A Review on Feature Extraction with Classification Methods for Cardiac and Pulmonary Diseases

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Abstract: The Heart and Lung Sounds are produced due to the Mechanical and Functional Properties of the Heart and the Lungs. Auscultation of the Heart and Lung Sound assists the Physician to diagnose the Clinical conditions. Acoustic characteristics of Heart and Lung sounds like fundamental frequency, Amplitude, duration of one event such as S1, S2, Inspiration, and Expiration and Interval of the Repeated period of the Cardiac and Pulmonary Sounds are used to diagnose the Condition of the Heart and Lungs. This paper reviews the General Methods used for Feature Extraction and Classification of the Cardiac and the Pulmonary Sounds into Normal and Pathological Category.

***Index Terms* – FFT, SVM, DWT, Hilbert Transfer, Pulmonary Disease, Cardiac Disease.**

I. INTRODUCTION

The Heart Sounds are produced due to the turbulence in blood flow and due to the mechanical function of the Cardiac and Vascular structure. Which provides valuable information about the functioning of Heart and Heart Valves. S1-1st HS, S2-2nd HS, and murmurs are the Heart Sounds of normal and abnormal conditions.

The Lung Sounds or Breath Sounds are generated due to the mechanical function of the lungs and due to the breathing process. The Lung Sound includes Vesicular, Tracheal and Bronchial are the common breath sounds. And crackles (rales), wheezes (rhonchi), stridor, pleural rub are the adventitious lung sounds.

The clinical condition of the Heart and the Lungs causes changes in the acoustic characteristic of the Heart and the Lung sounds. These acoustic characteristics are fundamental frequency, Amplitude, S1-S2 and Inspiration-Expiration duration and intervals. These characteristics are used as features to distinguish between the normal and pathological condition of the Heart and the Lungs using various classification methods. Recorded heart and lung sounds are used for further analysis.

II. GENERAL BLOCK DIAGRAM

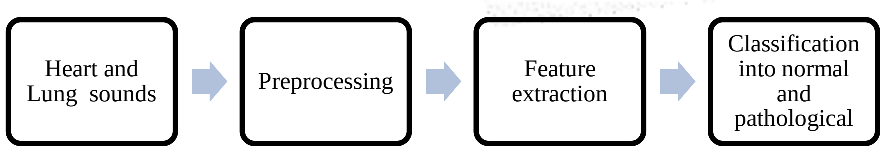

fig. 1 block diagram

The figure shows the general block diagram for the feature extraction and classification of the cardiac and the pulmonary sounds into normal and pathological. The input signal of Heart and the Lung sound is recorded from the front chest area and from the back area. The input signal is pre-processed and the features are extracted using various methods such as FFT Analysis, Discrete Wavelet Transform, Hilbert Transfer and MFCC methods. These extracted features are used in the classification of the Heart and the Lung Sounds. The different types of classifiers are Support Vector Machine, Kth Nearest Network, Back-Propagation Network, Radial Basis Function etc.

III. METHODS FOR FEATURE EXTRACTION

Methods used for the Feature Extraction of Heart and Lung Sounds are:

A. Fast Fourier Transform (FFT)

Fast Fourier Transform (FFT) characterizes the time-frequency property of each segment. It Samples the input signal over a period of time (or space) and then divides it into fundamental frequency components. The fundamental frequency has a single sinusoidal oscillation at distinct frequencies with its own Phase and Amplitude. The FFT Analysis is performed by below equation:

$$x_i = \sum_{n=0}^{N-1} x_n \, e^{-k2\pi in/N}$$

$$i = 0, 1, \ldots, N-1. \qquad (1)$$

here, x_n is the signal, x_k is the transformed signal, i is the number of samples and N is the length of the window. By using FFT, fundamental frequency and magnitude of the signal can be obtained. FFT on systolic signals is used to get the spectral parameters such as mean frequency, and peak value [1].

B. Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) was a time-scale approach to analyse the non-stationary signal. DWT yields a feature vector with high dimensional which increases classifier's learning parameters [2].

Filter output of high pass is beginning with DWT wavelet coefficients. which are connected with all discrete wavelets at the smallest single scale. Filter output of Low Pass is a set of coefficients of DWT. Which is associated with a set of pair functions (Scaling factor) which captures energy of all waveforms with lower frequency [2]. DFT of signal x(t) is given by the following equation:

$$X(t) = \sum_{m \in z} u_{j_0,m} \, \phi_{j_0,m}(t) + \sum_{j=-\infty}^{J_0} \sum_{m \in z} w_{j,m} \, \psi_{J,m}(t) \qquad (2)$$

Here, $w_{j,m}$ are wavelet coefficients and $u_{j_0,m}$ ($j < j_0$) are scaling coefficients. $\phi_{j_0,m}$ is Scaling function and $\psi_{J,m}$ is shifted or dilated wavelet function.

