Journal of Medical Engineering & Technology, 2012; 36(6): 303–307

ISSN 0309-1902 print/ISSN 1464-522X online
DOI: 10.3109/03091902.2012.684831

informa
healthcare

REVIEW

A review of signal processing techniques for heart sound analysis in clinical diagnosis

Babatunde S. Emmanuel*

Department of Electrical and Computer Engineering, Ahmadu Bello University, Zaria, Nigeria

This paper presents an overview of approaches to analysis of heart sound signals. The paper reviews the milestones in the development of phonocardiogram (PCG) signal analysis. It describes the various stages involved in the analysis of heart sounds and discrete wavelet transform as a preferred method for bio-signal processing. In addition, the gaps that still exist between contemporary methods of signal analysis of heart sounds and their applications for clinical diagnosis is reviewed. A lot of progress has been made but crucial gaps still exist. The findings of this review paper are as follows: there is a lack of consensus in research outputs; inter-patient adaptability of signal processing algorithm is still problematic; the process of clinical validation of analysis techniques was not sufficiently rigorous in most of the reviewed literature; and as such data integrity and measurement are still in doubt, which most of the time led to inaccurate interpretation of results. In addition, the existing diagnostic systems are too complex and expensive. The paper concluded that the ability to correctly acquire, analyse and interpret heart sound signals for improved clinical diagnostic processes has become a priority.

Keywords: Phonocardiogram, Auscultation, Signal processing, Wavelet transform, Clinical diagnosis, Heart sounds

1. Introduction

As far back as 1816, Hyacinth Laennec invented a device to listen to the sound of the heart which was called acoustic stethoscope [1]. Direct auscultation (listening to the sound of the body) has been the traditional method of cardiac diagnosis. At that time, insufficient physiologic knowledge of the cardiovascular system resulted in inaccurate interpretation of heart sounds. However, in 1895 the audio recording and graphical representation of heart sounds were achieved which enhanced clinical diagnosis [1]. Recording of heart sound in the form of a waveform display called phonocardiogram (PCG) has been developed to visually inspect heart sounds for the purpose of clinical diagnosis [2]. Valvular cardiac dysfunctions can be detected cheaply and efficiently using auscultation with advanced techniques of signal processing. The process of auscultation is in two stages: acquisition and analysis of heart sounds [3]. Acquisition involves collecting heart sound samples while analysis is used to diagnose the health or pathologic conditions of the heart.

According to Macartney [4] the increasing motivation for an improved approach to clinical diagnosis is that of efficient computer modelling of diagnostic process, which is essentially based on digital signal processing techniques.

Signal processing is the term used to describe the procedures applied on measured data or sampled data to reveal the information contained in the measurements [5]. These procedures essentially rely on various transformations that are mathematically based and which are implemented using digital techniques. By these signal processing techniques, it is possible to characterize a system process in a quantified way. The objective of this quantification is to reveal hidden information about the process and account for the system behaviour, and also it allows us to predict this behaviour when the system's condition changes. The complexity of physical processes (such as cardiovascular processes) is unlimited—and being able to characterize them in a quantified way relies on the use of physical 'laws' or other 'models' usually phrased within the language of mathematics [5]. Signal processing procedures have evolved over the years, providing methodologies for the analysis and interpretation of the phonocardiographic signal, following a procedure similar to that of the physician during auscultation. Recent advances in the field of digital signal processing have triggered a growing research interest in clinical application of heart sound analysis [2,6,7].

This paper presents an overview of approaches to analysis of heart sound signals. It reviews the milestones in the development of phonocardiogram (PCG) signal analysis. It describes the various stages involved in PCG signal analysis and the discrete wavelet transform techniques for bio-signal

*Corresponding author. Email: sbemmanuel@yahoo.com

processing. The study reviews the gaps that still exist between contemporary methods of signal analysis of heart sounds and their applications in clinical diagnosis.

2. Heart sounds and murmurs

In the studies carried out by Gabarda *et al* [8]. and Yuenyong *et al* [3]., it was observed that mechanical processes in the body produce sounds which indicate the health status of an individual, and this information is valuable in the diagnosis of patients with cardiovascular conditions. Martinez-Alajarin and Ruiz-Merino [9] and Amin and Fethi [10] noted that the auscultation of the heart, i.e. listening to the heart sound, is still the basic analysis tool used to evaluate the functional state of the heart. However, in the studies carried out by Amin and Fethi [10] and Singh and Anand [11] it was shown that heart sound analysis by auscultation is grossly insufficient as it does not allow for qualitative and quantitative characteristics of heart sound signals. The reasons for the insufficiency of auscultation technique were reported by Avendano-Valencia *et al* [12]. as being due to its inherent restrictions, namely human ear limitations; subjectivity of the analyst and the discriminatory skills that can take years to acquire.

