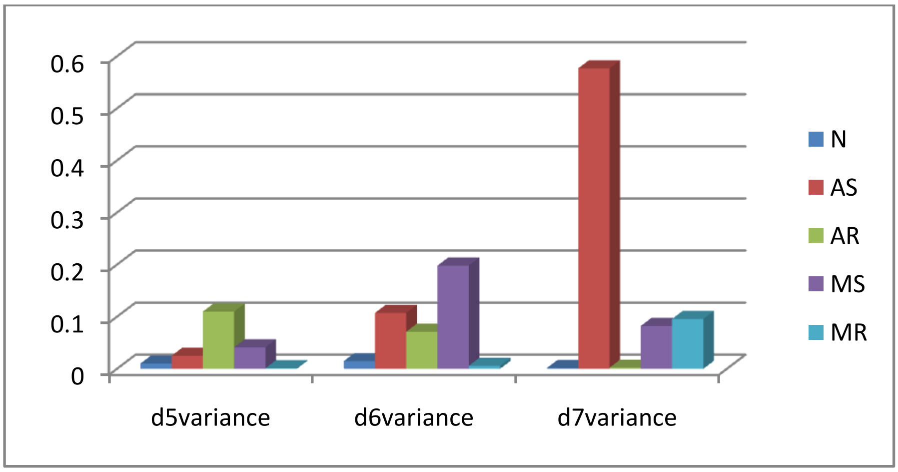


Figure 2. Variance of detail coefficients for N, AS, AR, MS and MR PCG signals

5. Conclusion

DWT can be used to classify different PCG signals. One can observe the variation in values of variance of detail coefficients at various levels. These values can be taken as set of feature set to classify normal and various abnormal PCG signals. The method is easy to implement. Proper classification tool like artificial neural network (ANN), Support Vector Machine (SVM) or any other classifier then can be selected to classify and take diagnostic decision.

6. References

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