# Heart Abnormality Detection using Acceleration Plethysmogram Signal

Khalida Hussin, Khairul Azami Sidek and Ahmad Fadzil Ismail
*Department of Electrical and Computer Engineering,*
*Faculty of Engineering, International Islamic University Malaysia,*
*P.O. Box 10, Jalan Gombak, 50728 Kuala Lumpur.*
*azami@iium.edu.my*

***Abstract*— For the past decade, irregularities of heart beat, or also known as Cardiac Arrhythmias has led to Cardiovascular Diseases (CVDs). It has been recorded as one of the main death cause in Malaysia as reported by the Ministry of Health Malaysia. This has become a major concern as many patients are unaware that early prevention can save them. In the past years, few systems that detects heart abnormality have been introduced. This includes various types of signal, such as the photoplethysmogram, electrocardiogram, electroencephalogram, ballistocardiogram and others. However, each of the systems have their own drawbacks. The study come out with a solution and proposed a system that can aid the problem, which is Heart Abnormality Detection Using Acceleration Plethysmogram (APG) signal. APG is more relevant as it displays obvious segments in the morphological cycle of the waveform. Throughout the study, datasets from PhysioNet, specifically MIMIC II Clinical Database waveform with sampling frequency of 125 Hz were used to obtain PPG and APG waveform. These signals undergoes five main processes before the abnormality can be detected. WEKA software was used for decision making process, where classifiers such as Multi-Layer Perceptron (MLP), Radial Basis Function (RBF) Network, and Bayesian Network were used to differentiate between the normal and abnormal heart beats. The percentage of correctly classified instances produced by the classifiers were able to show the significant differences between normal and abnormal APG signals. Based on the experimentation results, MLP and RBF classifier showed a significantly high classification accuracy of 96% as compared to Bayesian Network of 92%. This outcome suggest that APG signal can be used as an alternative in the detection of heart abnormalities with promising experimentation results.**

***Index Terms*—Acceleration Plethysmogram; WEKA Software; Multilayer Perceptron (MLP)**

## I. INTRODUCTION

The irregularities of heartbeat is known as Cardiac Arrhythmia, or Cardiac Dysrhythmia. This is a group of conditions where the heartbeat can be too slow, or too fast. Tachycardia is the condition when the heartbeat is too fast, that it exceeds 100 beats per minute, while Bradycardia is when the heartbeat is too slow, where the readings are below 60 beats per minute. These conditions, if not treated, leads to Cardiovascular Diseases (CVDs). As reported by the World Health Organization, annually, more people die from CVDs if compared to other cause, making CVDs as the number one source of death globally [1]. In the year 2012, an estimated of 17.5 million people died from CVDs. This amount represents CVDs as the major cause of deaths globally with percentage of 31% as compared to the other causes, published in a book by World Health Organization in collaboration with the World Heart Federation. People who are at high cardiovascular risk or with cardiovascular disease needs early detection that are convenient and effective. Therefore, this study proposes a better and more efficient technique to detect heart abnormalities, which is by using Accelerated Plethysmogram (APG) signal.

## II. LITERATURE REVIEW

Sengthippany et al. in [2] obtained the heart rate statistics of 33 participants, in the condition of resting and exercising, simultaneously, with the aid of PPG and ECG signals. However, the irregularity of the patterns recorded makes it difficult to analyze the peaks correctly. The inconsistent value of determination coefficient (R2) of SDNN, especially during exercising condition, results in poor quality of PPG and ECG signals. Jose et al. in [3] used the approach of detecting cardiac arrhythmia by using ballistocardiogram (BCG) signal. However, BCG devices are considered as complicated mechanical devices. Other than that, the signal analysis methods of BCG did not develop as well as ECG.

