

Heart Sounds Classification using Motif based Segmentation

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ABSTRACT

In this paper we describe an algorithm for heart sound classification (classes Normal, Murmur and Extrasystole) based on the discretization of sound signals using the SAX (Symbolic Aggregate Approximation) representation. The general strategy is to automatically discover relevant top frequent motifs and relate them with the occurrence of systolic ($S1$) and diastolic ($S2$) sounds in the audio signals. The algorithm was tuned using motifs generated from a collection of audio signals obtained from a clinical trial in a hospital. Validation was performed on a separate set of unlabeled audio signals. Results indicate ability to improve the precision of the classification of the classes Normal and Murmur.

Keywords

Heart sound classification, motif discovery, time series analysis, SAX.

1. INTRODUCTION

This work is part of an ongoing effort to define algorithms that are able to perform the first level of screening of cardiac pathologies. The aim is to perform automatic classification of heart sounds, by assigning a new sound to a clinical condition (class). In this case we consider three classes: Normal (N), Murmur (M) and Extrasystole (E). Heart sound signals of a normal heart have two main components: the first heart sound, $S1$ (or lub), corresponding to the systolic period, and the second heart sound, $S2$ (or dub), the diastolic period [3]. A normal heart sound has a clear "lub dub, lub dub" pattern, with the time from "lub" to "dub" shorter than the time

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from "dub" to the next "lub". In the Murmur category, the heart murmurs sound as though there is a turbulent fluid noise in one of two temporal locations: (1) between "lub" and "dub", or (2) between "dub" and "lub". They can be a symptom of many heart disorders, some serious. One of the things that confuses non-medically trained people is that murmurs happen between lub and dub or between dub and lub; not on lub and not on dub. Finally, the Extrasystole category sounds may appear occasionally and can be identified because there is a heart sound that is out of rhythm involving extra or skipped heartbeats, e.g. a "lub-lub dub" or a "lub dub-dub". Notice that an extrasystole may not be a sign of disease. It can happen normally in an adult and can be very common in children. However, in some situations extrasystoles can be caused by heart diseases. In practice, captured sounds may contain a variety of background or random noises such as breathing, or brushing the microphone against clothing or skin [1].

One common step previous to classification is segmentation, where $S1$ and $S2$ sound segments are located within the audio sequence. Being time series, recorded cardiac sounds can be processed to identify frequent motifs (sub-sequences). In this paper we use a SAX (Symbolic Aggregate Approximation) based approach to discover frequent motifs in heart sounds and then try to identify which motifs correspond to the sounds $S1$ and $S2$. This is done by aligning the frequencies of the discovered motifs with the expected frequencies of $S1$ and $S2$ for each different class. We call this alignment process "motif-based segmentation".

We have fine tuned our classification algorithm using a dataset prepared for the PASCAL Classifying Heart Sounds Challenge (dataset B) [1]. This dataset consists of 312 auscultations gathered using the DigiScope Collector system [4]. The 3 classes Normal, Murmur and Extrasystole have the following distribution: Normal - 200 cases (64.1 %); Murmur - 66 (21.2 %); Extrasystole - 46 (14.7 %).

In a previous approach we have used the SAX-based Multiresolution Motif Discovery, MrMotif, for Heart Sound Classification [2]. Motif discovery allows the surveying of frequent local patterns (motifs) in the time series, not necessarily peaks. Here, attributes were the motifs found char-

acterized by the frequency of each motif in each sound. A motif in a time series is a frequently repeated subsequence (frequent pattern).

2. OUR ALGORITHM

Our classification algorithm is based on the knowledge of the heart beats, particularly on the first sound, $S1$ (or lub) and the second sound, $S2$ (or dub). For each heart sound, Algorithm 1 starts by discovering the most frequent motifs using SAX discretization. Then, it obtains the frequencies of the three most frequent motifs. In the next steps it tries to map these motifs with the $S1$ and $S2$ sounds. A Normal heart sound is characterized by an approximately equal number of $S1$ and $S2$ without any other relevant motif. In this case we assume that the two most frequent motifs correspond to $S1$ and $S2$. If we have three top equally frequent motifs it is likely that we have a Murmur heart sound. Finally, the Extrasystole class has three $S2$ sounds for each two $S1$ sounds.

Algorithm 1: Proposed algorithm

Input: HS : a set of heart sounds; δ_1, δ_2 : error thresholds
Output: C : a set of assigned class labels

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1 for  $s \in HS$  do
2    $M \leftarrow$  motifs found in  $s$ 
3    $m_1 \leftarrow$  most frequent motif in  $M$ 
4    $m_2 \leftarrow$  2nd most frequent motif in  $M$ 
5    $m_3 \leftarrow$  3rd most frequent motif in  $M$ 
6    $f_1 \leftarrow$  frequency of  $m_1$ 
7    $f_2 \leftarrow$  frequency of  $m_2$ 
8    $f_3 \leftarrow$  frequency of  $m_3$ 
9   if  $|f_1 - f_2| < \delta_1$  and  $|f_2 - f_3| > \delta_2$  then
10     $C_s \leftarrow N$ ;
11  if  $|f_1 - f_3| < \delta_1$  then
12     $C_s \leftarrow M$ ;
13  if  $|2 \cdot f_1 - 3 \cdot f_2| < \delta_1$  and  $|f_2 - f_3| > \delta_2$  then
14     $C_s \leftarrow E$ ;
15 return  $C$ 

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3. RESULTS

Evaluation was performed on a set of unlabeled sounds made also available by the Pascal challenge. These test sounds were not used for motif discovery or the development of the algorithm. They allow an unbiased comparison with the previous peak-based approach. In our experiments we have used $\delta_1 = 2$ and $\delta_2 = 2$ for the error thresholds. We used, for the assessment of the effectiveness of our classification approach, three metrics calculated from the tp (true positives, where positives corresponds to disease classes), fp (false positives), tn (true negatives) and fn (false negatives) values. The metrics are precision per class, sensitivity ($tp/(tp + fn)$), specificity ($tn/(tn + fp)$) and F_1 score ($2 * specificity * sensitivity / (specificity + sensitivity)$). Precision gives us the positive predictive value (the proportion of samples that belong in category c that are correctly placed in category c).

As we can see in Table 1, our new method is better in classifying Normal and Murmur classes but it has problems

Table 1: Evaluation for Dataset using the previous and the new approach

	Previous	New
Precision of Normal	0.72	0.77
Precision of Murmur	0.32	0.38
Precision of Extrasystole	0.33	0.12
Sensitivity of heart problem	0.22	0.29
Specificity of heart problem	0.82	0.51
F_1 score	0.35	0.37

in classifying the Extrasystole heart beats. It also improves the F_1 measure which is a balanced combination sensitivity and specificity.

4. CONCLUSION AND FUTURE WORK

In this paper, we have proposed an algorithm for automatically discover relevant top frequent motifs and relate them with the occurrence of systolic ($S1$) and diastolic ($S2$) sounds in the audio signals (without ECG reference). We also compare the obtained results with the results obtained with our previous approach. This new algorithm is based on the discretization of sound signals using the SAX representation and was tuned using motifs generated from a collection of audio signals. Validation was performed on a separate set of unlabeled audio signals. Results indicate ability to improve the precision with respect to the classes Normal and Murmur as well the F_1 measure.

We will continue the exploration of motif based heart sound characterization and improve our algorithm, mainly, in the characterization the Extrasystole class. This class is very hard to detect by any technique applied on this dataset. We will also exploit these algorithm's ideas as a basis for the definition of attributes to be used in machine learning methods.

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