Phonocardiograms (PCG) are graphical representations of the heart sounds [13]. Phonocardiography overcomes some of the drawbacks of traditional auscultation, providing important information in the detection of heart valve disorders. This is because the typical waveform of a healthy PCG signal is well known to a cardiologist. Any significant variation from the waveform is usually considered to be a sign or symptom of pathology. However, according to Martínez-Alajarín and Ruiz-Merino [9], the interpretation of phonocardiograms still remains a very difficult task, due to the many variables that have an influence on the generation and transmission of heart sounds. In addition, the pathological condition of the heart may not always be identifiable in the raw time-domain PCG signal. This may be diagnosed more easily when the frequency contents and the time localization characteristics of the signal are analysed [14,15]. The drawbacks of phonocardiogram (PCG) for clinical diagnosis include:

1. failure to present information on frequency of heart sounds and their components;
2. inability to differentiate between separate frequencies of various sounds as well as lack of information on the energy variations in various sounds;
3. presence of artefacts and noises that can visually mask weak heart sounds; and
4. problems of identifying specific heart sound boundaries.

Normal heart sounds occur during the closure of heart valves, while pathological murmurs are produced by turbulent blood flow caused by narrowed or leaking valves [10,16]. A murmur is one of the more common abnormal phenomena of the heart's activities. Murmurs are distinguished from basic heart sounds in that they are noisy and have a longer duration. Typical conditions in the cardiovascular system, which cause blood flow turbulence, are local obstructions, shunts, abrupt changes in diameter, and valve insufficiency [17]. Murmurs can be benign or innocent, but they can also be the first signs of pathological changes in heart valves. Murmurs can be a sign of abnormal cardiac structure or of abnormally increased blood flow through normal cardiac structure [18]. In evaluating a potential heart murmur, it is important for physicians to characterize a number of factors, namely timing and duration, pitch, intensity, pattern, quality, location and respiratory phase variations [19]. Systolic murmurs are systolic noises that last longer than a heart sound. A vast majority of children with systolic murmurs have normal hearts. This class of murmurs is a common clinical diagnosis finding that may be insignificant or may be an indicator of significant cardiac disease processes [18].

3. Clinical diagnosis

Diagnosis is the determination of the characteristic nature of a disease. Diagnosis rests upon two broad bases: the acquisition of information about the patient and about their disease, and, the evaluation and interpretation of that information [20]. The pattern of heart beats varies considerably in health and in disease. Martínez-Alajarín and Ruiz-Merino [9] observed that the auscultation of the heart is the first basic analysis tool used to evaluate the functional condition of the heart and in order to improve the diagnosis capabilities of auscultation, signal processing techniques are currently being developed for the analysis of phonocardiographic signals. It was observed in the literature that most of the existing digital techniques for cardiovascular diagnosis are imperfect but at the same time cardiologists cannot do without them [4].

It was noted by Macartney [4] that the measure of usefulness of a diagnosis method is that it should be sufficiently accurate. However, brevity or parsimony is the second most important criterion by which a diagnostic method should be judged. The shorter and simpler a diagnostic procedure, the better it is.

Clinical diagnosis of cardiovascular conditions is often achieved using digital signal processing algorithms. This entails the simplification of diagnostic processes. The concept has been broadened to what is now known as the production rule system. Production rule systems require a database of knowledge consisting of production rules of Boolean statements. However, for the efficiency of the system, a huge database of patients is required and this is usually very expensive and time consuming to obtain. The alternative approach is to translate the experience and knowledge of medical experts into series of production rules which is used to develop diagnostic algorithms [4].

Research on signal processing of heart sound signals for the characterization of cardiac sounds and murmurs has been extensive [3,10,16,21]. According to Amin and Fethi [10] the characteristics of the heart sounds, i.e. phonocardiogram (PCG) signals which include features such as heart sound S1 and S2 location, the number of components for each sound, their frequency content, and their time interval (or split S2), all can be measured more accurately by digital signal processing techniques.

4. Heart sound analysis

According to Yuenyong *et al.* [3], heart sound analysis can be broadly categorized into three stages: segmentation, feature extraction and classification. Segmentation identifies the borders of a complete heartbeat, i.e. a cardiac cycle from an acquired heart sound signal sample. Feature extraction computes distinctive characteristics or parameters from the cardiac cycle. Classification determines the nature of the heart sounds based on the distinctive characteristics.