Joysly et al. in [4] used the combination of two different signals in abnormality recognition, which are the ECG signal and Electroencephalogram (EEG) signal. However, this method is costly and expensive. The method of acquiring signals from brain scalp is found to be inconvenient. Based on the previous related works, the detection of heart abnormalities has never been investigated using APG signal. Theoretically, APG signal produces clear and better results than PPG signal. Thus, we are proposing of applying APG signal in detecting heart abnormalities.The manuscript article should be written in English in the font of Times New Roman, which includes the following: abstract, introduction, literature review, objectives, research methodology, theory, testing and analysis, results and discussions, conclusion, acknowledgement and references. Manuscript should be prepared via the Microsoft Word processor.

## III. METHODOLOGY

The procedures involved in obtaining the APG signal to detect heart abnormality are as shown in Figure 1.

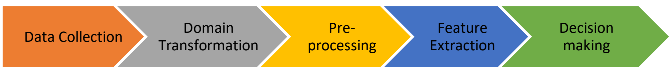


Figure 1: Proposed methodology of the study

### A. Data Collection

The PPG data used throughout this study were taken from a publicly available signal archive known as PhysioNet [5]. MIMIC II Waveform Version 3 database was selected, where PPG samples were gathered for this study. PPG samples of 10 subjects will be collected in a 10 second duration. Recorded PPG signals are digitized at a frequency of 125Hz with 12-bit resolution.

### B. Domain Transformation

The PPG signals must be first filtered, and then differentiated, which produces an APG waveform. The signals are then analyzed by applying the second order derivative to the filtered PPG. Due to the lack of accuracy and reproducibility of PPG signal, this study will be using APG signal waveform consisting of four different systolic waves (a,b,c and d waves) and also one diastolic wave (e wave). The differences of how detailed APG signal is as compared to PPG signal is shown in Figure 2.

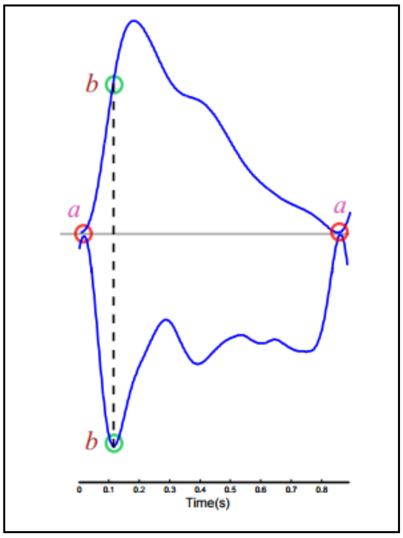


Figure 2: One heartbeat of PPG and its APG

### C. Pre-processing

In the pre-processing stage, the PPG signal is being filtered, and then differentiated to obtain clear and better APG signals. The type of filter used is Butterworth filter with 0.5-10Hz band pass. This filter offers good transition of band characteristics at low coefficient orders.

### D. Feature extraction

The beginning of APG cycle which is the a wave will be extracted until the c wave. This process will be repeated for at least five times for each subject. The reason we have selected a wave until c wave is because, according to Elgendi [6], the detection of a wave has recorded the highest detection accuracy with 99.78% sensitivity and 100% of positive predictivity. While the b wave recorded an overall sensitivity of 99.78% with 99.95% positive predictivity. These waves have high sensitivity and positive predictivity values. Moreover, these waveforms are prevalent and obvious in the APG morphology.

### E. Decision Making / Classification

Classification algorithm in this study comprises of two different types of classifiers. The first one is the neural network classifiers, which consists of the Multilayer Perceptron (MLP) Network and Radial Basis Function (RBF) Network. The second classifier is a non-neural network classifier,that is the Bayesian Network.

#### a. Multilayer Perceptron (MLP)

Multilayer Perceptrons (MLPs) is one of the frequently used type of networks applied in the task of classification. The MLP architecture consists of three layers; an input layer, a hidden layer, and an output layer. The MLPs ability to learn from examples makes neural network very powerful and flexible. There is no necessity to understand the internal mechanism of a task, or even the need to formulate an algorithm to carry out any specific tasks [7].

