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Heart Disease Detection Based on ECG Signal: A Survey

Ranjan Kumar Kashyap
M. Tech. Scholar, Department of ETC,
BIT, Durg, Chhattisgarh, India

Prof. R. M. Potdar
Professor, Department of ETC,
BIT, Durg, Chhattisgarh, India

***Abstract:** All around the world there are various diseases acquired by the human being. These diseases are of various kinds and affect almost all the part of the human body. ECG signal processing is an effective method through which the heart disease can be identified and can help the doctors to fastly and accurately cure the disease. Various researches has been done on ECG signals to identify the problems acquired by any human being. To work on this field the basic knowledge is very important regarding the processing of the signal like how ECG signals are acquired, how it can be processed, how it can be used to identify the disease, what methods can be applied in the processing, how the signal can be segmented, how it can be analyzed and identified thorough processing. For all such information the survey of various research paper has been done and are presented below.*

***Keywords:** ECG (Electrocardiogram), CMRR (Common Mode Rejection Ratio), RLD (Right Leg Drive), PCS (Personal Care Service), PRM (Patient Record Monitoring & Feedback System).*

I. INTRODUCTION

Heart is a very important functional part of the body. Due to various types of disease acquired by the person the functioning of the heart get perturb and hence cause serious issues in the health. The reason behind such abnormalities in the heart is many like the pollution in the air, smoking, and alcohol intake are the major causes of the heart disease. The death in the world due to heart disease has been ranked second. The problem is the detection of the disease. These diseases are not identified at the early stages. People sometimes ignore the problem considering it a small problem but as it grows caused major problems in the heart. The issue is so serious but the detection of the disease at their early stage is still a challenging task. The pathologist also comes to know about the disease at the severe stage of the disease. The undetectability is not only due to the accurate detection but also due to the ignorance of the people about this issue of the disease. The people should be informed about its lakshans by campaigning and preaching the causes and consequences of the these diseases and that all what can be done for the people to make them informed. The other issue is the detectability of the heart condition at any time. Now this is the task of the doctor to identify the problem accurately and cure the disease. Due to the unavailability of the accurate measuring devices it was hard for a doctor to identify and cure the disease accurately. The researches in the recent past has provided many ways to detect the disease although some of them are still not able to identify the disease accurately. Researchers presented many method among them PCG signal and ECG signal has gained enormous attention due to its measurement techniques. PCG signal is the sound within the heart which is produced due to the movement of the blood in different chamber. This basically causes the valve to open and close resulting in production of sound inside heart. These sounds provide major information about the condition of the heart as being direct representative of the heart condition. Here the main problem is to analyze the sound and identify the disease which is absolutely not an easy task. Much experience is required to do so. Due to the lack of such experienced doctors it is hard to implement on real time basis. Researches have been done on the issues also and some improvement has also been presented but still it needs much modifications and improvements. Due to this drawback ECG signals has been utilized much in the real time scenarios. ECG signal can be measured by the sum of currents from various parts of the heart. Vector characteristics of ECG signal depends on the measurement location and the size of the ECG signal. The

ECG measurement hardware reads physiological signals from a patient, does the Difference-Amplifier for subtle biological signals, and applies various filter technologies to eliminate any signal noise. There are well-known technologies avalilabe such as the instrumentation amplifier for CMRR (Common Mode Rejection Ratio) and the RLD (Right Leg Drive) feedback circuit filter to eliminate the noise from the signal. The isolation amplifier, band-pass filters, and the Butterworth filter for electrical stabilization to solve current leakage issues and to reduce some noise can also be applied. In addition, it is necessary to remove the ECG artifact depending on the patient or the location of measurement. It may be problematic for ECG signal detection and analysis. Thus the ground plane design is required for the integrity of the ECG signal. To cope with this, signal isolation can be performed using the phototransistor. Based on this various types of equipment has also been presented by the researchers are discussed below.

