Augmented Phonocardiogram Acquisition and Analysis

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Abstract. Heart auscultation (the interpretation of heart sounds by a physician) is a widely used screening method for heart disease. It is well documented, however, that with the exception of expert cardiologists, physicians' auscultation skills are limited. It has also been shown that standard training methods do little to improve these skills. In this paper, we propose an architecture for a phonocardiogram analysis system that can augment a physician's auscultation abilities and serve as a training aid to improve those abilities.

1 Introduction

This paper presents a system to augment a physician's evaluation of a patient for heart disease, or to serve as a stand-alone screening system in countries where access to physicians is limited.

Analyzing heart sound recordings (phonocardiograms or PCGs) requires the detection of various sounds produced by the heart, while removing or ignoring the sounds caused by other factors (patient motion, speech, etc). Most physicians and other health care workers are not able to distinguish normal sounds from ones indicating disease. The less than desirable auscultatory performance of non-specialists (those that are not cardiologists) has been well documented [6,9,13,15,25].

Our goal is to provide both diagnostic advice and a training aid. Our system has the potential for use in developing countries due to simplicity of operation and low cost.

Previous work has focused on phonocardiograms taken from a single site (location on the chest), and often acquired under carefully controlled, non-clinical conditions. This is not how cardiologists perform auscultation. Because different locations provide cues to different pathologies, multiple sites are examined. Clinically acquired sounds often include noise and other artifacts that make analysis challenging. These must be dealt with by any system intended for clinical use. For these reasons, we base this work on simultaneously acquired multi-site phonocardiograms, acquired under clinical conditions.

Fig. 1. The acoustic signal from a normal heart over three cardiac cycles. The peaks show the first and second heart sounds, respectively.

The rest of this paper is organized as follows. The next section describes the heart sound signal, and the signal processing and analysis methods that form the basis of symptom detection. The next section describes the design of software to complement the signal processing and analysis in a decision-support system. The last section contains a summary of this work.

2 Signal Processing, Analysis and Symptom Detection

The *cardiac cycle* refers to the events related to the flow of blood that occurs from the beginning of one heartbeat to the beginning of the next [26]. Every 'beat' of the heart involves two major phases, systole (ventricular contraction) and diastole (ventricular relaxation). Heart sounds S_1 and S_2 mark the beginning of systole and diastole respectively (Figure 1). The phonocardiogram shown was acquired from a patient in the supine position, from the aortic location on the chest. The sampling rate is 8kHz, with 16 bits/sample.

S_1 is associated with the closure of the mitral and tricuspid valves. In the vast majority of cases, the valves close nearly simultaneously, so that the individual closures are not discernible in the S_1 . S_2 is primarily due to the closure of the aortic and pulmonary valves. These valves may close at significantly different times, such that the individual events may be audible. The resulting S_2 is referred to as "split", with subcomponents A_2 (aortic) and P_2 (pulmonary). The time between these subcomponents and their relative amplitudes can be diagnostically important.

Figure 2 shows a computer generated figure representing two (non consecutive) heart cycles. S_1 is the same in both sections of the figure. The distance

Fig. 2. A computer-generated idealized image of a normal person's heart sounds displaying 2 heart cycles, inspiration on the left and expiration on the right. Vertical bars indicate S_1 and S_2 .

between the components of S_2 , A_2 and P_2 (associated with the aortic and pulmonary valves respectively) change. On the left, A_2 and P_2 are separated by a small amount, while on the right, they are overlapping. This is normal, and called a physiological split. The change in S_2 is produced by a difference in pressure on the two sides of the heart that occur due to breathing. If the width of the split doesn't change over time, if it is wider than shown, or if the two components do not have the relative difference in volume indicated, it is a symptom of disease.

Two additional heart sound components are referred to as S_3 and S_4 . The S_3 is associated with rapid ventricular filling. When present, it appears shortly after the S_2 . Often associated with innocent murmurs in children, when heard in patients over the age of 35, it is a sign of pathology. The S_4 , associated with late diastolic filling, occurs shortly before the S_1 (when present). An audible S_4 is always an indicator of abnormality.

Murmurs are another category of sounds with diagnostic utility. Murmurs may appear in systole, diastole or both (in which case they are referred to as continuous). They appear as segments of increased (noise-like) activity over extended periods of time. There are also innocent murmurs (that do not indicate pathology) that must be identified as distinct from the murmurs which indicate disease.

Finally, very short, impulsive sounds sometimes called *clicks* and *snaps* may be heard. Clicks are associated with mitral (and possibly tricuspid) valve closures and occur shortly after S_1 . An opening snap sometimes accompanies mitral stenosis and is heard after S_2 . When audible they are always a sign of underlying abnormality.

Physicians listen primarily to six locations on the torso, as shown by the large and small circles in Figure 3. Using multi-site auscultation, all six sites are acquired simultaneously from pediatric patients under clinical conditions. Diagnostically important information is contained in the differences among heart sounds when the patient is inhaling compared to exhaling. Trying to align breathing as well as cardiac cycles in multiple signals recorded at different times on the same patient has proven exceedingly difficult.

