Wavelet Packet VS Backpropagation for localization and Classification PCG Signals

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Abstract: Phonocardiography signals (PCG) show the enrolment of sounds and distortions generated from cardiac auscultation. Cardiac signal analysis is crucial for the diagnosis of various diseases. In previous years, there are several groups and different techniques, freshness, and methods have been proposed to analyze the cardiac signal. Auscultation is a manner in which a stethoscope is used to hearken to the cardiac sound. Structural trouble of the heart is often reflected in the cardiac sound created and Listening to the heart’s sound helped doctors diagnose and predict diseases. Whilst a cardiac sound examine via Listening is appropriate as a scientific tool, it is tough to analysis PCG signals in the time(T) or frequency(F) scale. The PCG signals have many benefits over conventional Listening, in that they may be rebuilt and analyzed for time(T) and frequency(F) information. Using a wavelet packet transform(WPT). Where the signal is decomposed and rebuild without the first-rate loss of data within the signal content. Reconstruction mistakes can be thoughtfulness an important piece of information in classifying the pathological severity of phonocardiography signals. In this paper we will focus on how to choose the level and the mother wave of the wave to cry out so that it is appropriate to analyze the cardiac signal in good mathematical and analytical ways to train the neural network (error backpropagation) on it. It will be explained in the following details.

Keywords: Phonocardiography, Cardiac Auscultation, WPT, Decomposed, Reconstruction, Backpropagation.

1. Introduction
Heart sounds are loud because of the blocking off valves and blood flow through it. Especially, the sounds mirror the disturbances that stand up in the heart valves if they are all of sudden closed. Your doctor may generally use stethoscopes to pay attention to these particular sounds that provide essential auditory and information related to a heart condition. When listening to the heart using a stethoscope, the examiner does not hear the valves open because it is a relatively slow process and does not cause any noise in the normal state. However, when the valves are closed, their leaves and surrounding fluid vibrate under the influence of the following pressure differences, causing a sound to travel in all directions through the chest wall. When the ventricles contract, the examiner first hears a sound that results from the tricuspid valve closing and Mitral valve it is a relatively low and melodic vibration known as the first heart sound. It is a sound (lub) the first natural heart sounds (lub-dub). When the pulmonary valve and the aorta valve close at the end of the systole, a relatively rapid shelling is heard because these valves close quickly and vibrate the surrounding structures for a short time and this sound is called the sound of the second heart component of the (dub), and it is the second (lub-dub) [1 - 4].
A cardiac signal is an unstable signal, as it means that applying the methods of analysis directly to this signal is not efficient in practice [5]. Previous studies used methods of analysis in the time and frequency domain also these works were done in a way to classify normal and abnormal heart signals that are subject to ambiguity without entering into the cumbersome process of dividing the basic heart sounds using an electrocardiogram [6].

This research provides a special study in the analysis of the cardiac signal, where a complex method will be used to determine and classify the sounds of the heart, one of the mission methods will be used in the analysis, namely, the wavelet packet and in the classification, and artificial intelligence will be used. The method of analysis, wavelet packet and artificial intelligence will be used with a special technique whose details will be mentioned later. In the method of analysis (wavelet packet), the challenge will be how to choose the level decomposition and choose the mother wavelet. These two challenges are very important in determining the accuracy of the work and the accuracy of the choice of the frequencies that are within the frequency of the heart’s sound recovery. In this paper, specifically in the election of the mother wavelet and the level decomposition, mathematical and numerical calculations were used depending on the error ratio between the types of mother wavelet. In this paper, explains the set of data used in this research work, as well as methods of analysis and Categorization.

2. DATA USED AND METHOD

2.1. Data used
A collection of available data to the public from accredited universities and will be used in this work dataset in [7] (Heart Sound and Murmur Library). The data set is divided into four sections. The first set of data is taken from Apex Area - Supine, hearing with the bell of stethoscope, the second group is taken from Apex Area - Left Decubitus, hearing with the bell of the stethoscope. The third group is taken from Aortic Area - Sitting, hearing with the bell of the stethoscope, and the fourth group is taken from Pulmonic Area - Supine, hearing with the diaphragm of a stethoscope. Maximum duration for the sample is around 1:15 second and minimum duration is 1:00 second. Figure 1 shows two cases of PCG signals (normal and abnormal).

