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Classification of heart murmurs using cepstral features and support vector machines

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Abstract— **Murmurs are auscultatory sounds produced by turbulent blood flow in and around the heart. These sounds usually signify an underlying cardiac pathology, which may include diseased valves or an abnormal passage of blood flow. The murmurs are classified based on their occurrence in different parts of the heart cycle; systolic murmurs and diastolic murmurs. This paper investigates features derived from cepstrum of the heart sound signals and use them to train three classifiers; k-nearest neighbor (kNN) classifier, multi-layer perceptron (MLP) neural networks and support vector machines (SVM) for classification of heart sounds into normal, systolic murmurs and diastolic murmurs. These features have been compared with features extracted from short-term Fourier transform (STFT) and discrete wavelet transform (DWT) in combination with the above three classifiers. The classification experiments were carried out on the heart sounds samples collected from various web sources. Among various combinations of the above features and classifiers, SVM trained on cepstral features are most promising for murmur classification with an accuracy of around 95%.**

I. INTRODUCTION

Auscultation, listening to sounds emanating from human organs, is a primary routine for screening and diagnosing many pathological conditions of the heart. Various mechanical events occur during the functioning of heart produce different heart sounds. There is a definite pattern of heart sounds for normal people and any deviation from that pattern clearly states the presence of an underlying cardiac pathology.

A normal heart cycle consists of two major sounds: the first heart sound, S1 and the second heart sound, S2. The interval between S1 and S2 sounds of a heart cycle demarcates the contraction phase of heart and is called as ventricular systole. Similarly, the interval between S2 and S1 demarcates ventricular diastole during which ventricles relax and the atria pushes the blood through the atrio-ventricular valves. Extraneous sounds like, murmurs, clicks, snaps, S3 (people above the age of 40 years) and S4 may present in abnormal heart sounds.

Murmurs are noise-like events, which can appear either during systole or diastole representing different cardiac pathologies. Murmurs are caused by turbulent blood flow within the heart. These sounds usually signify an underlying pathology which may include diseased valves or an abnormal passage of blood flow. Murmurs are commonly classified based on their occurrence in different parts of the heart cycle [1]. The systolic murmurs occur during contraction of ventricles while the diastolic murmurs occur during their relaxation. Since most of the heart conditions are associated with a known pattern of sounds, a computer-aided automatic classification of murmurs would assist in identification of underlying pathology. However, this is not a trivial task as the murmurs include noise-like components and the detection of which is commonly confounded by other noises. The focus of this paper and the papers discussed in the following literature survey is on the classification of murmurs without explicitly finding the locations of S1 and S2.

Most of the previous studies on classification of abnormal heart sounds used artificial neural networks as a classifier [2], [3], [4], [5], [6]. One of the first reported studies using neural networks for classification is by Barschdorff et al. [2], they discussed the advantages of using neural networks over traditional classifiers, such as nearest neighbors. Spectral features obtained from short-term Fourier transform (STFT) analysis of the signal and mean values of corresponding sections of the signal envelope were used to train the neural network.

In [3], probabilistic neural networks (PNNs) were used for classification of pathological murmurs and obtained promising results. The input feature vector to the neural network consists of trimmed mean spectrogram features from systole and diastole, and amplitudes of systolic and diastolic segments of the heart sound signal. Another study by Ölmez and Dokur [4], have used grow and learn network for classification. The input features for the network were formed by using wavelet detail coefficients. Seven types of heart sounds were classified in this study.

Multi-layer perceptron (MLP) neural network was used to detect the presence of heart murmurs in [5]. The input features to the network were extracted from individual systolic and diastolic periods of heart sounds using spectrogram. The detected murmur was then classified into seven classes (e.g. early systolic, pan systolic, early diastolic, etc) depending on their timing in the cardiac cycle using Pseudo Wigner-Ville distribution. In [6], grow and learn and multilayer perceptron neural networks were used for classification of heart murmurs. Input features were extracted from wavelet (Daubechies-2) detail coefficients at the second decomposition level.

The above studies have shown that neural networks trained with features derived from frequency spectrum and wavelet transform perform well for the classification of heart murmurs. However, still there is no single feature set which can perform well with various classifiers. In this paper, I have investigated features derived from cepstrum of the heart

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sounds and used them to train three well known classifiers; k-nearest neighbor (kNN) classifier, multi-layer perceptron (MLP) neural network and support vector machines (SVM) for the classification of heart sounds into normal sounds, systolic and diastolic murmurs. I have also compared these features with features extracted from STFT and discrete wavelet transform (DWT) in combination with the above three classifiers.

