×

- Upload
- Home
- Explore

- Login
- Signup

- Home
- Explore

Search Submit Search

- Upload
- Login
- Signup

We've updated our privacy policy. Click here to review the details. Tap here to review the details.

×

Search

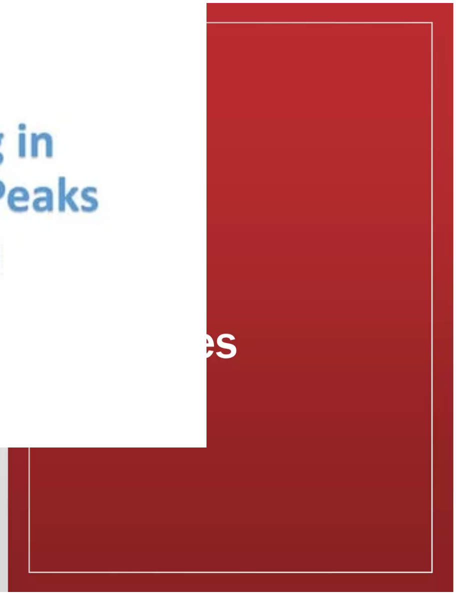
Successfully reported this slideshow.

Your SlideShare is downloading. ×

Project

Report

Upcoming SlideShare



ECG

Loading in …3

×

▪ Live Demo

Check these out next

n

afa

ed

Presented By

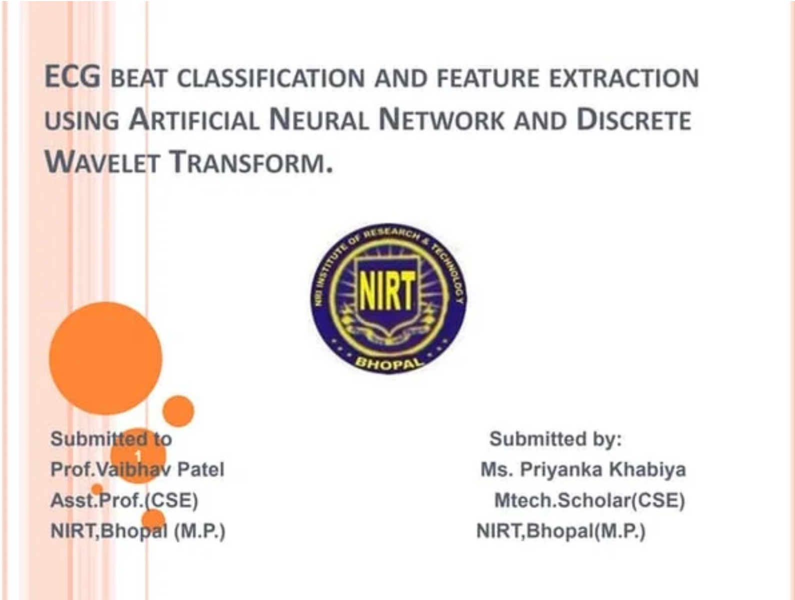
[Automatic Detection of Heart Disease Using Discreet Wavelet Transform and Art...](#)
[Editor IJMTER](#)

Latifa Mahmoud

[Matthew Gray Summer 2015 Presentation](#)
[Matthew Gray](#)

[Jq3516631668](#)
[IJERA Editor](#)

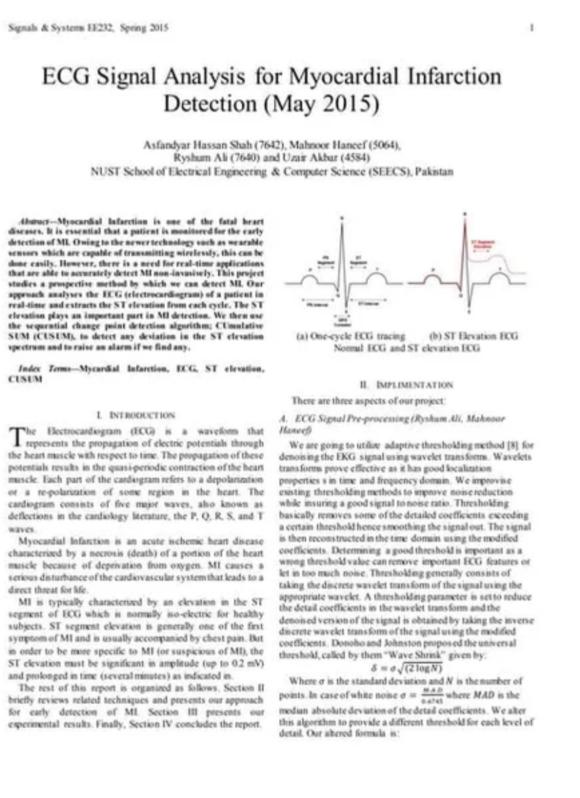
Introduction



[Ecg beat classification and feature extraction using artificial neural networ...](https://www.slideshare.net)
priyanka leenakhabiya

Problem Cont.