![Figure 1](image-url)
2.2. general structure
The general basic form of the working method is shown in the drawing of Figure 2. Initially, the sound of the heart signal is taken and analyzed by MATLAB using Wavelet packet. The analysis process of energy for the third level is calculated for each part. Then, artificial intelligence is used to train on the energy values, for each pathology has its own energy values, in the end eight energy values are extracted from the heart sound signal (four values for details and four for approximate). On this basis, the diagnosis of referrals is made and more details on these methods used in the following subsections.

3. PCG Decomposition VS Wavelet packet
The PCG signal passes through a set of filters at each level of analysis. In each level of analysis, there are filters for extracting high frequencies from the PCG signal (detail coefficient) and filters for extracting low frequencies from the PCG signal (approximate coefficient). In the third level of analysis, we have eight sub-signals generated according to the frequencies arising from them. The entropy for these signals is calculated and used as a basis for identifying diseases in this work. Frequency BW for PCG signals between (0-500) Hz [8]. Fig (4) shows approximate and details parameters taken away from a PCG fragment of "09 Apex, Holo Sys Mur, Supine, Bell".

Figure 2. Diagram for PCG signal and analysis process
Figure 3. PCG signal analysis at 3-level

Figure 4. Coefficients of Approximate and Detail a PCG Segment.
4. Entropy

It can be carried out to gauge the difficulty and harmony of time chain data. Shannon entropy is used in this work [9]. Given time chain info X=[x1, x2… xN], entropy worth can get employ the following expression [10] [11]:

$$H = \sum_{n=0}^{m} H \log_2 p(n) \quad \ldots (1)$$

Energy is calculated for third-level coefficients, where it is through the calculated energy that diseases are distinguished by artificial intelligence.

5. Selective of Mother Wavelet Function

This section discusses the selection of optimal mother wavelets. The choice is based on the likeness between the main signal and the resulted signal of analysis after rebuilding. The selection is based on the least difference between the two signals[9] [12]. It depends on taking five cycles from the heart sound signal and analyzed by WPT, after analysis the signal will be rebuilding. The rebuilding signal has the same number of samples in the main signal with different amplitude values as shown in Fig. (5). The choice of optimal mother wavelet depends on the difference between the amplitude sample in the main signal compared with its corresponding amplitude sample in the rebuilding signal as shown in the follows criterion:

$$s = \sum_{i=0}^{n} (X_i - R_i) \quad \ldots (2)$$

Where: n = number of samples, Xi samples from main signal, Ri sample of rebuilding signal, and s is the summation of different.

![Figure 5. Samples of main signal and rebuilding signal](image)

Table 1. The lower Entropy values of S that will be based in choice of mother wavelet for several normal and abnormal states

