An Approach towards a Heartbeat Sound Information Retrieval System

E Safar Khorasani, S Doraisamy, A Azman, M Azmi Murad

Faculty of Computer Science, University Putra Malaysia, Malaysia

Abstract

Interpretation of heart sounds can be a problematic and difficult task for cardiology specialists. Diagnosis of heart diseases requires special skill and clinical experience along with detailed and expensive tests. However, heart disease diagnosis by heartbeat sounds is preferable and still widely used as the first step of diagnosis. Recently, Computer aided auscultation has emerged as a cost-effective technique to analyze and interpret the heart sounds. In this study we propose a feasible technique for developing a heartbeat sound retrieval system using text based approaches useful towards automated heart disease detection. The feasibility of these text based retrieval approaches are shown from retrieval experiments with around 100 digital heart sound recordings and eight categories of heart diseases. Each recording include ten heartbeat cycles.

1. Introduction

Digital Heart sound recordings with background noise, similarity among heart diseases, recording environment conditions, auscultation body points makes detection of heart diseases complicated. The heart sounds are the sounds generated by blood turbulence and beating heart. These sounds provide important and routine ways for diagnosis of heart diseases with easy accessibility and the reasonably low cost therefore auscultation is an important diagnostic method for cardiovascular analysis.

Computer aided auscultation has emerged as a cost-effective technique to analyze and interpret the heart sounds. It equips physicians with an unbiased tool to make accurate diagnostic and treatment decisions [1, 2]. Since the heart sounds mixed by background noise, detection of heart diseases is complicated. However, complication of such detections increases by a number of other factors including similarity among heart diseases, recording environment conditions, auscultation body points.

There are several methods for automated detection and classification of heart diseases and heart sound analysis that have been proposed. Some of them used Artificial Neural Network method for detection and classification of heart sound [3-5].Another technique that it used for diagnosis the heart problem is Hidden Markov Model [6,7] that they suggest HMM for segmentation of heart sound recorded for clinical and classification purpose.

In this study we propose an approach towards developing a heartbeat sound retrieval system using text based approaches useful towards automated heart disease detection. The audio format of heart sound recordings are preprocessed and transcribed into the MIDI format. The MIDI files are then encoded to text strings using N-grams [8]. These text strings are then indexed and tested for retrieval using both database and Information Retrieval (IR) systems. The Longest common subsequence (LCS) string matching algorithm was used for identifying similarities from the database. With IR, full text indexing of the recordings was used and retrieved using known item searches from a search engine.

2. Retrieval approaches

Two differing retrieval approaches to study the feasibility of text-based techniques for heartbeat sound file retrieval are described in this section.

2.1. Information retrieval

The method of finding material (usually documents) of an unstructured nature (usually text) that satisfies an information need from large collections that are stored on computers called IR [9] where documents relevant to a user query can be retrieved quickly.

To obtain text strings or musical words from MIDI encodings, the N-gram approach is used [8]. The n-grams encoded as musical words using text representations has been used in previous studies for indexing, searching and retrieving a set of sequences from a polyphonic music data collection. In adopting this technique, the heartbeat sounds would be transcribed to musical notation. The summary of steps taken in obtaining monophonic musical sequences from polyphonic sequences is as follows:

1. Divide the piece using a gliding window approach into overlapping windows of n different adjacent onset times
2. Obtain all possible combinations of melodic strings from each window

N-grams are constructed from the interval sequences of one or more monophonic sequences within a window. Intervals are a common mechanism for deriving patterns from melodic strings, being invariant to transpositions [4]. For a sequence of n pitches, an interval sequence is derived with n-1 intervals by Equation (1).

$$\text{Interval}_i = \text{Pitch}_{i+1} - \text{Pitch}_i \qquad (1)$$

For a sequence of n onset times, a rhythmic ratio sequence is derived with n-2 ratios obtained by Equation (2).

$$\text{Ratio}_i = \left(\frac{\text{Onset}_{i+2} - \text{Onset}_{i+1}}{\text{Onset}_{i+1} - \text{Onset}_i} \right) \qquad (2)$$

In obtaining n-grams that incorporate interval and rhythmic ratio sequences using n onset times and pitches, the n-gram would be constructed in the pattern form of:

$$[\text{Interval}_1 \text{Ratio}_1 \ldots \text{Interval}_{n-2} \text{Ratio}_{n-2} \text{Interval}_{n-1}] \qquad (3)$$

The details of encoding these n-grams into musical words are available in Doraisamy et.al [8].