- Elderly patients who live alone.
- Patients who don't know how to deal with mobiles or modern technologies.
- Patients with slow gait or even bed ridden.
- Ambulance late arrival.



ECG Signal Analysis for Myocardial Infarction Detection (May 2015)

Asfandyar Hassan Shah (7642), Mahnoor Haneef (5064),
Ryshum Ali (7640) and Uzair Akbar (4584)
NUST School of Electrical Engineering & Computer Science (SEECS), Pakistan

***Abstract*—Myocardial Infarction is one of the fatal heart diseases. It is essential that a patient is monitored for the early detection of MI. Owing to the newer technology such as wearable sensors which are capable of transmitting wirelessly, this can be done easily. However, there is a need for real-time applications that are able to accurately detect MI non-invasively. This project studies a prospective method by which we can detect MI. Our approach analyses the ECG (electrocardiogram) of a patient in real-time and extracts the ST elevation from each cycle. The ST elevation plays an important part in MI detection. We then use the sequential change point detection algorithm; CUmulative SUM (CUSUM), to detect any deviation in the ST elevation spectrum and to raise an alarm if we find any.**

***Index Terms*—Mycardial Infarction, ECG, ST elevation, CUSUM**

I. Introduction

The Electrocardiogram (ECG) is a waveform that repesents the propagation of electric potentials through the heart muscle with respect to time. The propagation of these potentials results in the quasi-periodic contraction of the heart muscle. Each part of the cardiogram refers to a depolarization or a re-polarization of some region in the heart. The cardiogram consists of five major waves, also known as deflections in the cardiology literature, the P, Q, R, S, and T waves.

Myocardial Infarction is an acute ischemic heart disease characterized by a necrosis (death) of a portion of the heart muscle because of deprivation from oxygen. MI causes a serious disturbance of the cardiovascular system that leads to a direct threat for life.

MI is typically characterized by an elevation in the ST segment of ECG which is normally iso-electric for healthy subjects. ST segment elevation is generally one of the first symptom of MI and is usually accompanied by chest pain. But in order to be more specific to MI (or suspicious of MI), the ST elevation must be significant in amplitude (up to 0.2 mV) and prolonged in time (several minutes) as indicated in.

The rest of this report is organized as follows. Section II briefly reviews related techniques and presents our approach for early detection of MI. Section III presents our experimental results. Finally, Section IV concludes the report.

(a) One-cycle ECG tracing (b) ST Elevation ECG
Normal ECG and ST elevation ECG

II. Implimentation

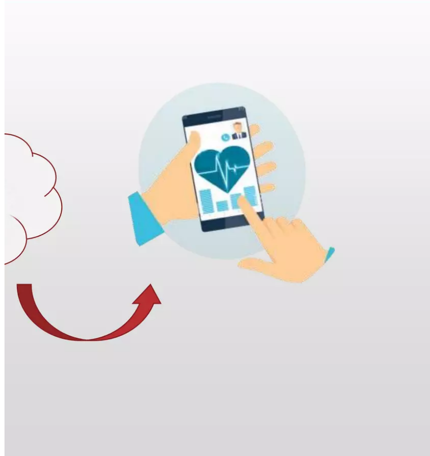
There are three aspects of our project:

A. ECG Signal Pre-processing (Ryshum Ali, Mahnoor Haneef)

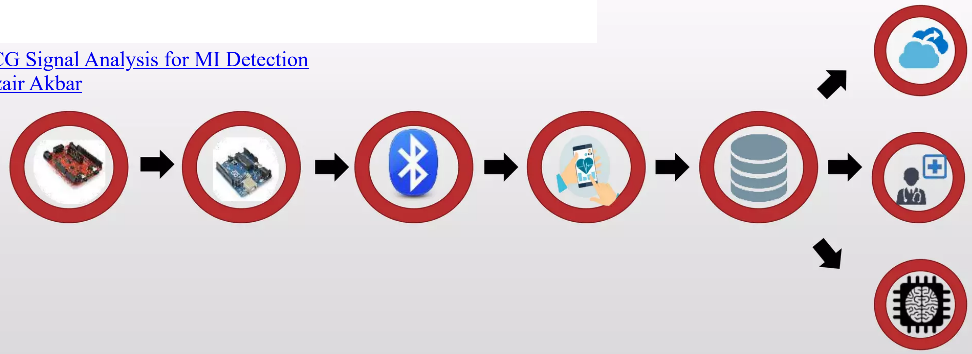
We are going to utilize adaptive thresholding method [8] for denoising the EKG signal using wavelet transforms. Wavelets transforms prove effective as it has good localization properties s in time and frequency domain. We improvise existing thresholding methods to improve noise reduction while insuring a good signal to noise ratio. Thresholding basically removes some of the detailed coefficients exceeding a certain threshold hence smoothing the signal out. The signal is then reconstructed in the time domain using the modified coefficients. Determining a good threshold is important as a wrong threshold value can remove important ECG features or let in too much noise. Thresholding generally consists of taking the discrete wavelet transform of the signal using the appropriate wavelet. A thresholding parameter is set to reduce the detail coefficients in the wavelet transform and the denoised version of the signal is obtained by taking the inverse discrete wavelet transform of the signal using the modified coefficients. Donoho and Johnston proposed the universal threshold, called by them "Wave Shrink" given by:

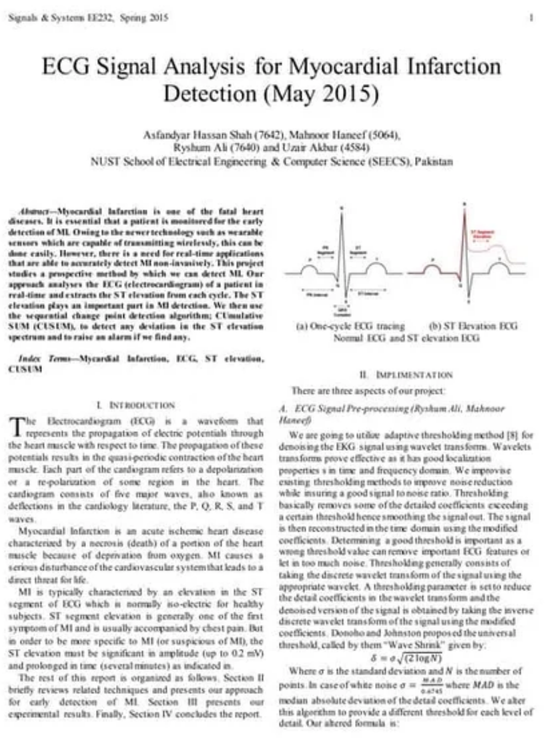
$$\delta = \sigma\sqrt{(2\log N)}$$

Where σ is the standard deviation and N is the number of points. In case of white noise $\sigma = \frac{MAD}{0.6745}$ where MAD is the median absolute deviation of the detail coefficients. We alter this algorithm to provide a different threshold for each level of detail. Our altered formula is:



[ECG Signal Analysis for MI Detection](#)
[Uzair Akbar](#)





Signals & Systems EE232, Spring 2015 1

ECG Signal Analysis for Myocardial Infarction Detection (May 2015)

Asfandyar Hassan Shah (7642), Mahnoor Haneef (5064),
Ryshum Ali (7640) and Uzair Akbar (4584)
NUST School of Electrical Engineering & Computer Science (SEECS), Pakistan

Abstract—Myocardial Infarction is one of the fatal heart diseases. It is essential that a patient is monitored for the early detection of MI. Owing to the newer technology such as wearable sensors which are capable of transmitting wirelessly, this can be done easily. However, there is a need for real-time applications that are able to accurately detect MI non-invasively. This project studies a prospective method by which we can detect MI. Our approach analyses the ECG (electrocardiogram) of a patient in real-time and extracts the ST elevation from each cycle. The ST elevation plays an important part in MI detection. We then use the sequential change point detection algorithm; CUmulative SUM (CUSUM), to detect any deviation in the ST elevation spectrum and to raise an alarm if we find any.

Index Terms—Mycardial Infarction, ECG, ST elevation, CUSUM

I. INTRODUCTION

The Electrocardiogram (ECG) is a waveform that repesents the propagation of electric potentials through the heart muscle with respect to time. The propagation of these potentials results in the quasi-periodic contraction of the heart muscle. Each part of the cardiogram refers to a depolarization or a re-polarization of some region in the heart. The cardiogram consists of five major waves, also known as deflections in the cardiology literature, the P, Q, R, S, and T waves.