| Class | dx1 | dx2 | dx3 | dx4 | dx5 | dx6 | dx7 | dx8 | dy1 | dy2 | dy3 | dy4 | dy5 |
|-------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 01    | 1.48E-12 | 1.47E-12 | 1.01E-12 | 1.03E-12 | 7.49E-14 | 1.49E-12 | 1.48E-12 | 1.48E-12 | 3.15E-12 | 3.49E-12 | 3.15E-12 | 3.49E-12 | 3.15E-12 |
| 02    | 1.17E-12 | 1.18E-12 | 1.08E-12 | 1.09E-12 | 6.20E-12 | 1.33E-12 | 1.35E-12 | 1.37E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 |
| 03    | 1.10E-12 | 1.10E-12 | 1.08E-12 | 1.08E-12 | 6.20E-12 | 1.33E-12 | 1.35E-12 | 1.37E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 |
| 04    | 1.15E-12 | 1.10E-12 | 1.08E-12 | 1.08E-12 | 6.20E-12 | 1.33E-12 | 1.35E-12 | 1.37E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 |
| 05    | 1.10E-12 | 1.10E-12 | 1.08E-12 | 1.08E-12 | 6.20E-12 | 1.33E-12 | 1.35E-12 | 1.37E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 |
| 06    | 0.97E-12 | 1.00E-12 | 1.00E-12 | 1.00E-12 | 6.20E-12 | 1.33E-12 | 1.35E-12 | 1.37E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 |
| 07    | 1.22E-12 | 1.41E-12 | 1.22E-12 | 1.22E-12 | 6.20E-12 | 1.33E-12 | 1.35E-12 | 1.37E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 |
| 08    | 1.10E-12 | 1.10E-12 | 1.08E-12 | 1.08E-12 | 6.20E-12 | 1.33E-12 | 1.35E-12 | 1.37E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 |
| 09    | 1.00E-12 | 1.10E-12 | 1.10E-12 | 1.10E-12 | 6.20E-12 | 1.33E-12 | 1.35E-12 | 1.37E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 |
| 10    | 1.10E-12 | 1.10E-12 | 1.10E-12 | 1.10E-12 | 6.20E-12 | 1.33E-12 | 1.35E-12 | 1.37E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 |
| 11    | 1.10E-12 | 1.10E-12 | 1.10E-12 | 1.10E-12 | 6.20E-12 | 1.33E-12 | 1.35E-12 | 1.37E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 |
| 12    | 1.10E-12 | 1.10E-12 | 1.10E-12 | 1.10E-12 | 6.20E-12 | 1.33E-12 | 1.35E-12 | 1.37E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 |
| 13    | 1.10E-12 | 1.10E-12 | 1.10E-12 | 1.10E-12 | 6.20E-12 | 1.33E-12 | 1.35E-12 | 1.37E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 |
| 14    | 1.10E-12 | 1.10E-12 | 1.10E-12 | 1.10E-12 | 6.20E-12 | 1.33E-12 | 1.35E-12 | 1.37E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 | 2.60E-12 | 2.64E-12 |
Through the Table 1 above, a 'db4' mother wavelet will be selected as is shown in Fig. (6), because it has the lowest error value (S).

Our symbol for the sick cases, all the sick cases are in [7] (Heart Sound and Murmur Library).

Figure 6. (a) db4 scaling signal and (b) db4 wavelet signal

6. Selective Level of Decomposition

It is possible to define optimum level resolution as minimum level where the decomposed signal can be reconstructed to its original while maintaining the entire information signal [9]. The traditional entropy (WL energy) meets these requirements and describes information about its characterized by a precise indication of particular signal energy. It’s concept is found in many fields, mainly in signal processing [13].

The entropy (E) for E(0) = 0 and for E(S) = \sum_i E(S_i), where S = original signal S_i = coefficients of S, i is number of coefficients. There are four types of entropy criterion [10]:

1. The non-normalized Shannon entropy.
   \[ E(S) = - \sum_i E_i^2 \log(S_i^2) \]  
   …. (3)

2. The concentration in Ip norm entropy with P \geq 1
   \[ E(S) = \sum_i |S_i|^p \]  
   …. (4)

3. The logarithm of entropy
   \[ E(S) = \sum_i \log(S_i^2) \]  
   …. (5)

4. The threshold entropy
   \[ E(S) = \begin{cases} 
   1 & \text{if } S_i > E_t; E_t = \text{threshold} \\
   0 & \text{else where} 
   \end{cases} \]  
   …. (6)

In this research, the entropy was found by the non-normalized Shannon entropy criterion siren by Eq. (3) with mother wavelet function 'db4'.

To find the selective level of decomposition, the entropy value of apparent sub-space with entropy value of children sub-space are compared using relationship [14].
The values of entropy for each sub-space in WPT tree are shown in Fig. (7) For healthy case.

\[ E(s)_j \geq E(s)_{j-1} \] .... (7)

After calculating the entropy in each bath, we note that the entropy in the children (the 3-level depth (3, 1) node (001)) is greater than the entropy in the parents (2-level depth (2, 0) node (00)). When the energy at the level of the child is greater than the energy at the level of the parents we stop, the (3-level) is chosen as the best decomposition level.

