Detection, Isolation, and Diagnosis of PCG Diseases

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Abstract. The phonocardiography signal (PCG) is an important part of reflecting the activities and activities of the main valves in the heart (Aortic valve, Pulmonic valve, Tricuspid valve, and Mitral valve). Where the heart is considered to be in mechanically part movement and as a result of blood flow through the valves with also the blockage and opening of the valves produce the sound of the heart (PCG). The doctor listens to this sound of PCG through a stethoscope and the diagnosis is made clinically, then the patient is referred to an echocardiogram to confirm the activities of the heart valves. The signals of PCG are analysed by passing through multi-resolution analysis (MRS) in the wavelet packet tree. The extracted information from WPT-Tree at the third level of decomposition is a tool for analysis. Finally, entropy value was calculated at a third level decomposition and diagnosis by the artificial neural network. The important advance that used max bit rate of 200 KHz and 24-bit resolution. In addition to the diagnosis of ten disease cases, work was done to diagnose heart disease in an normal and abnormal state. Where the maximum frequency rate is 94 KHz and is used multi tools and multi algorithms for analysis and classification.

Key words: PCG, multi-resolution analysis, WPT, disease detection.

1. Introduction

Heart sounds are repeated during a certain period of time. During each time cycle, heart activity is shown; this activity includes contraction of the heart muscle, internal coverage, blood flow and opening and closing of the heart valves [1]. Closing and opening of the valves generates vibrations, these vibrations spread through the tissue to the chest cage, where it is measured in the form of sound. The sound generated is the result of vibrations: Heart sounds are divided into four main sections such as first heart sound (S1), second heart sound (S2), third heart sound (S3) and fourth heart sound (S4). Each sound has its own characteristics [2], [3], and it varies from one voice to another as in table (1), that is shown the most important differences.
Table 1. Frequency and duration of PCG components

| No. | Type            | Duration(s) | Frequency(Hz) |
|-----|-----------------|-------------|---------------|
| 1   | First sound(S1) | 0.12-0.15   | 10-200        |
| 2   | Second sound(S2)| 0.08-0.12   | 20-250        |
| 3   | Third sound(S3) | 0.04        | 25-70         |
| 4   | Fourth sound(S4)| 0.02        | 15-70         |

2. Execution of Wavelet Packet Transform (WPT)

WPT is a technique that is used to extract features from current signals in a certain number of levels by decomposition using mother wavelet function. Both time and frequency domain analysis are used when WPT is adopted [4], [5]. That means, the localization is at all frequencies in time term after setting upscale of signal to extract required features. WPT tree is divided into a high pass filter (HPF) and a low pass filter (LPF). HPF coefficients [d's] contain high-frequency information and LPF coefficients [a's] contain low-frequency information. A current signature can be obtained when these signals are decomposed to a certain level [5] [6]. The best level of decomposition is the third level, therefore eight coefficients will be obtained; four with low-frequency a3, a4, a5 and a6 and four with the high-frequency d3, d4, d5 and d6. Samples of these coefficients are drawn in Figure 1, for normal and Figure 2 for abnormal of PCG signals [7], [8].

Figure 1. Data-set (B) the third level WPT-coefficients for healthy condition (a3, d3, a4, d4, a5, d5, a6 and d6)
Figure 2. Data-set (B) the third level WPT-coefficients for Abnormal (VSD) condition (a3, d3, a4, d4, a5, d5, a6 and d6)

3. Evaluation of Wavelet Energy
A non-normalized Shannon entropy criterion is shown by equation (1) that is used to calculate the wavelet energy in the third level coefficients. The values of the energy in Shannon entropy are proposed to detect and diagnose disease. Table (2) displays these energy values for coefficients at the third level of decomposition of the PCG disease cases studied data-set (B) with sample frequency of 44.1 kHz [9] [10]

$$E(S) = -\sum E_i^2 \log(S_i^2)$$

Table 2. Data-set (B), the energy values for varies Disease [11]

