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Heart Murmurs Clustering Using Machine Learning

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Abstract—**This paper presents an approach of utilizing machine learning to assist cardiac auscultation for heart murmur detection. Our aims are to compare the effectiveness and advantages of both supervised and unsupervised techniques in performing clustering and classification of selected sets of different heart murmur episodes. The supervised approach uses a decision tree while the unsupervised method uses as few parameters as possible and can also reveal the most effective parameters in clustering. The clustering results are then compared and the boons and banes are drawn. The supervised approach implementation is straightforward following the known diagnosis procedure with little training. The caveat, however, is that it fails to detect extreme anomalies. The unsupervised clustering approach needs more computation and training with the advantage of self-learning and revealing most effective features in clustering the murmur episodes caused by different cardiovascular anomalies.**

Keywords- heart sounds and murmurs, k-means clustering, machine learning

I. INTRODUCTION

Heart disease is the leading cause of death for both men and women. The National Center for Health Statistics reported 28.4 million adults with diagnosed heart disease in the US alone [1]. Over 630,000 Americans die from heart disease each year, approximately one in every four deaths. Diagnostic approaches capable of detecting cardiac disorders can potentially save lives and reduce the frequency and/or intensity of the disease. Among the noninvasive approaches, cardiac auscultation and electrocardiograph are two widely used methods. Electrocardiograph usually serves as an additional procedure after cardiac auscultation. Meanwhile, cardiac auscultation is more effective than electrocardiograph in revealing information to the mechanical activities of cardiac cycle [2-3]. These techniques, however, rely heavily on the experience of the examiner and the result is often subject to the descriptions from the examinee.

Heart sound can serve as a measure of the mechanical movements in the heart and the cardiovascular system. Not only does it contain the information about each part of the heart, it can also reflect interactions among different sections in the physiological and pathological fields. Notably, noise and distortion in the heart sound can provide useful information in early detection of cardiovascular diseases. Patients with severe cardiac disorder are usually found with a murmur during diagnosis. A common procedure used in murmur detection is echocardiography. The complexity in cardiac auscultation causes a large percentage of patients with

benign flow murmur to undergo echocardiography, which is not necessary for the patients [2]. Hence, there is a need for more precise and objective detection methods.

Recent years have witnessed a surge of interest in incorporating digital signal processing, data science and machine learning for cardiac auscultation [4-8]. Models that emphasize several underlying factors and their interactions, are trained with voluminous data and can aid in the detection and classification process. A popular belief is that big data can be explained with a relatively simple model that utilizes a small number of hidden factors [9].

Following these trends, this paper presents two methods for murmur clustering and classification, several parameters are used (in section II.A) to outline the characteristics of a particular type of murmur. Firstly, we propose a supervised approach (in section II.B) with a decision tree to construct clusters. Secondly, an unsupervised learning algorithm is described below in II.C that employs predefined parameters to construct the clusters.

The predefined parameters can be extracted using algorithms from our previous studies [13-16] as well as new techniques. The extracted information serves as the bedrock on which the decision tree is built. The result of the supervised method is then compared to the unsupervised results, which can reveal valuable insights into the weightage of each factor.

The remainder of this paper is organized as follows. Section II is devoted to murmur feature description and model building. The validity of the proposed methods is assessed with heart sound episodes containing distinct types of murmurs in Section III, including: early, mid-, late and holo-systolic murmurs, as well as early and mid-diastolic murmurs. Results are presented and discussed in Section III. We conclude in Section IV.

II. MURMUR FEATURE DESCRIPTION AND MODEL BUILDING

Murmur signals examined in this paper are clinical data collected from patients with various heart diseases. They were chosen to represent murmurs occurred at different locations, such as early and mid- diastolic murmurs, early, late, mid- and holo-systolic murmurs. Following our earlier work [12-15], we first segment the input phonocardiogram signal into small segments and calculate the average magnitude (AM) for each segment as the following

$$AM(n) = \frac{1}{k}\sum_{i=1}^{k}|x(i) - \mu_x| \quad (1)$$

where k is the number of data points in each segment, and μ_x is the mean amplitude of the input signal.

We can then successfully mark the first and second heart sound (S_1 and S_2) in phonocardiograms and label systole and diastole in cardiac cycles, S_1 occurs at the start of ventricular systole, while S_2 happens at the start of ventricular diastole. Furthermore, we can retrieve information about murmurs occurring within systoles and diastoles. Together with preceding understanding and studies [13-16], we can detect murmurs in phonocardiograms, if the murmur intensity exceeds a preset threshold.