C. Hilbert Transfer

The PCG Features are extracted from the envelope of Hilbert Transfer's envelope by relocating boundaries from segmented envelope of energy [3]. The energy of Signal obtained by calculating each segment energy from windows with 0.01 sec time using the equation:

$$E_s(i) = \sum_{(i-1)\,X\,(Sw+1)}^{(i\,X\,Sw)} X^2(j)$$

$$i = 0, 1, 2, 3, \ldots, Ne. \qquad (3)$$

here, X(j) is the original signal, $E_s(i)$ is the energy of i^{th} segment, and S_w is segment length. Ne is calculated by:

$$Ne = \frac{N}{0.01\,x\,fs + 1} \qquad (4)$$

where sampling frequency fs and Number of Samples N. Energy envelop is accurately identifies the peak of S1, S2 [8]. For detection of other features such as S3, S4 and the split. For these Hilbert Transfer is used [3].

$$H(x(t)) = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{x(\tau)}{t-\tau}\,d\tau \tag{5}$$

$$Z(x) = x(t) + H(x(t)) \tag{6}$$

Here, H(x(t)) – signal derived from Hilbert transfer, Z(x) - envelope.

H(x(t)) equation is used to find zero slope points from Envelop of Hilbert Transfer and relocates the position of start and end, (i) smoothed the *Z(x)* envelop, (ii) the *S(k)* dataset of the signal values at the i starting (or ending) is located from energy segmentation, (iii) the Differential Data *D(x)* is calculated.

To detect an S1 peak, find a 2nd highest peak to left and right is detected. The location of that peak is used to calculate time (similar to S2 peak). To determine M1 and T1: M1 on left and T1 on right and for delay time the 1st split of M1, T1 (similar to A2, P2 and 2nd split).

To derive S3, S3 appears in 0.12 - 0.18 sec after S2 and lasts between 0.03 – 0.8 sec. to detect S3 find peaks at the 0.12 - 0.18 sec after S2 from zero slopes of the envelope and by locate starting – ending of S3. For S4, S4 appear in 0.07 – 0.1 sec before S1 and duration is 0.06 – 0.16 sec [3].

D. Mel-Freq cepstral coefficients (MFCC)

The Cepstrum coefficients are based on the Mel criteria and it is derived from the human auditory perception properties and the intelligibility of speech. The human auditory system is function a way that its frequency of perception is different from the original sound frequencies [4]. The sound signal spectrum (heart or Lung) can be considered regarding terms of signal correlation with tones of harmonic with regularly spaced peaks [5]. MFCC represents the information of spectral in a sound signal. To obtain MFCC,

(i) Take window with N samples.
(ii) Calculate amplitude spectrum of each window.
(iii) Convert to Mel Scale (filtering). (human hearing)
(iv) Take the log of amplitude spectrum.
(v) Apply Discrete Cosine Transform.

A single Mel is perceived from measure of the pitch. it doesn't depend linearly on the frequency step. the human ear functions as in this frequency it does not perceived as the same physical size. Below formula shows the relationship between the frequencies.

$$Fmel = 2595\ log10\ (\ 1\ + \frac{Fhz}{700}) \tag{7}$$

From MFCC features such as zero crossing overall standard deviation, MFCC overall standard deviation, zero crossing overall average, and MFCC overall average are calculated. The filter is applied using F_{mel} equation. After filtering the signal spectrum, the filter output is calculated. For feature extraction of the heart sound (Lung sound) [4].

table 1 comparison of feature extraction methods.

	Algorithm	Accuracy
1	Fast Fourier Transform	90.8 %
2	Discrete Wavelet Transform	91 %
3	Hilbert Transfer	92 %

4	Mel – Freq cepstral coefficients	95 %

CLASSIFICATION METHODS

For the classification of Heart and Lung sounds into normal and pathological various classification methods are used.

A. BPN – Back Propagation Network, a Feed-Forward Network with 3 - layers, Input layer, Hidden layer and Output layer. To reduce the complexity of the problem a number of hidden layers are used. The modification of back-propagated signals is the derivative of transfer function with relative connection weights are used and Delta Rule is used to adjust weights [6].

The MSE with minimum value between desired Output and Actual output is calculated. gradient descent algorithm is used for error minimization. For the classification of three classes of diseases due to similar properties of biological neuron a sigmoid function is used. for each disease a state numerical code is assigned.