Myocardial Infarction is an acute ischemic heart disease characterized by a necrosis (death) of a portion of the heart muscle because of deprivation from oxygen. MI causes a serious disturbance of the cardiovascular system that leads to a direct threat for life.

MI is typically characterized by an elevation in the ST segment of ECG which is normally iso-electric for healthy subjects. ST segment elevation is generally one of the first symptom of MI and is usually accompanied by chest pain. But in order to be more specific to MI (or suspicious of MI), the ST elevation must be significant in amplitude (up to 0.2 mV) and prolonged in time (several minutes) as indicated in.

The rest of this report is organized as follows. Section II briefly reviews related techniques and presents our approach for early detection of MI. Section III presents our experimental results. Finally, Section IV concludes the report.

(a) One-cycle ECG tracing (b) ST Elevation ECG
Normal ECG and ST elevation ECG

II. IMPLIMENTATION

There are three aspects of our project:

A. ECG Signal Pre-processing (Ryshum Ali, Mahnoor Haneef)

We are going to utilize adaptive thresholding method [8] for denoising the EKG signal using wavelet transforms. Wavelets transforms prove effective as it has good localization properties s in time and frequency domain. We improvise existing thresholding methods to improve noise reduction while insuring a good signal to noise ratio. Thresholding basically removes some of the detailed coefficients exceeding a certain threshold hence smoothing the signal out. The signal is then reconstructed in the time domain using the modified coefficients. Determining a good threshold is important as a wrong threshold value can remove important ECG features or let in too much noise. Thresholding generally consists of taking the discrete wavelet transform of the signal using the appropriate wavelet. A thresholding parameter is set to reduce the detail coefficients in the wavelet transform and the denoised version of the signal is obtained by taking the inverse discrete wavelet transform of the signal using the modified coefficients. Donoho and Johnston proposed the universal threshold, called by them "Wave Shrink" given by:

$$\delta = \sigma\sqrt{(2\log N)}$$

Where σ is the standard deviation and N is the number of points. In case of white noise $\sigma = \frac{MAD}{0.6745}$ where MAD is the median absolute deviation of the detail coefficients. We alter this algorithm to provide a different threshold for each level of detail. Our altered formula is:

[ECG Signal Analysis for Myocardial Infarction Detection](https://www.slideshare.net/minamedhat723/project-190441763)
Uzair Akbar

Outlines

- ECG wave structure
- Electrodes placement
- Arrhythmia

International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 04 Issue: 06 | June -2017 www.irjet.net p-ISSN: 2395-0072

Cardio logical Signal Processing for Arrhythmia Detection with Comparative Analysis of Q-Factor

Ms. Sulata Bhandari[1], Dr. Sandeep Kaur[2], Rohit Gupta[3]

[1] Asst. professor, PEC University of technology, Chandigarh, India
[2] Asst. professor, PEC University of technology, Chandigarh, India
[3] ME scholar, PEC University of technology, Chandigarh, India

Abstract - *Electrocardiogram is a graph which measures the electrical activity of the heart. Normal heart beat for human is 70 cycles per minute. Any change in natural sequence of activities of heart e.g. beating too fast, too slow or erratically is Arrhythmia, and this can be detected by analyzing ECG of the subject. The recorded ECG potentials are usually contaminated by power-line frequencies, which lie within the frequency spectrum of ECG signal making it difficult to extract useful information from it, this interference is suppressed using 50/60Hz notch filter. . ECG signals first filtered by IIR notch, to remove the power line artifacts. It has been shown that notch filter application deforms the QRS complex of the electrocardiogram. In this paper a comparative analysis of the impact for different values of Q-factor of the notch filter, on QRS complex of Electrocardiogram has been shown. After filtering, QRS complex of an ECG signal identified. For detection of QRS complex DOM (difference operation method) is used. After successfully detection of QRS complex its R-peak, sharpness, slope and duration is calculated. For the classification purpose linear classifier is used, in which the ECG data were divided into two partition-one for trained the data called training set in which we used 75% data to trained the classifier and another for test the data called test set in which we used 25% data to test the classifier and classify the normal and arrhythmia signals.*

Key Words: Electrocardiogram (ECG), Difference operation method (DOM), QRS complex, Arrhythmia.