A. *Vocabulary for murmur clustering and data extraction*

Murmurs occur with distinct features and we have found the following parameters useful in distinguishing between murmurs:

- Location: where the murmur happens. If there is no murmur, L=0, if a murmur occurs in systole, L=1, L=2 if murmur is detected during diastole.
- Onset time t_s: the time when the murmur starts after a preceding heart sound. It is estimated that early murmurs are less than 20-30 milliseconds; mid-murmur's onset time is around 120-150 milliseconds; late murmur's onset time generally is more than 150 milliseconds.
- Duration of the murmur, t_m.
- Duration of the systole or diastole in which the murmur occurs, t_h. Usually systoles last from 250 milliseconds to 450 milliseconds while diastoles from 360 milliseconds to 750 milliseconds.
- Pitch frequency, f_{pitch}: the dominant frequency in the murmur. It is approximated using a second-order auto-regressive (AR) model as follows, where the coefficients $\{a_1, a_2\}$ are estimated for each segment:

$$\varepsilon(k) = x(k) - a_1 x(k-1) - a_2 x(k-2) \quad (2)$$

$$f_{pitch} = \frac{f_{sample}}{2\pi}\tan^{-1}\left(\frac{\sqrt{4a_2 - a_1^2}}{a_1}\right) \quad (3)$$

B. *The supervised model and decision tree construction*

After successful collection of parameter data, we designed a supervised clustering algorithm with a decision tree which follows the steps below:

1. Each predefined type of murmur is assigned a non-zero number. This is known as the type number.
2. A murmur is checked first based on the location. It is designated as a systolic murmur if its location parameter is set to 0, or a diastolic murmur otherwise. The number is defined as the stage number.
3. The duration of associated systole or diastole, t_h, is compared to the acceptable durations of systoles if the stage number is 0, or to the acceptable durations of diastoles if the stage number is 1. If t_h does not lie within the range of acceptable systole or diastole durations, then there are errors in the data extraction phase and the procedure should cease, while the classification process is labeled a failure. Otherwise, the process continues.
4. The onset time t_s of the murmur is compared to the mean onset time of each category of murmurs. Based on how close t_s is to the mean onset times of different types of murmur, the murmur receives its first type number. If t_s matches none of the range of onset times, the type number will be 0.
5. The duration of the murmur, t_m, is compared to the acceptable durations of each category of murmurs. Based on whether t_m is within the range of durations of different types of murmur, the murmur receives its second type number. If t_m matches none of the range of durations of murmurs, the type number will be 0.
6. The pitch of the murmur, f_{pitch}, is compared to the range of pitches of each category of murmurs. Based on whether f_{pitch} lies within the range of acceptable pitches, the murmur receives its third type number. If f_{pitch} matches none of the range of frequencies, the type number will be 0.
7. The mode of the three type numbers defines the murmur type. If the mode is 0, the classification and clustering process is considered as a failure. The stage number is used for validation.
8. In case that no number in the three type numbers repeat, the classification and clustering process is considered to fail.

C. *Clustering via machine learning*

We implemented k-means clustering [17] to categorize each murmur episode into one of six categories: early, mid-, late and holo-systolic murmurs, as well as early and mid-diastolic murmurs. K-means clustering can automatically partition the dataset into k groups. It starts off with selecting k initial cluster centers and then iteratively refining them. The algorithm converges when there is no further change in the assignment of instances to clusters. In our context, we take $\mathbf{P}$ to be a set of n episodes of heart murmurs, and each element of $\mathbf{P}$, $\mathbf{p}_j$, has a pair of two randomly selected parameters mentioned above. One parameter is assigned as x co-ordinate while the second one is designated as y co-ordinate. We begin by creating a set $\mathbf{C}$ with k elements, where each element $\mathbf{c}_i$ corresponds to a category of heart murmur, and each point in $\mathbf{P}$ are assigned to the nearest $\mathbf{c}_i$ to form a set $\mathbf{S}$. Each element in $\mathbf{S}$, $\mathbf{s}_i$, is obtained as the sum of distance between centroid $\mathbf{c}_i$ and l elements in $\mathbf{X}$ that have $\mathbf{c}_i$ as their closest centroid:

$$\boldsymbol{s_i} = \sum_{j=1}^{l}||\boldsymbol{p_j} - \boldsymbol{c_i}||^2 \quad (4)$$

The co-ordinates of each $\mathbf{c}_i$ are updated to minimize the distance between each point and the nearest centroid, and iterations are done until the distance between all the points in $\mathbf{X}$ and the corresponding nearest centroid are minimized. The iteration is repeated for a defined number of times, and while no optimum set of points is guaranteed [18], iteration may be terminated after obtaining a desirable result.