2.2. String matching

To test the retrieval of the database of n-grams with another text-based approach, string matching was used. The database construction process is based on the n-gram approach described in the previous sub-section. To measure the similarity of entered query and the existing records of heart sounds within the database, a Text-based system is employed. In a full text search, the Longest Common Subsequence (LCS), a frequently used search algorithm that examines all words in every stored text file is used to match search words supplied by the heartbeat sound. In this approach LCS examine the similarity of query with exist heart records in the data base.

For each beat we have a word that we can use it in text matching and information text retrieval system.

3. Data collection

This section describes the preprocessing of the audio sound files and MIDI encoding.

3.1. Data preprocessing

The number of Dataset is 100 and they are classified in eight categories as shown in Table 1. In addition, 11 records of Normal heart sounds used in the experiment were captured by means of an electronic digital Littman 3M stethoscope model 4100. Other heart sounds already captured by well-known academic and industrial setting in the form of a comprehensive data set as benchmarks to evaluate the proposed technique. The rationale behind is that these benchmarks or in other words subject heart sounds have already been used by different outstanding work and researchers including [13].

All the records that collected include ten cycles of heart sounds and approximately 10 sec long.

Table 1. Properties of subject heart sounds.

Name of category	Number of records
Normal Sound	16 records
Split Second Sound	12 records
Ejection Sound	10 records
Clicks	12 records
Gallop Rhythm	13 records
Systolic Murmurs	14 records
Diastolic Murmurs	11 records
Continues Murmurs	12 records

Background noises and undesirable sounds which get mixed with the heartbeat sound are the main problems faced in the process of recording heart sounds. Such sounds are originated from the touch of stethoscope diagram with patient's skin. Lung sounds and breathing are other internal sources of noise. Moreover, external noises existing in the recording site are disturbing to the recording process. For solving these problems the collection of heart sounds are preprocessed prior to encoding. Preprocessing steps are as followed for each record of heart sound:

Audio format conversion to wave format, amplifying and normalizing Heart sound records and then apply noise reduction effect on the data sets. Figure 1 shows the Normal record sound before and after the preprocessing.

(a)


(b)


Figure 1. Heart sound (a) before and (b) after preprocessing

3.2. MIDI encoding

MIDI is a popular format in computer-based music production such as composition, transcription, etc. Size of MIDI files is generally smaller than other music formats. With wave to MIDI converters, we will be able to generate MIDI data of PCM-based sounds rather easily. It extracts acoustical characteristics such as pitch, volume, and duration for converting them into a sequence of notes for producing music scores. Thus, melodies will be translated into chromatic pitches without human intervention [10]. The quality of MIDI transcribed would also depend on the algorithm capabilities which are utilized.

Since the heart sound frequency is between 25-50Hz [11] therefore the encoding component just filtered heart sound with this frequency and ignore another sounds. In other hand the lowest note and highest note that will be encode are between C0-C2 (16 Hz-65 Hz).

In the first step we needed to select a tool for MIDI encoder for changing audio files to MIDI format. For this objective, 4 MIDI convertors were compared that are shown in Figure 2.

Since the heart sound has low frequency and small duration .Therefore, the tools should be able of accurate transcription of these parameters. To achieve this objective we played 30 different pitches in C1 channel and select Drums Program of YAMAHA Electronic synthesizer.

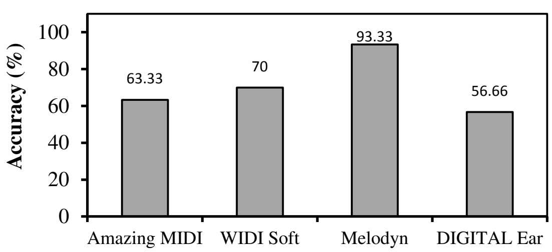

Figure 2. MIDI Encoding correct ratio percentages

The MIDI correct ratio percentages are calculated by this formula:

$$Correct\ (\%) = \frac{The\ number\ of\ Correctly\ encoded\ pitches}{Total\ number\ of\ played\ pitches} \quad (4)$$

From the results shown in Figure 2, the Melodyn [12] software was selected for encoding audio format to MIDI files.