II. ECG SYSTEM SURVEY

The signal processing on ECG provides a way to accurately identify the disease acquired by any person. For clear understanding of ECG signal processing the survey has been done and are presented here.

Jeon et al. designed and implemented a wearable ECG (electrocardiogram) system with smartphones for real-time monitoring, self-diagnosis, and remote-diagnosis for chronic heart disease patients before sudden outbreaks. Use of mobile phone for healthcare was the first of its kind to cater the issue but has failed due to limited functionalities. Due to the recent popularity of much more powerful smartphones, new efforts on mobile healthcare systems are flowing throughout academics and industries.

In June 2011, MTM Ltd. developed the 'Smart Patient Care System (SPaCS)' with the support of the Ministry of Knowledge Economy of Korea [6]. SPaCS is a healthcare system that is consisted of two applications such as PCS (Personal Care Service) and PRM (Patient Record Monitoring & Feedback System) in order to manage personal health using smart phones. Pukyong University in Korea developed the 'Wearable ECG module (USN Lab ver. 2.0)' which does not require electrodes on bare skin [7]. This module can be made into t-shirts which patients can easily put on and take off, and test results can be transferred wirelessly in real-time devices for analysis.

The medical engineering researcher team in UBC (University of British Columbia) developed a portable pulse oximeter - Phone Oximeter - using smart phones and released laboratory-level technology [8]. As shown in Figure below, the Phone Oximeter measures oxygen levels in your bloodstream, heart rate, respiratory rate, and can to send the measured values to the remote hospital.

Figure 1: Oxygen Saturation Measurements of the Oximeter Coupled with Smartphones

In this paper, the authors have designed and implemented a wearable ECG measurement device and an App system based on the Android OS platform. This system can monitor and diagnose patients' heart conditions in real time by having them wear a sports-shirt with a compact ECG sensor. In addition, the application provides graphical information with personal history management tools and an automatic emergency call system. Further the authors suggested the study and improvement for less energy consumption and more accurate measurements in the system developed.

Cvetkovic et al. presented the experimental pilot study to investigate the effects of pulsed electromagnetic field (PEMF) at extremely low frequency (ELF) in response to photoplethysmographic (PPG), electrocardiographic (ECG), electroencephalographic (EEG) activity. The assessment of wavelet transform (WT) as a feature extraction method was used in representing the electrophysiological signals. Considering that classification is often more accurate when the pattern is simplified through representation by important features, the feature extraction and selection play an important role in classifying systems such as neural networks. The PPG, ECG, EEG signals were decomposed into time-frequency representations using discrete wavelet transform (DWT) and the statistical features were calculated to depict their distribution. A feature is a distinctive or characteristic measurement, transform, structural component extracted from a segment of a pattern. Features are used to represent patterns with the goal of minimizing the loss of important information.

The feature vector, which is composed of the set of all features used to describe a pattern, reduces the dimensional space needed to represent the pattern. Thus the set of all features that could be used to describe a given pattern (a large and in theory an infinite number as very small changes in some parameters are allowed to separate different features) is limited to those actually represented in the feature vector. The author informs that one purpose of the dimension reduction is to satisfy engineering constraints in software and hardware complexity, the cost of data processing, and the desirability of compressing pattern information. In addition, the classification often becomes more accurate when the pattern is simplified by including important features or properties only. Feature extraction methods could be based on either calculating statistical characteristics or producing syntactic descriptions.