B. RBF – Radial Basis Function, a 3-layered network with Input layer, Output layer, and Hidden layer in which each Hidden unit implements radial activated function in hidden layer. RBF function have lower accuracy and shorter computational time compared to Feed-Forward Networks. The gradient descent algorithm is used to minimize error arises between desired and target output. RBF networks are also used as an activation functions in ANN and for approximation of function, prediction of time series, classification, and system controlling [6].

Venkatesan et al. explains the j^{th} hidden units of response are represented as: where Φ - strictly positive, symmetrical function and maxima with unique value around centre area, μj, σj^2 are the receptive fields width. The Wavelet transform is used for prepossessing and features with independent characteristics are extracted from PCG signals.

Features are applied to Inputs of 2 - Neural Networks. Then Networks are tested after training using Data samples with more than two types of diseases. Performance of RBF networks is higher than traditional BPN Networks, with 98% and 90.8% accuracy Respectively [6].

Based on time-frequency analysis, Boutana et al. [2010] presents one method. Which perform segmentation and identification of normal and pathological condition of PCG sounds. It classifies the abnormal murmur caused by other heart related diseases such as Aortic and Pulmonary stenosis, and Mitral regurgitation. For these components of HS (s1 and s2) and the features of clinical murmur were extracted.

For these appropriate threshold is set to determine the boundary between signal events from upper bound of the entropy. These methods were applied to the PCG signals and the speech signal and it is helpful especially for the case of clinical condition of HS with Murmurs.

C. KNN - K-Nearest Neighbour's Network, the rule is an old and simple pattern classification method which produces good results. Most KNN classifiers by default uses Euclidean distances for measurement of dissimilarities. Euclidean distance metrics doesn't capitalize on statistical data regularity which is Estimated from a large labelled examples training sets. Ideally, KNN classifications distance metric must adapt for problem solving. KNN classification is enhanced by Learning of distance metric from example with labels. An input features with linear transformation produces much better KNN classifiers [6].

D. SVMs – Support Vector Machine, is a machine learning Algorithm. Which is used for classification of binary problems [4]. SVM Algorithm classifies in to two categories by deciding a centre passed hyperplane through the closest samples from each class, known as Support Vectors.

$$f(x) = \omega^T \phi(x) + c \quad (1)$$

(8)

The Training data is given as $S = \{X_i, Y_i\}$, i = 1, 2 …, n; $Xi \in R^d$ where i - index number, d - dimension, and $Yi \in \{-1,1\}$ - label of each sample. which determines the separating hyperplane $f(x)$ of optimal class defined as follows: Where ω and c is the normal vector which separates the bias and the hyperplane, Respectively.

If $\phi(x)$ is the transformation from the input space to feature space, then hyperplanes which solved the optimization problem is given as follows:

$$\min\|\omega\|^2 + b \ \sum_{i=1}^{n} \xi_j \quad (2)$$

(9)

$$y_j\left[\omega^T \phi(x_j) + b\right] \geq 1 - \xi_j \text{ and } \xi_j \geq 0 \text{ , j=1,2 …, n}$$

Here, trade-off parameter b (between margin size) and error ξ_j, j=1,2 …, n. Slack factors characterized to unwind the requirements of the distinguishable information issue. Equation (9) minimizes the error cost of optimization problem and maximizes the margin of hyperplane. During Testing, $f(x)$ function sign is given in equation (10) which is determined from SVM algorithm and classify test data into classes.

$$f(x) = sign\,[\sum_{1}^{N_s} \alpha_i y_i \phi(s_i)^T \phi(x) + c] \tag{10}$$

$$= sign\,[\sum_{1}^{N_s} \alpha_i y_i K(Si, x) + c] \tag{11}$$

Where, support vector s_i, total number of support vectors N_s. transformation K transforms the data into Euclidean spaces, which is defined as follows:

$$k(x_i, x_j) = \phi(x_i)^T \phi(x_j) \tag{12}$$

$k(x_i, x_j) = e^{-\gamma\|x_i - x_j\|^2}$ is Gauss kernel function. Here γ is the free parameter of Gaussian kernel function, is the bandwidth (variance) of the Gaussian function.

table 2 comparison of classification methods.

Classifier	Accuracy (%)	Classification Category
BPN	90.08	2 or more
RBF	98	2 or more
KNN	78	2 or more
SVM	85	2

CONCLUSION

In this Review, Various methods for feature extraction including Fast Fourier Transform, Discrete Wavelet Transform, Hilbert Transfer, and Mel-Frequency Cepstral Coefficients Method with their accuracy and response time have been reviewed. and Different classifiers including Back-Propagation network, Radial Basis Function, Kth Nearest Network, and Support Vector Machine classifier have been reviewed along with their advantages.

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