7. Categorization by artificial intelligence

In the Categorization, an error backpropagation is used; in this paper we will use [15] and [16]:

1. A classification of four cases, one normal and three abnormal
2. Input layer we use \( x_1 \) and \( x_2 \)
   - Iteration of \( x_1 \) is approximation coefficient (A3, A4, A5, A6) while iteration in \( x_2 \) detail coefficients (D3, D4, D5, D6).
3. Error 1% for the error backpropagation.

The first case will be trained on one number, where one number will be represented in neural as a binary number 4 bits (0001). The second case is trained on number two, where number two will be represented in the neural as a binary number of (0010), third case as a binary of (0011), and fourth case as a binary of (0100)

A. First case \( \Rightarrow \) target output is 0001.
B. Second case \( \Rightarrow \) target output is 0010.
C. Third case \( \Rightarrow \) target output is 0011.
D. Fourth case \( \Rightarrow \) target output is 0100.

\[ \text{Network Architecture:} \]

\[ \text{Figure 8. Network Architecture} \]
**Backpropagation Algorithm**

i. The method calculates the gradient of a loss characteristic with respect to all of the weights in the network [17] and [18].

ii. Backpropagation requires a known, preferred output for every input value in order to calculate the loss feature gradient.

The following steps are the recursive definition of set of rules step:-

1. Randomly pick out the preliminary weights.
2. For each education pattern observe the inputs to the network.
3. Calculate the output for each neuron from the enter layer, via the hidden layer (s) to the output layer.
4. Calculate the error output:

   - Use the output errors to compute mistakes indicators for pre-output layers.

**Forward vs. backward passes**

When the learning stage begins, there are two directions (front and back). [19].

8. **OUTCOME AND DISCUSSION**

Various parameters are used to assess the categorization performance of the suggested method such as Total-Sum-Squared-Error (TSSE) and Root-Mean-Squared-Error (RMSE). These parameters are obtained using

The following formulas [20 – 22]:

- **Total-Sum-Squared-Error (TSSE)**

\[
TSSE = \frac{1}{2} \sum_{\text{patterns}} \sum_{\text{outputs}} (\text{desired} - \text{actual})^2 
\]

- **RootMeanSquaredError (RMSE)**

\[
RMSE = \sqrt{\frac{2 * TSSE}{# \text{patterns} * # \text{outputs}}} 
\]

Where #patterns = no. of .input and #output = no. of .output.

In this paper, four classification diseases were taken. Initially the neural network is trained in these pathological conditions and then we calculate TSSE and RMSE as shown in Table 2 below:

| Case | Target output | Actual output | TSSE | RMSE |
|------|---------------|---------------|------|------|
| 01 Appet. Normal 51 SE, Supine, Glut | 0 0 1 | 0.00 0.00 0.89 | 0.02% 0.02% | 0.00% 0.00% |
| 02 Appet. Nat Syr Oral, Supine, Glut | 0 1 0 | 0.00 0.00 0.89 | 0.02% 0.02% | 0.00% 0.00% |
| 03 Appet. 52, Glut | 0 0 1 | 0.00 0.00 0.89 | 0.02% 0.02% | 0.00% 0.00% |
| 04 Appet. 54 & Mod Sys Mex, U1O, Glut | 0 0 0 | 0.00 0.00 0.89 | 0.02% 0.02% | 0.00% 0.00% |

![Diagram](image)
Best validation performance is $1.0491 \times 10^{-14}$ at epoch 5; we can show Performance the error backpropagation through the following figures:

![performance](image1)

**Figure 9.** Performance of the error backpropagation: (a) performance, (b) Test training, (c) Regression.

9. **Conclusions and future work**

In this paper, a new method has been presented for PCG diagnosis by using wavelet packet transforms (WPT), Shannon, Entropy and Error Backpropagation. We have a challenge. If we solve something in artificial intelligence, we must show that it is not solved through conventional techniques. Artificial intelligence is faster than conventional techniques. The suggested procedure achieved perfect Error 1% for the Error Backpropagation estimated. By the general public PCG dataset provided by means of Heart Sound and Murmur Library, in the resulting sketch, overall performance represent decay in mistakes and regression show schooling test. The destiny works contain experimentation the suggested manner the usage of a larger and greater thorough database adaptive gaining knowledge of will even be precise to boost system execution over time.

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