| Disease                  | a3     | d3     | a4     | d4     | a5     | d5     | a6     | d6     |
|--------------------------|--------|--------|--------|--------|--------|--------|--------|--------|
| Normal Heart             | -299.515 | 13.43586 | 4.373019 | 0.249819 | 1.370159 | 0.092617 | 0.04437 | 0.035248 |
| Normal Split             | 96.36743 | 8.055585 | 2.54079 | 0.096036 | 0.776702 | 0.04139 | 0.02312 | 0.019301 |
| ASD                      | 86.49956 | 11.0239 | 3.373313 | 0.688057 | 0.99575 | 0.196613 | 0.1167 | 0.099357 |
| Diastolic Aortic Insufficiency | 121.3545 | 34.34192 | 11.15923 | 3.342415 | 3.446166 | 1.139335 | 0.461506 | 0.381083 |
| Condition                          | Value    | Value    | Value    | Value    | Value    | Value    | Value    | Value    |
|-----------------------------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Diastolic Aortic Regurgitation    | 80.09416 | 37.01534 | 9.921127 | 6.359968 | 2.954792 | 1.836277 | 0.421705 | 0.469512 |
| Diastolic Mitral Stenosis         | 64.3746  | 7.586898 | 2.298345 | 0.627427 | 0.68971  | 0.252658 | 0.229101 | 0.198743 |
| Diastolic Physiologic S2 Split    | 93.20585 | 3.054629 | 0.932072 | 0.094571 | 0.34431  | 0.104476 | 0.049256 | 0.078116 |
| Diastolic Pulmonic Regurgitation  | 79.28687 | 17.6908  | 5.379092 | 1.589403 | 1.624518 | 0.498225 | 0.209033 | 0.170195 |
| Diastolic Rumble                  | -188.617 | 23.66612 | 7.672294 | 0.210798 | 2.363986 | 0.077105 | 0.038397 | 0.028263 |
| Diastolic Severe Aortic Regurgitation | 126.5191 | 35.32495 | 12.05979 | 2.623118 | 3.86735  | 0.782178 | 0.223113 | 0.111561 |
| Diastolic Tricuspid Stenosis      | 73.4196  | 5.251418 | 1.62445  | 0.359161 | 0.490745 | 0.104834 | 0.042079 | 0.042139 |
| early systolic                    | -325.132 | 17.07471 | 5.476118 | 0.348467 | 1.70077  | 0.122505 | 0.055413 | 0.038291 |
| Ejection Click                    | -115.965 | 12.51097 | 4.003508 | 0.237087 | 1.250321 | 0.08691  | 0.041597 | 0.030094 |
| Late Systolic                     | -163.859 | 16.65779 | 5.341319 | 0.41784  | 1.647196 | 0.143224 | 0.062432 | 0.039237 |
| opening snap                      | -216.714 | 19.76894 | 6.639622 | 0.577943 | 2.12691  | 0.190284 | 0.072573 | 0.037567 |
| pansystolic                       | -148.967 | 19.37936 | 6.09211  | 0.55917  | 1.849638 | 0.175971 | 0.064267 | 0.037036 |
| S3                                | 97.03198 | 9.932383 | 3.146938 | 0.117828 | 0.963166 | 0.046098 | 0.024598 | 0.020602 |
| S4                                | -326.191 | 13.99832 | 4.56439  | 0.166126 | 1.423403 | 0.067886 | 0.041273 | 0.036062 |
| Systolic Aortic Stenosis #3       | 85.60449 | 16.16333 | 4.916208 | 1.359021 | 1.482625 | 0.438177 | 0.281066 | 0.235284 |
| Systolic Mitral Regurg.           | 55.14457 | 21.99591 | 6.517548 | 2.198323 | 3.271165 | 1.056063 | 0.386049 | 0.260188 |
| Systolic Pulmonary Stenosis       | 126.2608 | 35.87278 | 11.70722 | 2.930314 | 3.718157 | 0.907173 | 0.298468 | 0.246985 |
| Tricuspid Regurgitation           | 42.95088 | 1.36922  | 0.457494 | 0.203831 | 0          | 0          | 0          | 0          |
| VSD                               | 199.0148 | 43.99528 | 14.51542 | 3.014519 | 4.565794 | 0.903669 | 0.269954 | 0.170543 |
4. The Proposed Algorithm for Disease Detection
The proposed algorithm for disease detection is presented and mainly based on calculation of entropy values for WPT-coefficients in the third level. Energy values in the third level consist of eight values such as (a3, d3, a4, d4, a5, d5, a6, and d6) as shown in Table (1). We performed regression to find out the extent of the energy values at change in the third level for each pathological case from the database (B). Concerning on the basis of regression, it will be a suggestion of a method for classification and also know which of the high or low frequencies will be directly affected by the change of the pathological condition, until it is approved. A mathematical process was adopted to find out the change due to the difficulty of observing the change through the values as in the Table (1) and Table (1) by the naked eye. It can be concluded that the difference between the entropy values of different disease types can be used to diagnose diseases.