The rest of the paper is organized as follows: In section II, three different feature extraction techniques are presented. This is followed by a review on classification techniques used in this paper in section III. The classification experiments and results are discussed in section IV and conclusions are presented in section V.

II. FEATURE EXTRACTION

Usually time, intensity and frequency characteristics of heart sounds are the most important features used by physicians for the diagnosis of heart diseases using auscultation. Hence, it is appropriate to start the discussion on feature extraction methods for heart sound analysis with traditional frequency spectrum or spectrogram.

A. Spectral Features

Since heart sound signals are highly non-stationary, it is appropriate to compute discrete Fourier transform (DFT) for short segments, which is known as short-term Fourier transform (STFT). First the heart sound signal, $x[n]$ is divided into overlapping segments and then Hamming window is applied on these segments. The DFT is computed for each segment as shown below:

$$X[k] = \sum_{n=0}^{N-1} \hat{x}[n]\, exp^{\frac{-j2\pi nk}{N}} \qquad 0 \leq k < N \tag{1}$$

where $\hat{x}[n]$ is the windowed signal and N is the length of the windowed segment. It was found from the experiments carried out with various segment sizes that 25msec segment with 10msec time shift is a good choice for the STFT analysis of heart sounds. The spectral coefficients corresponding to frequencies of up to 1000 Hz are summed up for each time frame to obtain the relevant features.

Fig. 1 shows the features derived from STFT analysis of normal heart sound, heart sound with systolic murmur and heart sound with diastolic murmur. In the first plot, two large peaks corresponding to S1 and S2 components can be observed. However, in the second plot, there is energy only in the systolic part. Similarly, there is significant energy in the diastolic part in the third plot because the heart sound signal has diastolic murmur.

B. Wavelet-based Features

The wavelet transform decomposes the signal into several parts and analyzes the parts using a family of wavelet functions and its associated scaling functions [7]. This way it will give more information about when and where of

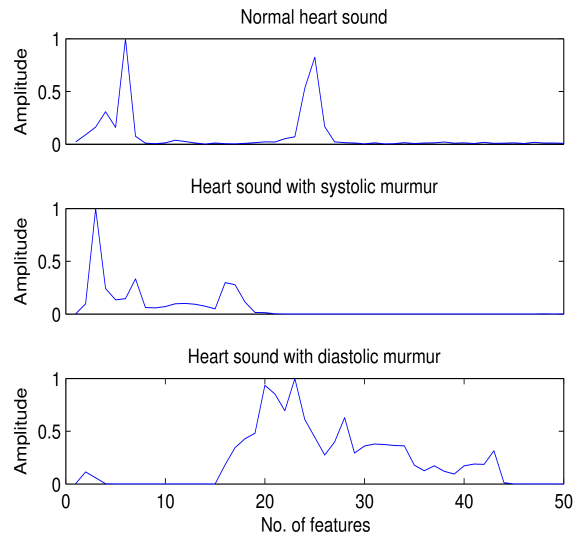

Fig. 1. Spectral features for normal and abnormal (systolic and diastolic murmurs) heart sounds

different frequency components of the signal. The continuous wavelet transform (CWT) is given by,

$$W(s,\tau) = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x(t)\, \psi^{*}(\frac{t-\tau}{s})\, dt \tag{2}$$

where, $x(t)$ is the input signal, $\psi(t)$ is a mother wavelet function, and $*$ denotes complex conjugation. To overcome the problem of redundancy in CWT representation, the discrete wavelet transform (DWT) is introduced, where the mother wavelets are scaled and translated in discrete steps. The DWT of a signal is calculated by passing it through a series of filters. At each level, the signal is decomposed into approximation and detail coefficients using low-pass and high-pass filters. The choice of filters determines the shape of the wavelet.

To compute these features, first the wavelet coefficients were obtained using wavelet (Daubechies 6) decomposition of a heart sound signal. I found that fourth level decomposed signal have the characteristics of the frequency spectrum of S1, S2 and murmurs. The signal obtained from the fourth level decomposition was divided into smaller segments, and energy was computed for each segment. The above energies formed the feature vector for the classifiers. The features for normal heart sound, heart sound with systolic murmur and heart sound with diastolic murmur are shown in Fig. 2.