#### b. Radial Basis Function (RBF) Network

Radial Basis Function Network (RBFN) is one more type of neural network that can be applied throughout this study. The RBFN approach is found to be more intuitive than the MLPs. A typical RFBN architecture consists of three layers; the input vector, layer of RBF neurons, and the output layer [8].

#### c. Bayesian Network

A Bayesian network consists of a set of local distributions and a directed acyclic graph. Bayesian Network saves a lot of table space and computation, since it only relates nodes that are probabilistically related by some dependency. Secondly, Bayesian network is useful because of their adaptability. It requires only small amount of data, and from there, it can evaluate essential parameters on its own. [9]

## IV. Experimentation and Results

A total of 20 datasets from 10 different subjects obtained from PhysioNet were used in this study. The original data were in the form of PPG signals. In order to obtain the APG signal, each data undergoes differentiation process using MATLAB. Next, data will be filtered out using the second order Butterworth low-pass filter. This is to reduce noise in the APG signal. After that, in the feature extraction process, the most visible peaks will be selected that are peaks a, b, and c. The extracted data obtained will be the input for classification algorithm using the WEKA software [10]. In this software, the datasets that has undergo the feature extraction process is separated into three different sets, which are the normal signal, the abnormal signal, and the combination of normal and abnormal signal datasets.