The multi-site signals are recorded simultaneously so that (within propagation time differences) they are time-aligned (Figure 4). The signals are acquired at the locations indicated in Figure 3 and are titled accordingly. Pulse and ECG

Fig. 3. The four primary sites used in auscultation are shown in large circles in the figure. From left to right and top to bottom they are the Aortic, Pulmonic, Tricuspid, and Mitral. The two smaller circles identify the right and left axilla.

Fig. 4. Heartsounds collected (simultaneously) from the six locations indicated in Figure 3. Note that the signals have distinctively different characteristics, indicating differences in the information emphasized at each site.

signals (not shown) are simultaneously recorded as well. The signals shown are from a patient in the sitting position. The sampling rate is 10 kHz, with 16 bits/sample. The phonocardiograms exhibit a small atrial septal defect (ASD), a breach between the upper two chambers of the heart.

As described in the following sections, the signal processing system performs noise reduction, heart rate estimation, feature extraction, segmentation, labeling and symptom detection on the multi-site signals. The resulting symptoms are passed to the decision support system.

2.1 Noise Reduction

The reduction of noise is very important when designing a system intended for use in a clinical or otherwise difficult to constrain setting (e.g., in the home). A variety of approaches have been considered [16,17,21].

In signal processing, it is often assumed that noise is random (typically with a uniform or Gaussian statistical distribution), with a relatively wideband spectrum. It is also assumed that the desired signal has a spectrum that is largely disjoint from the noise spectrum, and concentrated at low frequencies. When these assumptions are met, noise reduction can be accomplished by simple low-pass filtering.

Phonocardiograms violate both of these assumptions. In addition to the typical random component due, e.g., to electronic noise, there may be deterministic components due to speech, footsteps, and patient motion. We will refer to these noise sources as environmental noise. The spectra of these components may overlap significantly with the desired signal. The desired signal may also contain random components due to turbulent blood flow (referred to as “murmurs”). These components are important for diagnosis, so should be retained.

In addition, the analysis required to establish symptoms has different (and conflicting) requirements for noise reduction. Identifying the heart sound events (S_1 , S_2 and S_3 and S_4 if they exist) is made difficult by the conventional noise, environmental noise, and murmurs. For this task, then, it is desirable to remove all three. In identifying symptoms, however, as mentioned previously, murmurs are important. There are also events with high frequency components (valve closures) that can be diagnostically relevant.

We therefore propose two parallel approaches to noise reduction: one that removes electronic and environmental noise and murmurs; and a second that removes noise to the degree possible while preserving murmurs and valve closure signatures. In the simplest form, these could be implemented using lowpass filters with different cutoff frequencies. A wavelet based approach, which also facilitates feature selection (Section 2.3) is used currently. More sophisticated methods (mostly nonlinear) are under investigation.

2.2 Heart Rate Estimation

The estimation of heart rate (both average and instantaneous) [7,10] is important in determining the parameters of feature extraction, segmentation and labeling

(below). For example, expected relative timing between the S_1 and S_2 and S_2 and the following S_1 is often used to label the S_1 and S_2 components in a phonocardiogram. The relative timing changes with heart rate, and is less reliable at high heart rates (the two intervals approach equality).

Instantaneous heart rate is also important in determining the degree of heart rate variability. This is an important symptom for diagnosing, e.g., arrhythmia.

One approach to finding the average heart rate is to identify maxima in the phonocardiogram spectrum. Time-frequency approaches, discussed briefly in the next section, are also a useful mechanism for estimating instantaneous heart rate.

2.3 Feature Extraction

The features derived from the phonocardiogram are important for identifying components of the heartsound (S_1, S_2, S_3, S_4 and murmurs), the characteristics of the components (e.g., the murmur is rising or falling in amplitude) and for detecting impulsive events (clicks, snaps, and valve closures).

To accomplish these tasks, features must be localized in time. It is also desirable that the features be concise. That is, characteristics of interest should be described in as few features as possible. To facilitate this, the signal representation from which the features are derived should itself be concise (in mathematical terms, “sparse”).

Two classes of representations that have been of considerable interest in the signal processing community are the time-frequency [2,4] and time-scale (wavelet) [12,19] representations. For the current application, both approaches have merit. Wavelet representations have proven especially suitable for detecting impulsive events (e.g., valve closures). Time-frequency approaches are particularly suitable for determining, e.g., heart rate variability. Both have promise for the overall segmentation task (Section 2.4).

An additional process may be applied to make the signal description even more concise. Principle component analysis (PCA) is widely used. Independent component analysis (ICA) may also be used.

In our current investigations, we use a wavelet decomposition (based on the Daubechies 15 wavelet) followed by principle component analysis.

2.4 Segmentation and Labeling

Different heartsound components occur at different times in the cardiac cycle. S_1 and S_2 occur periodically, at intervals predicted by the heart rate. This is also true of S_3 and S_4 if they exist. Murmurs may occur throughout the cardiac cycle. The expected interval between murmurs in successive cycles is also often indicated by the heart rate.