C. Cepstral Features

Cepstrum is defined as the inverse Fourier transform of the logarithm of the power spectrum of a signal. The cepstrum represents the rate of change in the different spectrum bands, e.g. first cepstral coefficient can provide the information on shape of the power spectrum.

The block diagram of cepstral feature computation is shown in Fig. 3. First STFT of the signal is computed, and then fit triangular filters to initial frequencies (up to 1000

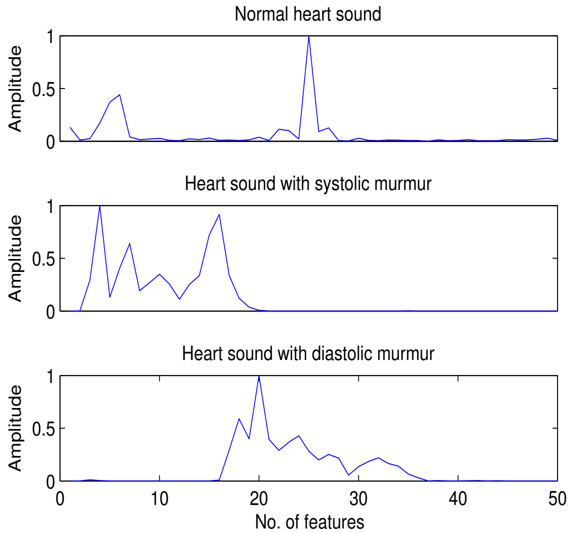

Fig. 2. Features derived from discrete wavelet transform (DWT) for normal and abnormal (systolic and diastolic murmurs) heart sounds

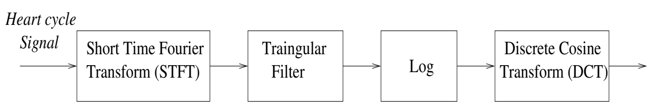

Fig. 3. Block diagram of cepstral feature computation

Hz) of each spectrum followed by logarithmic compression. Finally, a discrete cosine transform (DCT) is used to compute features from the above coefficients. Let m_j denote the log binned filter bank coefficients, then the cepstral coefficients are computed using the following equation:

$$C_i = \sqrt{\frac{2}{N}} \sum_{j=1}^{N} m_j \, cos\Big(\frac{\pi i}{N}(j - 0.5)\Big) \tag{3}$$

Fig. 4 shows the cepstral features extracted for normal and abnormal (both systolic and diastolic murmurs) heart sounds.

III. CLASSIFICATION APPROACHES

I have performed experiments using three well-known classifiers for the classification of murmurs in the heart sounds.

A. k-nearest neighbor (kNN) classifier

It is the simplest among the three classifiers I have used. In this method, a new sample is classified based on the majority vote of its neighbors, with the sample being assigned to the class most common amongst its k nearest neighbors. The choice of the k depends on the data. The neighbors are identified using the distances computed between the feature representations of the samples. Usually, the Euclidean distance is used.

B. Multilayer perceptron (MLP) classifier

Multi-layer perceptron (MLP) [8] is a feedforward artificial neural network and is the most widely used neural

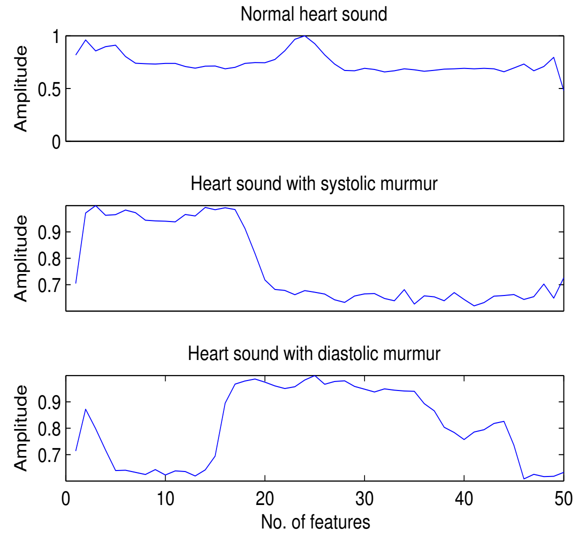

Fig. 4. Cepstral features for normal and abnormal (systolic and diastolic murmurs) heart sounds

network classifier. The MLP consists of a network of processing nodes arranged in layers, typically three layers: an input layer which takes the features/patterns of the training data, a hidden layer, an output layer with one node per class. The back-propagation algorithm is used to compute weights carried by the connections of the network. The number of nodes in the hidden layer is determined experimentally.