### A. Normal signal datasets :

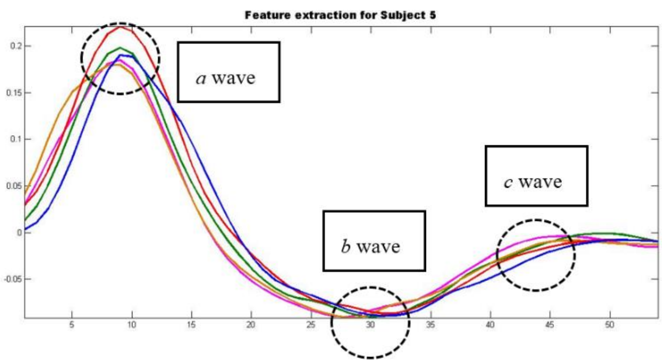


Figure 3: Feature Extraction of Subject 5

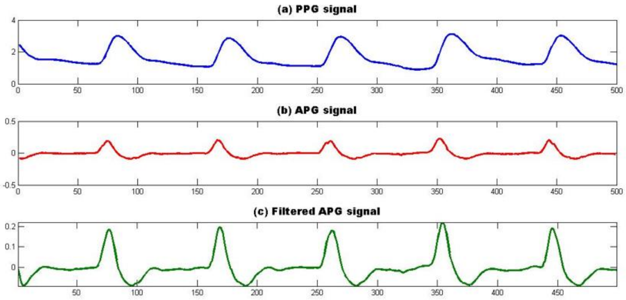


Figure 4: Conversion PPG signal to APG signal of Subject 5

### B. *Abnormal signal datasets*

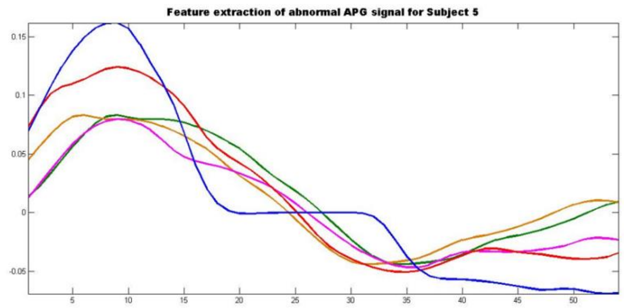


Figure 5: Feature extraction of abnormal signal for Subject 5

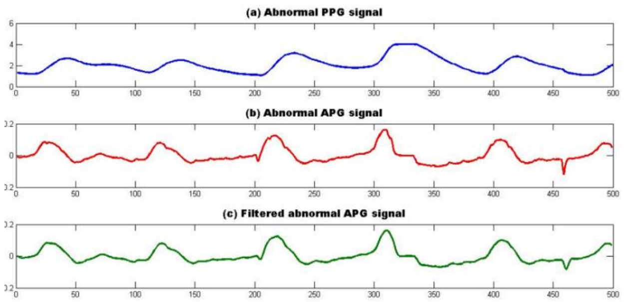


Figure 6: Conversion of abnormal PPG signal to abnormal APG signal of Subject 5

It can be observed from the three subplot figures that APG signal provides clearer waveform as compared to PPG signal. Due to that, peaks are much more visible when viewed in the APG signal form. In the feature extraction stage, three visible peaks could be obtained from the APG signal, which are the a, b, and c waves. These three waves are used in the classification process. This process is done with the aid of the WEKA software. Readings of five samples per cycle containing 54 instances of each subject is collected and being grouped into three different datasets. The first dataset contains the readings of data with normal signals. The second dataset contains the readings of data with abnormal signal. While the third dataset contains the readings of data of the combination between normal and abnormal signals. These datasets are later being keyed in into the software, and selected classifiers produces results that differentiate the normal and abnormal signals. The results produced are as shown in Table 1.

From the results obtained, the differences in percentage of correctly classified instances between the normal and abnormal signals are shown. All three classifiers produced high percentage for the normal signals, while the percentage for the abnormal signals are significantly low. MLP and RBF Network seemed to produce better results than Bayes Network. This is because, performance of neural networks that inhibit additional hidden layers appear to be much better than networks with lesser hidden layers. [11] Apart from that, neural networks work better with continuous data as compared to Bayesian network that works better with discrete data. It can be concluded that heart abnormality can be detected when the APG signal of a subject appears to be abnormal from the normal APG signal.

Table 1
Classification Techniques

| Classification Technique | Percentage of normal signal | Percentage of abnormal signal | Percentage of combination of normal and abnormal signal |
|---|---|---|---|
| Bayes Network | 92% | 68% | 66% |
| Radial Basis Function | 96% | 70% | 75% |
| Multilayer Perceptron | 96% | 72% | 76% |

## V. CONCLUSION

In this study, this study have proposed a system in detecting heart abnormality by using APG signal. Theoretically, APG waveform has been said to provide clearer and more detailed signals as compared to the PPG signal. In the process of analyzing the data, each signal will undergo five processes in order to obtain the desired APG signal. It can be seen that APG signal shows a clearer view of the rise and fall of each wave and peaks as compared to PPG signal. Besides that, from the comparison done between normal and abnormal signals, it is easier to differentiate the APG signal of a healthy patient with a patient diagnosed with heart abnormality. The three classifiers used for this study which are the Multilayer Perceptron Network, the Radial Basis Function Network and the Bayesian Network were able to categorize the normal and abnormal APG waveform from the resultant percentages of correctly classified instances. This study has achieved the objectives. However, there is still room for improvements. Among the suggestions to improvise the study consists the following:

i. To gather data directly from patients diagnosed with heart abnormality
   In this study, there's some issue with the hospital's confidentiality in obtaining data of patients that has already been diagnosed with heart abnormality. Besides that, due to time constraint in obtaining permission from hospitals to perform this study, it has been decided to proceed this study by using the data from PhysioNet. Therefore, it would be an advantage in the future if this study were able to use data from patients directly in hospitals.
ii. To include gender variability from collected data
   The data obtained from PhysioNet does not specify any information of the subject. Research on this study can be expanded more in the future by including gender variability of the subjects and whether gender affects heart abnormality or not.
iii. To include age variability from collected data
   Age variability of subjects can be included in collecting data and further research can be done on whether or not subjects of certain ages are more prone

to inhibit heart abnormality.

## ACKNOWLEDGMENT

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