4. Experiments

On this regards, this section presents the evaluation process for the proposed system in this paper. Specifically, a comprehensive experimental analysis using simulation is carried out in order to show the usefulness of the proposed work. Finally, the results of experiment are presented and discussed.

4.1. Document length

Several tests were performed to determine the number of cycles needed to obtain the highest retrieval accuracy. 6 random cases were selected from each category, as a result we had 8 categories which send 48 query from different cases to system in every step. We started our test with a single cycle queries and then calculate the accuracy with the below metric:

$$Retrieval\ Accuracy = \frac{Number\ of\ correct\ diagnosis}{Total\ number\ of\ query} \quad (5)$$

Then we repeated the test until each query contained 14 cycles. As shown in Figure 3, the best performance is achieved when we use 10-14 cycles for each heart sound record therefore we need at least 10 cycles for each heart sound case. The experiment was carried out under Microsoft Windows 7 on a Core2 Duo processor at 3 GHz and 4 GB RAM.

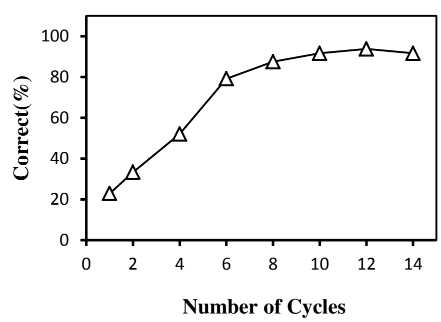

Figure 3. Effect of number of cycles on System performance

4.2. Retrieval experiments

The experimental operation process is defined as follows:

In the first place, the heartbeat sounds, explained in the above Table 1, were used to feed the proposed technique described section 2. In this experiment, we collectively used 100 heartbeat sounds (90 heart sounds kept in database as base for production results and 10 heart sounds using for queries). However, as we mentioned earlier in section 2, the heartbeat sounds were further classified into 8 categories.

In the process of saving records in database, in order to easily distinguish relevant results, we assign relevant category by using relation between Category table and Auscultation Area table of the database to show the category of the ranked disease in addition to the name of the disease. This helps us to find relevant result more conveniently. For instance, Systolic Murmur is the relevant category for Aortic Stenosis problem.

According to this classification the sample queries related to different categories were made to database randomly to measure the similarity between the made queries and the existing records or indexes in the database. The number of queries made in this experiment was 10; however, the performance metrics were calculated for the whole retrieved heart sounds and their returned ranked results were all taken into account. It is important to note that the exact correspondence of the given queries were not available in the database.

In order to search the given textual query in the database in this experiment we used two types of ways:

In the first way, we used Lemur search engine [14] in order to retrieve the relevant data according to the submitted query. The Lemur Toolkit (version 4.12) is designed to facilitate research in language modeling and information retrieval.

In the second way, using our developed LCS algorithm for retrieve and searching database [15]. This algorithm has been based on the text matching mechanism.

In order to compare the similarity of two strings LCS algorithm has been used. Similarities more that 70% is relevant for our method. If result categories are similar with query categories they will be consider as correct retrieved heart diseases. It should be consider that the queries that we used have two important properties, first it should not be exist in the pre-created database and second categorization of the query is known.

Table 2 summarizes the precision values obtained from the retrieval experiments.

5. Conclusion

The feasibility of diagnosis by matching text strings obtained from by heart-beat sound transcriptions has been shown. Precision values for around 50% were obtained for the retrieval of certain heart sound categories. However, more experiments and tests would be required in order for this to be used as large-scale heartbeat sound information retrieval system.

Table 2 Precision Values

Category	Lemur	LCS
Normal Sound	57%	89%
Split Second Sound	22%	17%
Ejection Sound	27%	25%
Clicks	22%	19%
Gallop Rhythm	32%	38%
Systolic Murmurs	20%	36%
Diastolic Murmurs	65%	78%
Continues Murmurs	40%	21%

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Address for correspondence:

Ehsan Safar Khorasani
Universiti Putra Malaysia, 43400 UPM SERDANG, Selangor
Ehsan.Safar@gmail.com