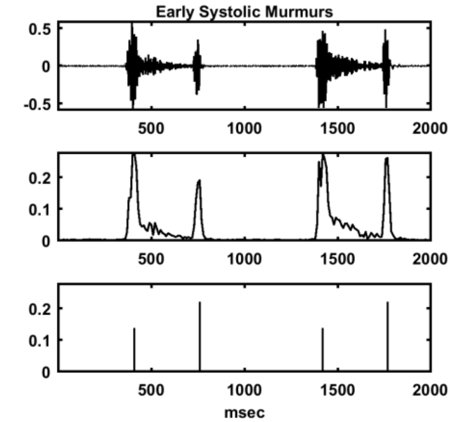

Figure 1. Early systolic murmurs with raw input signal (upper), AM calculated (middle) and S_1 and S_2 identified (lower).

III. RESULTS AND DISCUSSION

The heart murmurs were first processed through the signal processing algorithms previously described by first identifying the timing locations of the first and second heart sounds, S_1 and S_2. Figure 1 exemplifies the processing of an early systolic murmur episode using (1) and the assumption that the duration of the diastole is longer than that of the systole. S_1 and S_2 are identified, thus the systoles and diastoles. The murmur detected will be further processed to generate the pitch frequency using the 2nd order AR model described in (2) and (3) as shown in Fig.2. Figures 3 and 4 show another example of an early diastolic murmur episode processed with similar techniques. It can be quickly observed that, even both episodes are murmurs occur early, their frequency profiles are different, where systolic murmur in Fig.2 has higher pitch frequency than diastolic murmur in Fig.4.

To examine the performance of our algorithms, we first randomized the input data set of episodes. An example of randomized set is shown in Fig.5. More than fifty clinically recorded heart murmur episodes were examined in the performance evaluation. The sequence is then tested using the supervised and unsupervised clustering techniques described in Section II.

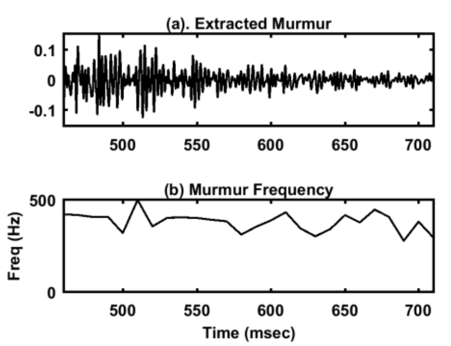

Figure 2. Extracted early systolic murmur and frequency profile

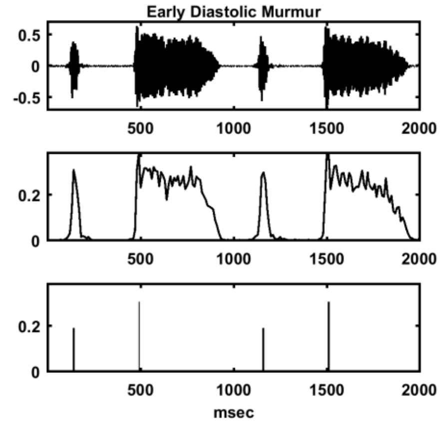

Figure 3. Early diastolic murmurs with raw input signal (upper), AM calculated (middle) and S_1 and S_2 identified (lower).

The heart murmur test data were examined by the underlying algorithm and heart murmur features were extracted as shown in Figures 1-4, namely the location that a murmur was detected (L), the onset time of the detected murmur (OT), the average murmur pitch frequency (F), and systole length, diastole length and murmur duration. After implementing k-means clustering and running the simulation for different combinations of extracted features. we observed the following:

1. Clustering with murmur location (L) and pitch frequency (F) will allow early-systolic, early-diastolic, and late-systolic murmurs detection. These two parameters can classify some holo-systolic and mid-systolic murmurs but fail to separate mid-systolic murmurs (Fig.6).
2. Clustering with murmur location (L), murmur onset time (OT) will improve accuracy of detecting mid-diastolic murmur and improve mid-systolic detecting accuracy (Fig.7).
3. Clustering with three features (L, OT, and F) will further improve the accuracy of detecting holo-systolic murmurs.