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The feature selection process is usually designed to provide a means for choosing the features which are best for classification optimized against various criteria. The feature selection process is basically performed on a set of predetermined features. The authors informed that various methodologies of automated diagnosis have been adopted, however the entire process can generally be subdivided into a number of disjoint processing modules: preprocessing, feature extraction/selection, and classification. The signal acquisition, artefact removing, averaging, thresholding, signal enhancement, and edge detection are the main operations in the course of preprocessing. Authors also inform that the accuracy of signal acquisition is of great importance since it contributes significantly to the overall classification result. With the spectral analysis performed using the DWT the authors concluded that the selection of appropriate wavelet and the number of decomposition levels is very important in analysis of signals using Wavelet Transform. The number of decomposition levels was chosen based on the dominant frequency components of the signal such that those parts of the signal that correlate well with the frequencies required for classification of the signal are retained in the wavelet coefficients. The number of decomposition levels chosen was 4. Thus the signals were decomposed into the details D1–D4 and one final approximation, A4. The author informs that usually the tests are performed with different types of wavelets and the one which gives maximum efficiency is selected for the particular application. The smoothing feature of the Daubechies wavelet of order 2 (db2) made it more suitable to detect changes of the signals under the considered circumstances. Therefore, the wavelet coefficients were computed using the db2. The coefficient of the decomposition at various levels as reported by the authors is shown below.

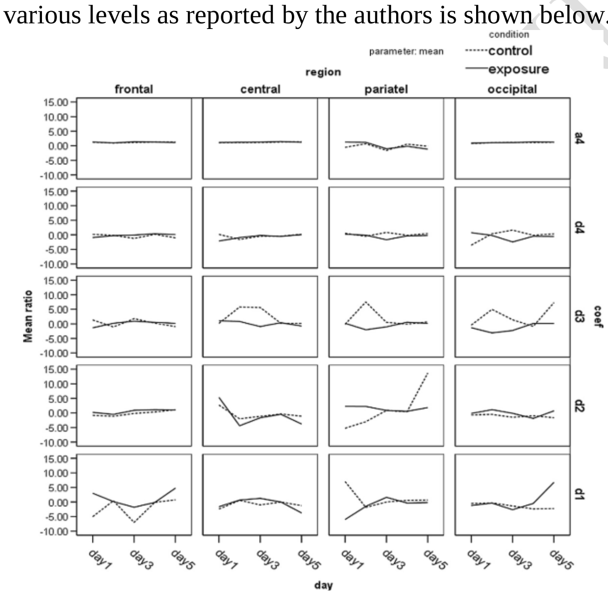

Figure 2: Extracted (a) maximum, (b) mean, (c) minimum, and (d) standard deviation statistical Features of Signals

Gupta et al. presented a method for segmentation of heart sounds (HSs) into single cardiac cycle (S1-Systole S2-Diastole) using homomorphic filtering and K-means clustering. In this paper also the authors used features of the signal to categorize the signal. Feature vectors were formed after segmentation by using Daubechies-2 wavelet detail coefficients at the second decomposition level. These feature vectors are taken as an input to the neural network architecture for the classification purpose. There can be various type of structures that can be utilized based on the application. The author in this study used Grow and Learn (GAL) and Multilayer perceptron-Backpropagation (MLP-BP) neural networks for classification of three different HSs (Normal, Systolic murmur and Diastolic murmur).

Author in this paper worked on the segmentation and Peak detection using Homomorphic filtering of the signal. The automatic segmentation algorithm was based on Homomorphic filtering and used K-means clustering to indicate single detected cycle. Homomorphic filtering technique resulted in smooth envelope enabling easy peak detection.

Peak conditioning was performed to remove peaks, which do not correspond to S1 and S2. K-means clustering of the time intervals between peaks was used to indicate the occurrence of single cardiac cycles and also to point to missed cycles. Peaks corresponding to only S1 and S2 were obtained after peak conditioning as shown in figure below. K-means clustering helps to indicate single cardiac cycles and is a non-hierarchical partitioning method that partitions the observations in the data into K mutually exclusive clusters, and returns a vector of indices indicating to which of the K clusters it has assigned each observation. It uses an iterative algorithm that minimizes the sum of distances from each object to its cluster centroid, over all clusters. This algorithm moves objects between clusters until the sum cannot be decreased further.