4.1. Heart sound localization and segmentation

Heart sound localization and segmentation has been a subject of several investigations by researchers [1,22–25]. According to Ahlström [24], PCG signal derived from heart sounds digital recordings has a transient waveform that is superimposed with other signal disturbances such as noise and murmurs; hence the need for accurate heart sounds localization. Heart sound localization refers to the task of locating in time the occurrence of heart sounds in the cardiac cycle. The main applications of localization are as a pre-processing step applied before heart sound segmentation.

Heart sound segmentation partitions the PCG signal into cardiac cycles and further into S1, systole, S2 and diastole. Ahlström [24] reported that segmentation approaches can be divided into direct and indirect approaches. However, Yuenyong *et al.* [3] categorized segmentation approaches into envelope and machine learning approaches. Kumar *et al.* [25] classified the two approaches into segmentation using ECG as a reference signal and segmentation without ECG. Essentially, the two approaches involve (i) direct segmentation of the PCG signal; and (ii) indirect segmentation of PCG signal that involves using ECG as a reference. The indirect segmentation method demarcates the heart sound boundaries using the QRS complex and T-waves of electrocardiograph (ECG) signal; whereas direct segmentation demarcates the cardiac cycle boundary solely from the PCG signal. However, in the studies carried out by Gharehbaghi *et al.* [22] it was shown that complete cardiac segmentation algorithm using ECG reference is difficult because the T-wave is too weak to be identified in some patients. In some cases, manual segmentation by a phonocardiography expert is employed to find the boundaries of heart sounds. This is used to achieve the machine learning approach reported by Yuenyong *et al.* [3]

The direct heart sound segmentation approach computes the envelope signal of a heart sound, detects peaks of the envelope signal, establishes which peaks correspond to S1 and which correspond to S2, and then forms cardiac cycles using the S1–S1 intervals [24].

According to Ahlström [24] the most important step in direct heart sound localization and segmentation is to find a transform that takes the signal into a domain where S1 and S2 are emphasized. Several choices of this transformation have been presented over the years. Shannon energy, homomorphic filtering, frequency analysis, entropy analysis and recurrence time statistics are a few examples as reported by Ahlström [3]. Other examples include: auto regressive and autoregressive moving average spectral methods; power spectral density; Wigner–Ville distribution [25]; average normalized Shannon energy, complexity signatures, and energy of wavelet coefficients [3]. After the transformation, a threshold is applied to locate the heart sounds. Heart sound localization and segmentation algorithms operating directly on PCG signal emphasize heart sound occurrences in time. Most of these algorithms reviewed entail signal filtering, conditioning and thresholding.

In the case of normal healthy heart sounds, segmentation is easy. Peaks in the envelope signal correspond to the fundamental heart sounds and are easily detected by thresholding. Based on the assumption that systole is shorter than diastole, it is easy to identify systole as the shorter interval; thus, S1 must be the peak to the left of systole, or equivalently, S2 must be to the right. Identifying one peak allows all other peaks to be identified by noting that S1 and S2 must alternate. Boundaries of cardiac cycles are then formed by the S1–S1 intervals and segmentation is completed. However, segmentation is not straightforward in unhealthy heart sounds as extra peaks such as S3 and S4 may be introduced [3]. Consequently, this results in the problem of false peak detection. Segmentation is even more challenging in the events of murmurs. Hence, the problem of signal corruption and uncertain localization where normal heart sounds are submerged in murmurs. The threshold parameter is very important for analysis results. A low threshold provides many correct detections but also a lot of false detections, while a high threshold might miss many heart sound occurrences. In this condition, direct segmentation will require elimination of extra peaks and disturbances while preserving the integrity of normal heart sounds. This is called 'peak conditioning [3]'. The authors argued that peak conditioning can be a tedious process due to the problems earlier noted.

4.2. Feature extraction

Feature extraction is about quantifying available information into a few descriptive measures. In phonocardiogram signal classification, the features are derived on a heart cycle basis. Feature sets found in the literature can roughly be organized in two groups [3]. The first employs medical knowledge about specific diseases and how they affect the generation of heart sounds. An example of a feature of this type is the split S2 interval. Many cardiac disorders cause S2 to split into two separate sounds. Other types of features are based on time–frequency signal representations. This type of representation is particularly suitable for heart sounds since they are non-stationary signals whose frequency content changes with time. A particular time–frequency representation commonly used in heart sound analysis is discrete wavelet transform (DWT). The meaningful features extracted from heart sounds with wavelet analysis are of great interest for clinical interpretation of heart diseases [14].