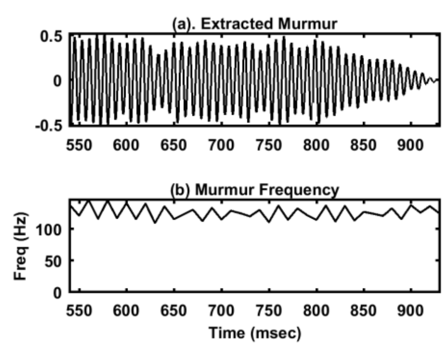

Figure 4. Extracted early diastolic murmur and frequency profile

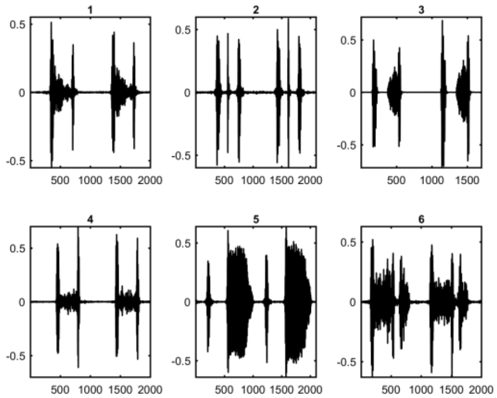

Figure 5. Representative murmurs examined in clustering. The episodes represent: (1) early systolic, (2) mid-systolic, (3) late diastolic, (4) holo-systolic, (5) early diastolic, (6) mid-diastolic murmurs.

4. Adding a fourth parameter, the percentage (PT) of the murmur duration within a systole or diastole, can further improve the detecting accuracy.

The clustering maps of using more than three parameters (as in the cases 3 and 4) are difficulty to visualize. The overall comparison of using different combinations of feature parameters for clustering is summarized in Table I

TALBE I.

Murmur Types	Detection Rate (%)			
	L,OT,F,PT	L,OT,F	L, OT	L, F
Early-systolic	100	100	100	100
Holo-systolic	42.7	35.8	0	33.2
Mid-systolic	87.5	87.5	62.5	37.5
Late-systolic	100	100	100	100
Early-diastolic	100	100	100	100
Mid-diastolic	100	100	100	0

IV. Conclusion

The supervised detection method is very accurate; its implementation is straightforward and requires less computation. It could, however, miss detection of anomalies in certain extreme cases. Improvement also can be made with an adaptive updating procedure to provide more accurate estimation of murmur features which are critical for classification. In contrast, clustering with machine approach requires more data to train and is slower to run, it can also produce reliable results and reveal parameters of importance.

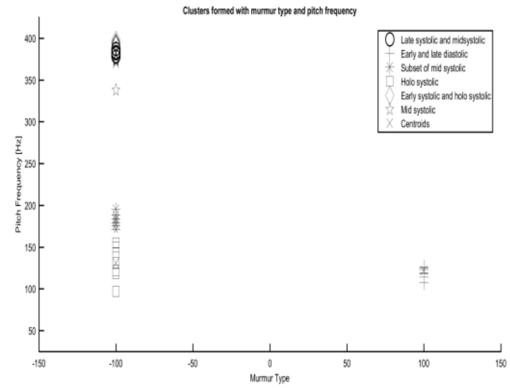

Figure 6. Clustering using murmur location and pitch frequency

Machine learning with clustering can become more effective and versatile with a large amount of clinical heart murmur training data. We have found that single-layer perception approach can classify murmurs with good accuracy. On the other hand, single-layer perceptron approach is insufficient under complicate situations. In the future, multi-layer perceptron neural network can be adopted to improve correct clustering and provide more accurate diagnostic assistance.

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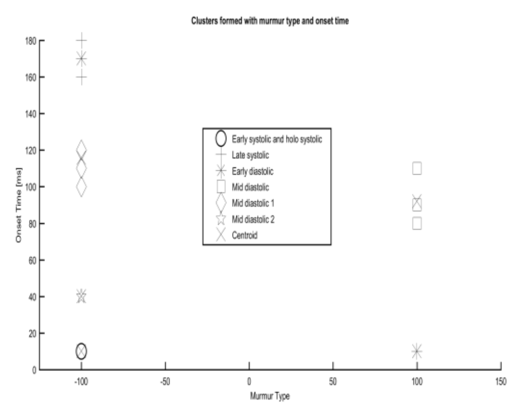

Figure 7. Clustering using murmur location and murmur onset

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