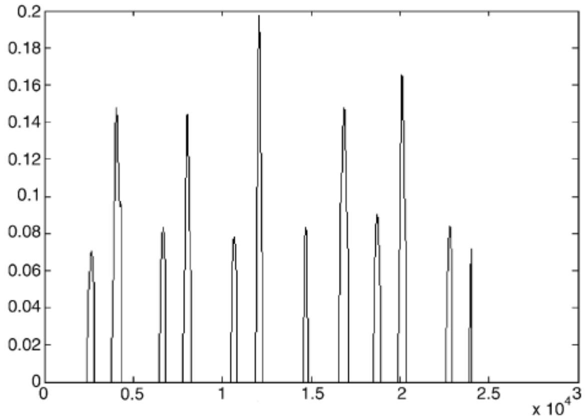

Figure 3: Combined peaks widths in PCG signal conditioned (Diastolic murmur)

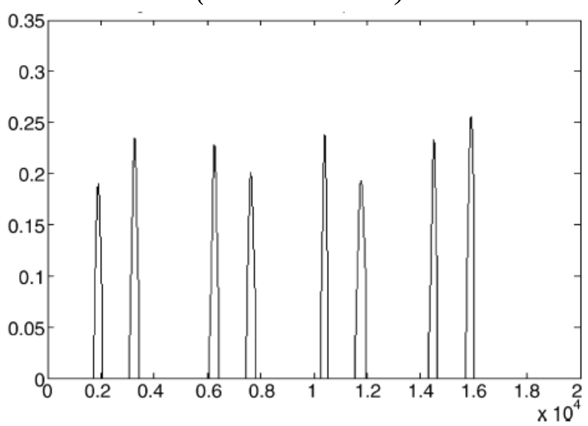

Figure 4: Peak conditioning of PCG signal (Normal)

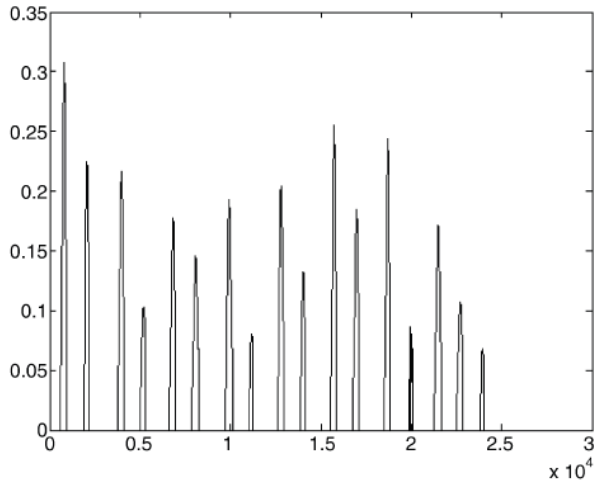

Figure 5: Peak conditioning of PCG signal (Systolic murmur)

The figure below shows the signal that has been acquired by the authors for the preparation of the database.

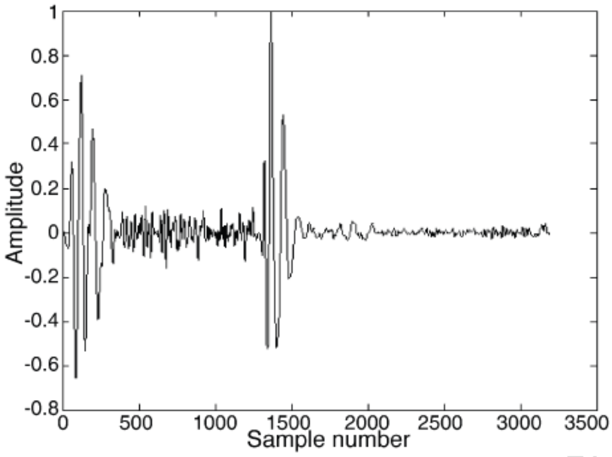

Figure 6: Single cycle heart sound (Systolic murmur)