4.3. Heart sound classification

Approaches that highlight the occurrences of heart sounds have been reviewed. The final task would then be to classify the identified characteristics of heart sound events for clinical diagnostic application. In the study carried out by

Bunluechokchai and Ussawawongaraya [14] the wavelet time-scale representation indicated a greater degree of non-uniformity in the PCG signal acquired from patients with a pathologic condition than those with healthy conditions. The concept of local intermittency factor computed from the wavelet transform was used for heart sounds classification.

5. Discrete wavelet transform

Mathematical transformations are applied to signals to obtain further information that is not readily obtainable in the raw signal. Most signals in practice are time-domain signal in their raw format. That is, the measurement of the signal is a function of time. The frequency spectrum represents the frequency components of a signal. Fourier transform is used to find the frequency-amplitude representation of a signal. Heart sound signal analysis for clinical diagnosis owes more to the Fourier transform theorems, as shown in the literature [15,21].

Signals whose frequency content does not change in time are called stationary signals, while those whose frequency content changes in time are called non-stationary signals. Most interesting signals contain numerous non-stationary or transitory characteristics: drift, trends, abrupt changes, and beginnings and ends of events. These characteristics are often the most important part of the signal. Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques cannot, e.g. trends, breakdown points, discontinuities in higher derivatives and self-similarity. Further, because it affords a different view of data than those presented by traditional techniques, wavelet analysis can often compress or denoise a signal without appreciable degradation. While Fourier analysis consists of breaking up a signal into sine waves of various frequencies, wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet [26]. Almost all biological signals are non-stationary signals, including the PCG signal. Wavelet transform is capable of simultaneously providing both the time and frequency information of a non-stationary signal. According to Debbal and Bereksi-Reguig [27] recent studies carried out to promote the understanding of signal components of heart sounds showed that the time–frequency representation methods are powerful tools; however, their application to analysis and synthesis of non-stationary heart sound signals is complex and difficult.

5.1. Heisenberg uncertainty principle

Heisenberg's uncertainty principle states that 'it is not possible to know what specific frequency exists at a particular instance of time but it is only possible to know what frequency bands exist at what time interval'. The problem of time and frequency resolution which is the result of the Heisenberg uncertainty principle constitutes a major challenge in the analysis of non-stationary signals. However it is possible to analyse this class of signals using the discrete wavelet transform approach called multi-resolution analysis [15]. The multi-resolution analysis (MRA) approach analyses a signal at different frequencies with different resolutions. The wavelet transform gives variable resolutions, that is, higher frequencies are better resolved in time, and lower frequencies are better resolved in frequency; i.e. good time resolution and poor frequency resolution at higher frequencies as well as good frequency resolution and poor time resolution at low frequencies. One notable application of wavelet transform is that it is very efficient in the analysis of non-stationary datasets and the characterization of sharp discontinuity [15].

In discrete wavelet transform (DWT), filters of different cut-off frequencies are used to analyse the signal at different scales. The signal is passed through a series of high-pass filters to analyse the high frequencies, and it is passed through a series of low-pass filters to analyse the low frequencies [15]. The DWT method analyses a segment of the signal at different frequency bands with different resolutions by decomposing the signal into course approximations and detailed information. DWT employs two sets of functions called scaling functions and wavelet functions, which are associated with low-pass and high-pass filters, respectively [11].

6. Conclusion

This study reviewed the gaps that still exist between contemporary methods of signal analysis of heart sounds and their applications for clinical diagnosis. A lot of progress has been made and the study of diagnostic techniques based on signal processing of heart sounds has been extremely instructive, but crucial gaps still exist. The findings of this review paper are as follows:

1. there is a general lack of consensus in research outputs, and inter-patient adaptability of signal processing algorithm is problematic;
2. the process of clinical validation of analysis techniques has not been sufficiently rigorous and as such data integrity and measurement procedures are still in doubt; and
3. in addition, the reviewed diagnostic algorithms and systems are too complex and very expensive.

In conclusion, our perspectives of how measured information is absorbed and analysed ultimately determine our views and understanding of the events described by the measured information. When our views are distorted, the information that is measured to make an accurate analysis of the observations of a system could lead to falsified interpretations. Therefore, our perception of information is greatly influenced by the complexity of the event that we observe. Consequently, the ability to correctly acquire, analyse and interpret phonocardiogram (PCG) signals for improved clinical diagnostic process has become a priority.

***Declaration of interest*:** The author reports no conflict of interest.

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