5. Regression of Third Level Decomposition
Through the following forms and regression, relationships are shown by Figures 3 to 10 respectively and for data-set (B) as it is difficult to distinguish from one condition to another through entropy values. It is very difficult to devise an algorithm to distinguish between conditions. As there is a strong overlap between energy values from one disease to another, so AI has been used to distinguish diseases.

5.1 Data-set (B):

![Figure 3. a3 distribution: (a) column type, (b) bubble type](image-url)
Figure 4. $d_3$ distribution: (a) column type, (b) bubble type

Figure 5. $a_4$ distribution: (a) column type, (b) bubble type

Figure 6. $d_4$ distribution: (a) column type, (b) bubble type
Figure 7. $a_5$ distribution: (a) column type, (b) bubble type

Figure 8. $d_5$ distribution: (a) column type, (b) bubble type

Figure 9. $a_6$ distribution: (a) column type, (b) bubble type
6. The Proposed Algorithm for Disease Diagnosis

The diagnosis of disease type is very important in diagnostic. It gives preformation before the diagnostic process as shown by Figure 11 and Figure 12 in this section with a proposed algorithm. Also, this algorithm depends on entropy values but these values are calculated for five seconds duration.

![Figure 10. d6 distribution: (a) column type, (b) bubble type](image)

**Figure 10.** d6 distribution: (a) column type, (b) bubble type

| STEP 1  | Start                   |
|---------|-------------------------|
| STEP 2  | Read 5 second from S[n] signal |
| STEP 3  | Decomposition S[n] by WPT with "Haar" as mother WT an third level resolution . |
| STEP 4  | Calculate the entropies value for [a3, d3, a4, d4, a5, d5, a6 and d6] coefficients E[s] in third level in WP tree by non-normalize shannon entropy. |
| STEP 5  | Enter values of entropy [a3, d3, a4, d4, a5, d5, a6 and d6] into the neural network |
| STEP 6  | Classification         |

**Figure 11.** Block diagram for diagnosis type of disease.
Figure 12. Block diagram details for diagnosis type of disease

7. Experimental Realization of the Proposed PCG Disease Diagnosis Algorithm Based on WL Energy Approach
In the previous sections, the application of the proposed disease algorithm is presented on the PCG diseases theoretically. Through the results which have been obtained by applying this theory, the proposed algorithm has proved with high reliability, more accurate, and high speed to detect PCG disease and isolate abnormal cases from normal cases. In this section, the practical implementation of the same previous algorithm was implemented. It is used to detect and diagnose valve disease. This section is divided into two parts, setup of experimental hardware which includes a stethoscope, sound sensor, data acquisition, and PC. The second part of the software system includes LabVIEW. The software part of the experiment includes the application of the proposed algorithm and makes a decision.

7.1 Hardware Design
In the hardware part, stethoscope and planting neck mic were used inside the stethoscope and finally connect wire neck mic to the PC as in Figure 13.

Figure 13. Block diagram for hardware design
7.2 The Software used to Gathering & Analysis Data & Diagnosis
In the software part, the LabVIEW program was used to receive data from the hardware part, it is converted from analog data to digital, in the software part, and data was received, as the analysis and diagnosis stage takes place within the LabVIEW program.

7.3 Software Stage
In the software stage, data passes through several stages, and in order to understand the stages of the software, it will be divided into several stages. Each stage will be explained separately. The following Figure 14 shows the software stages.