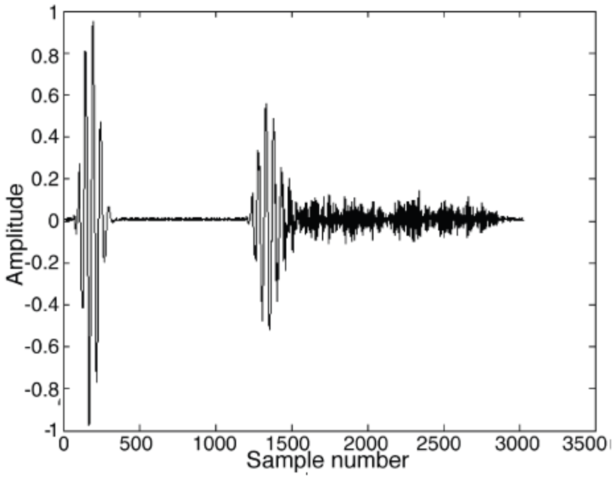

Figure 7: Single cycle heart sound (Diastolic murmur)

The performance of GAL for the classification of three datasets of HSs (normal: N, Systolic murmur: S, Diastolic murmur: D) is presented by the author as shown in the table below. The segmented heart sounds dataset (340 patterns) was divided into three datasets each with 112 patterns. Forty-five patterns (15N, 15S, 15D) were used for the training, and 67 patterns (21N, 26S, 20D) were used for testing. Three patterns (1N, 1S, 1D) were used as initial class patterns for the GAL network.

Performances	**Dataset 1**	**Dataset 2**	**Dataset 3**
Training time	0.187	0.266	0.39
Test time	0.016	0.017	0.015
Nodes before forgetting	5	6	3
Nodes after forgetting	4	5	3
Classification of normal	21/21	21/21	21/21
Classification of Systolic	24/26	25/26	24/26
Classification of Diastolic	20/20	20/20	19/20
Classification Percentage	97.01	98.5	95.55

Table 1: Classification using GAL

The author concluded that the classification performance of GAL was similar to MLP-BP. However, the training and testing times of GAL were lower as compared to MLPBP. The framework proposed by the author could be a solution for automatic analysis of HSs that may be implemented in real time for classification of HSs.

III. CONCLUSION

A deep survey on the ECG signal segmentation, feature extraction and classification has been done in this paper. According to the authors for the detection of the heart disease, first the signal needs to the acquired. This acquired signal then should be preprocessed to remove the noises in the signal usually termed as artefacts. After this the signal is segmented to clearly separate the signal parts and after segmentation the signal is processed to extract the features. Depending on the feature obtained the system should be trained to identify the signal. The system may be the neural network or the other one is the use of Adaptive Neuro Fuzzy Inference System (ANFIS). ANFIS is the new system that can be implemented not used till now for the ECG Signal classification. Classification of the signal plays a very important role in the detection of the disease and to help doctors to identify the disease accurately and quickly so that the curing can be done soon.

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The review on ECG signal processing is in important part for my research work and to clearly understand the processing on it, the paper used here provided immense information. Therefore I acknowledge all the researchers whose paper has been utilized for the survey.