Segmentation [1,3,8,12,19] involves the detection (but not identification) of heartsound components. This typically involves examining features (as described above) to look for time intervals with high activity. This task is complicated by the fact that murmurs may overlap other components. It is desirable to extract the murmurs, so that they can be analyzed separately.

Labeling consists in identifying the heart sound components (e.g., as S_1 , S_2 , murmurs, etc.) The multisite approach proposed in this work is of significant benefit in this effort, since different locations have different characteristics for certain components (such as S_1 and S_2). This allows labeling in cases of high heart rate, where relative timing is not reliable. Once heart sound components are identified and labeled, component-specific symptoms can be identified. An example is the time between the aortic and pulmonic components of the S_2 , referred to as the S_2 “split”.

2.5 Symptom Detection

Common structural heart diseases include aortic stenosis (AS), atrial septal defect (ASD), pulmonary stenosis (PS), ventricular septal defect (VSD), mitral insufficiency (MI), tricuspid insufficiency (TI) and tetralogy of Fallot (TF). In ASD and VSD, there is a communication (hole) between the upper and lower chambers of the heart, respectively. AS and PS are abnormal constrictions near the aortic and pulmonary valves, respectively. MI and TI indicate reverse (backward) blood flow through the mitral and tricuspid valves. TF consists of PS and VSD.

Identifying which (if any) of the diseases described above is the focus of the Decision Support system. Detecting symptoms that can lead to a diagnosis is the ultimate goal of the Signal Processing, Analysis and Symptom Detection system.

For example, for the case of an ASD (illustrated in Figure 4), symptoms include wide, fixed splitting of the S_2 . A mid-diastolic murmur is also common [18].

3 Decision Support

Decision-support for cardiac auscultation can focus on one or more tasks [14]. He describes two primary tasks, screening innocent from pathologic heart sounds, and differentiating among diseases and sub-types. The latter involves a detailed examination of case data with respect to expectations for specific diseases. Other tasks may be the focus, for example monitoring the severity of congestive heart failure or monitoring replaced valves.

The information acquired via cardiac auscultation is crucial to determining whether a patient has heart disease. Information from a physical exam, ECG, X-ray, or other tests may also be diagnostically useful. For example, blood pressure, external pulses and whether or not the patient has cyanosis (a bluish look to the skin from low oxygen levels) can suggest some diseases and rule others out.

A prototype system providing decision-support in identifying congenital heart disease is described in [22,23]. This program integrates data from multiple sources. In addition to single diseases, more than one disease may be present in the same patient. In cardiology there may be up to three co-occurring diseases. Multiple diseases may interact, which means that the cues from a case of X and Y are not the union of cues produced by X alone and Y alone. Cues may be missing, added, or altered.

Fig. 5. A screen shot displaying auscultation data in both text and graphic formats

Decision support for an example case, number 0212 follows. The patient was referred to a cardiologist because a murmur was detected during a routine exam. The heart auscultation reveals a normal S_1 and a wide, fixed split S_2 . There is a grade I/VI mid-systolic (ejection) murmur heard best in the pulmonic area, and radiating to the back. The murmur does not increase in loudness in the supine position, and does not disappear in a sitting or supine position. There are no clicks or snaps. No diastolic murmur is detected. The ECG shows normal rhythm and no hypertrophy.

The soft systolic ejection murmur detected is characteristic of an innocent (Stills) murmur, an Atrial Septal Defect or Pulmonary Stenosis. A normal S_1 and normal ECG are consistent with all three. The wide, fixed split of S_2 is characteristic of both ASD and PS, but not an innocent murmur. With PS, a systolic ejection click in the pulmonary area is also expected, but one was not observed.

A decision-support system using the explanation points metric [23,22] would report the following on this case. ASD explained all symptoms (the murmur and S_2), e.g. 2/2 abnormal cues or 100%. A Stills murmur could explain the systolic ejection murmur, but could not explain the abnormal S_2 , resulting in only 1 of 2 or 50% of the abnormal cues explained. The expected abnormal click for PS is not present, meaning PS can explain only 2 of 3 or 66% of the abnormal cues. Echocardiography, the "gold standard", revealed a small ASD.

It is highly desirable that the results of auscultation be displayed in an *idealized* graphical format in the electronic medical record. Nie, et al. [20,24]

developed a graphical format that is similar to those in medical textbooks such as [5,11,18]. It is thus recognizable by people at various skill levels without having to listen to 12 or more recordings. An example is shown in Figure 5.

The top part of the figure shows the timing and intensity of heart sounds in case 1105. The figure of the chest in the second row shows the location and radiation direction of the murmur. In this case, the murmur is in the Pulmonary area and radiates to the back (indicated with an arrow). The graphics are generated from the text shown in the lower left side of the figure when the case is viewed.

4 Summary

Heart auscultation is a widely used screening method for heart disease. It is well documented, however, that with the exception of expert cardiologists, physicians' auscultation skills are limited and that standard training methods do little to improve these skills. In this paper, we propose an architecture for a phonocardiogram analysis system that can augment a physician's auscultation abilities and serve as a training aid to improve those abilities.

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