![Software stages diagram](image)

**Figure 14. Software stages**

7.4 Online Test for disease diagnosis
Different conditions were implemented including Mitral regurgitation, Tricuspid regurgitation, Aortic stenosis, Pulmonic stenosis, Ventricular septal defect (VSD), and Mitral valve prolapse, conditions. These data were collected from the Medical City Department. The following Figures 15-21 show the waveform of the diseases that were diagnosed.

![Signal waveform](image)

**Figure 15. Normal state signal**
Figure 16. Mitral regurgitation signal

Figure 17. Tricuspid regurgitation signal

Figure 18. Aortic stenosis signal

Figure 19. Pulmonic stenosis signal
7.5 Diagnosis for Disease Type
Depending on the detection algorithm suggested, the signal is isolated, analysed, and entropy values were calculated in the third level of the analysis. The diagnostic algorithm depends on the entropy values of the parameters $aaa_3$, $daa_3$, $ada_3$, $dda_3$, $aad_3$, $dad_3$, $add_3$, $ddd_3$ which are relied upon in the diagnostic stage as shown in the Table (3).

| No. | Disease                  | Coef.       |
|-----|--------------------------|-------------|
|     |                          | $aaa_3$     | $daa_3$     | $ada_3$     | $dda_3$     | $aad_3$     | $dad_3$     | $add_3$     | $ddd_3$     |
| 1   | Normal                   | 925.25      | 9.494       | 2.823       | 0.099       | 1.062       | 0.042       | 0.013       | 0.015       |
| 2   | Mitral regurgitation     | 1001.85     | 5.051       | 1.456       | 0.058       | 0.518       | 0.022       | 0.007       | 0.006       |
| 3   | Tricuspid regurgitation  | 1075.44     | 8.71        | 2.568       | 0.099       | 0.999       | 0.043       | 0.014       | 0.015       |
| 4   | Aortic stenosis          | 1125.57     | 8.995       | 2.692       | 0.113       | 1.018       | 0.045       | 0.013       | 0.013       |

Figure 20. Ventricular septal defect (VSD) signal

Figure 21. Mitral valve prolapse signal
5 Pulmonic stenosis 1236.71 10.081 3.002 0.101 1.098 0.042 0.013 0.013
6 Ventricular septal defect (VSD) 1429.41 7.858 2.31 0.106 1.001 0.048 0.015 0.019
7 Mitral valve prolapse 1107.75 5.109 1.608 0.087 0.601 0.03 0.007 0.006
8 Aortic regurgitation 1067.51 31.864 9.684 0.668 2.914 0.193 0.052 0.003
9 Pulmonic regurgitation 1191.9 58.042 18.208 1.637 5.546 0.48 0.132 0.003
10 Mitral stenosis 1352.1 29.882 8.804 0.418 2.589 0.119 0.032 0.002

Through the practical results, we observe the energy values at the third level, all of which are to some extent very close, as the validity of their convergence of energy values is transmitted in the previous Figures that were drawn to illustrate the difficulty of summarizing through them by an algorithm. The table of practical results also gave a great convergence to theoretical results.

8. Conclusion
In this paper, a proposed diagnosis system was done to know the type of disease that causes heart valves. The diagnosis and analysis of the PCG signal based on WPT and EL energy was presented using the LabVIEW environment. Depending on data that are analyzed by WPT, the mother wavelet and decomposition level were selected. Experimental implementation of the whole system was conducted. From practical and theoretical results, the proposed technique was proved to be one of the most important techniques. This technique was used in the extract features of non-stationary signals so it is very suitable for extract features of the current signal. The proposed technique has been applied on two data-set, first Heart-sound and Murmur-Library, and second E-general-medical, The results show high speed and high accuracy in detecting and diagnosing the disease in the PCG signal due to the accuracy of the proposed technique and speed of the algorithm used which in LabVIEW TOOLS. The similarity between the results of the real analysis of PCG signal and the results of the reference analysis PCG signal which is doing in Matlab proves the possibility of using the proposed technique for any real PCG signal without the need to its parameters.

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