REFERENCES

[1] Byungkook Jeon, Jundong Lee and Jaehong Choi, Design and Implementation of a Wearable ECG System, International Journal of Smart Home, Vol. 7, No. 2, 2013, pp 61-70.
[2] Dean Cvetkovic, Elif Derya Übeyli and Irena Cosic, Wavelet transform feature extraction from human PPG, ECG, and EEG signal responses to ELF PEMF exposures: A pilot study, Science Direct: Digital Signal Processing, 2008, pp 861-874.
[3] Cota Navin Gupta, Ramaswamy Palaniappan, Sundaram Swaminathan and Shankar M. Krishnan, Neural network classification of homomorphic segmented heart sounds, Applied Soft Computing, 2007, pp 286–297.
[4] X. Jingping, L.G. Durand, P. Pibarot, Nonlinear transient chirp signal modeling of the aortic and pulmonary components of the second heart sound, IEEE Trans. Biomed. Eng, 2000, 1328–1335.
[5] X. Jingping, L.G. Durand, P. Pibarot, Extraction of the aortic and pulmonary components of the second heart sound using a nonlinear transient chirp signal model, IEEE Trans. Biomed. Eng. 48 (March (3)) (2001) 277–283.
[6] R.J. Lehner, R.M. Rangayyan, A three channel microcomputer system for segmentation and characterization of the phonocardiogram, IEEE Trans. Biomed. Eng., 1987, pp 485–489.
[7] T.S. Leung, P.R. White, W.B. Collis, A.P. Salmon, E. Brown, Time frequency methods for analyzing paediatric heart murmurs, Appl. Signal Process., 1997, pp 154–167.
[8] M.W. Groch, J.R. Domnanovich, W.D. Erwin, A new heart sounds gating device for medical imaging, IEEE Trans. Biomed. Eng., 1992, pp 307–310.
[9] A. Iwata, N. Ishii, N. Suzumura, Algorithm for detecting the first and second heart sounds by spectral tracking, Med. Biol.Eng. Comput., 1980, pp 19–26.
[10] H. Liang, S. Lukkarinen, I. Hartimo, A heart sound segmentation algorithm using wavelet decomposition and reconstruction, Proceedings of 19th International IEEE/EMBS Conference, vol. 4, 1997, pp 1630–1633.
[11] H. Liang, I. Hartimo, A heart sound feature extraction algorithm based on wavelet decomposition and reconstruction, Proceedings of 20th International IEEE/EMBS Conference, vol. 20, no. 3, 1998, pp 1539–1542.
[12] T.R. Reed, N.E. Reed, P. Fritzson, Heart sound analysis for symptom detection and computer aided diagnosis, Simulation Model. Pract. Theory, 2004, pp 129–146.
[13] H. Liang, I. Hartimo, A feature extraction algorithm based on wavelet packet decomposition for heart sound signals, Proceedings of IEEE-SP International Symposium on Time Frequency and Time Scale Analysis, 1998, pp 93–96.
[14] D. Barschdorff, S. Ester, E. Most, Phonocardiogram analysis of congenital and acquired heart diseases using artificial neural networks, in: Advances in Fuzzy Systems-Applications and Theory, vol. 3: Comparative Approaches to Medical Reasoning, World Scientific Publishing Co., 1995, pp 271–288.
[15] T.S. Leung, P.R. White, W.B. Collis, E. Brown, A.P. Salmon, Characterisation of paediatric heart murmurs using self organizing map, in: Proceedings of 21st Annual International Conference of IEEE-EMBS, vol. 2, 1999, p 926.
[16] Y.M. Akay, M. Akay, W. Welkowitz, J. Kostis, Non-invasive detection of coronary artery disease, IEEE Eng. Med. Biol. Mag., 1994, pp 761–764.
[17] T. Olmez, Z. Dokur, Classification of heart sounds using an artificial neural network, Pattern Recognit. Lett., 2003, pp 617–629.
[18] J.R. Deller, J.G. Proakis, J.L. Hansen, Discrete Time Processing of Speech Signals, Prentice Hall, 1993.
[19] A.P. Yoganathan, R. Gupta, F.E. Udwalia, J.W. Miller, W.H. Corcoran, R. Sarma, J.L. Johnson, R.J. Bing, Use of fast Fourier transform in the frequency analysis of the first heart sound in normal man, Med. Biol. Eng. Comput., 1976, pp 69–73.
[20] J.A. Shaver, R. Salerni, P.S. Reddy, Normal and abnormal heart sounds in cardiac diagnosis Part I: systolic sounds, Curr. Problems Cardiol., 1985, pp 2–68.
[21] E. Alpaydin, GAL: networks that grow when they learn and shrink when they forget, Int. J. Pattern Recognit. Artif. Intell., 1994, pp 391–414.