C. Support vector machines (SVM)

The support vector machines (SVM) are powerful classifiers that can efficiently address the non-linear and non-separable classification tasks [9]. An SVM first maps the input points into a high-dimensional feature space and finds a separating hyperplane that maximizes the margin between two classes in this space. Suppose, each input point, $\{\mathbf{x}_i, i = 1 \ldots l\}$ belongs to one of the two classes 1, -1 and the data is linearly separable,

$$f(\mathbf{x}_i) = sign(\mathbf{w}.\mathbf{z}_i + b) = \begin{cases} 1, & if\ y_i = 1 \\ -1, & if\ y_i = -1 \end{cases} \tag{4}$$

where, $\mathbf{z}_i$ is the corresponding feature space vector in higher dimension. To deal with data that is not linearly separable, the above equation can be extended by introducing a new set of non-negative variables (ξ_i).

$$y_i(\mathbf{w}.\mathbf{z}_i + b) \geq 1 - \xi_i \quad i = 1 \ldots l \tag{5}$$

Then the optimal hyperplane problem can be solved by

$$\min(\frac{1}{2}\mathbf{w}.\mathbf{w} + C\sum_{i=1}^{l}\xi_i) \;\; subject\ to \tag{6}$$

$$y_i(\mathbf{w}.\mathbf{z}_i + b) \geq 1 - \xi_i, \;\; \xi_i \geq 0 \tag{7}$$

where, parameter C is a constant, can be seen as regularization parameter which can make the balance between margin maximization and classification violation. The SVM does not explicitly do the mapping, it finds the optimal hyperplane by using the dot product functions in feature space which are called *kernels*. Functions which satisfy the Mercer's theorem can be used as kernels. These kernels enable the SVM to operate efficiently in high-dimensional space without being adversely affected by the dimensionality of that space.

IV. CLASSIFICATION EXPERIMENTS AND RESULTS

In order to compare the features and classifiers discussed in the previous sections, the classification experiments have been carried out using heart sound samples collected from various web sources (e.g. eGeneral Medical, Cardiosource, BioSignetics, Texas Heart Institute). Total number of heart sound samples available are 130, out of which 45 are normal heart sounds, 42 are heart sounds with systolic murmurs and 43 are heart sounds with diastolic murmurs.

First, the heart sounds are normalized against amplitude variations due to age, physiology, etc. The, heart cycles are extracted from these heart sounds both manually and using automatic segmentation [10]. Features are extracted from individual heart cycles, which are re-sampled to have same size across various heart cycles. These features are used to train the classifiers. I carried out 10-fold cross validation experiments, i.e. training the classifier for the first nine sets of the data and testing on the last set, then repeating the test set so that each data sample is tested. The classification accuracy is calculated as the average of ten accuracies. Table I presents the classification accuracies obtained with all the combinations of features and classifiers.

TABLE I

CLASSIFICATION RESULTS, PERCENTAGE OF CORRECTLY CLASSIFIED HEART SOUND SAMPLES.

Features/Classifiers	kNN	MLP	SVM
Spectral features	73.0	82.4	77.7
Wavelet-based features	86.3	86.4	81.0
Cepstral features	93.6	92.7	**95.2**

The best accuracy of 95.2% is obtained using SVM trained on cepstral features; kNN gives 93.6% and MLP classifier gives 92.7% accuracy using the same features. The wavelet-based features yield 86.3%, 86.4% and 81.0% using kNN, MLP and SVM respectively. Among three classifiers using the spectral features, MLP produced best accuracy of 82.4%. The above results conclude that among various features and classifiers used, SVM trained on cepstral features are most promising for murmur identification.

V. CONCLUSIONS

I have investigated various combinations of features and classifiers to identify murmurs in heart sounds. The features explored in this paper are: (1). Spectral-energy features obtained from short-term Fourier transform (STFT) analysis of the heart sounds, (2). Features obtained from wavelet decomposition of the heart sounds, (3). Features derived from cepstrum of the heart sounds. Three well-known classifiers are used; k-nearest neighbor classifier, multi-layer perceptron (MLP) neural networks and support vector machines (SVM).

Classification experiments were carried out on heart sounds obtained from various web sources. The best accuracy of 95.2% is obtained using SVM trained on Cepstral features; kNN gives 93.6% and MLP classifier gives 92.7% accuracy using the same features. These results indicate that cepstral features are good for this task and can give best performance when trained them using SVM.

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