1. INTRODUCTION

Electrocardiogram (ECG) is the record of the heart muscle electric impulse. ECG machine is a device through which we record this electrical activity. This device is connected by wires to electrodes pasted on patient's chests at particular position [1]. Around 12 million deaths occur worldwide each year due to cardiovascular diseases as stated by the World Health Organization. Due to the insufficient supply of blood in the heart the clogging occurs and thus Coronary Heart Disease (CHD) takes place [2][3][4]. The cardiac arrhythmias accounts for ninety percent of the deaths due to cardiovascular diseases [5]. Arrhythmias are seen as an abnormal function of the heart.

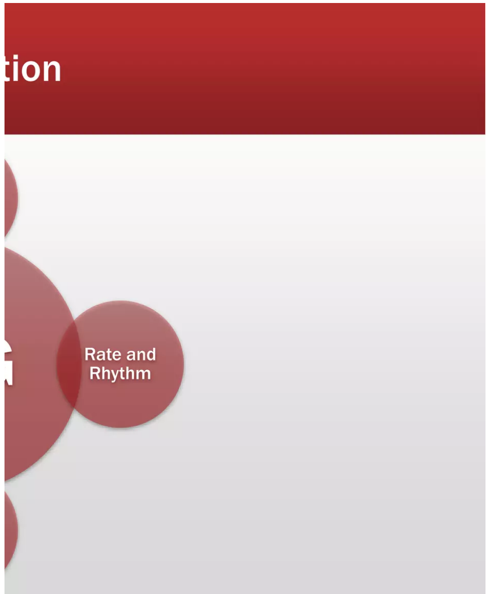
There have been several researches in the field of arrhythmia detection. Adams and Choi [5] proposed a method based on ANN to classify different arrhythmias using the QRS complex as features of ECG. Another neural network based classification of ECG for Premature Ventricular Contractions using Wavelet transform was done by Inan et al [6] with an accuracy of 88%. Patel et al [7] proposed arrhythmia detection method based on peak detection of QRS complex. They concluded that QR S complex is an important feature for classification of arrhythmia. Rahman and Nasor [8] used the QRS complex to define and classify different types of arrhythmia. Li, Zheng an d Tai [9] detected ECG characteristic points using wavelet transforms for the detection of QRS, T, and P waves[43].

Fig.- 1: Schematic representation of normal ECG waveform

Table -1: Amplitude and duration of waves, intervals and segments of ECG signal

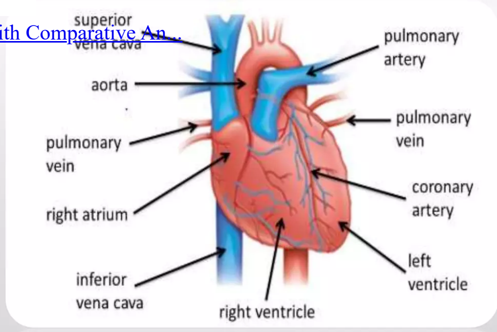
Sl. no.	Features	Amplitude (mV)	Duration (ms)
1	P wave	0.1-0.2	60-80
2	PR segment	-	50-120
3	PR interval	-	120-200
4	QRS complex	1	80-120
5	ST segment	-	100-120
6	T-wave	0.1-0.3	120-160
7	ST interval	-	320
8	RR interval	-	(0.4-1.2)s

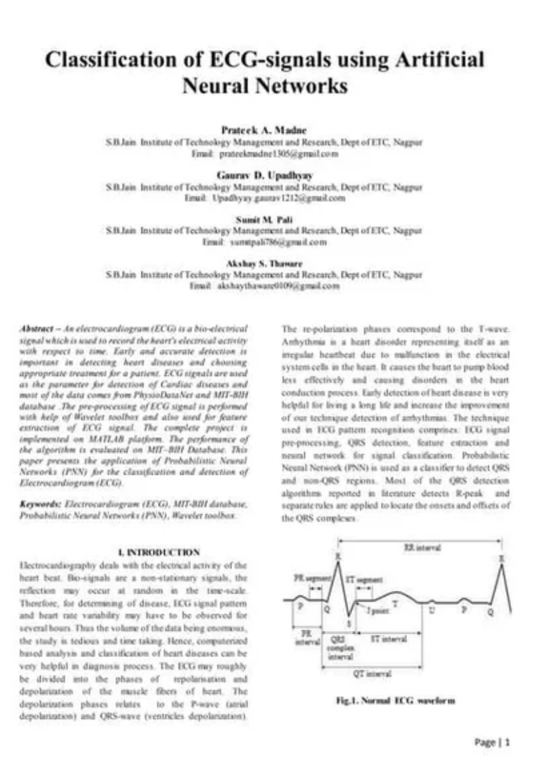
Cardio Logical Signal Processing for Arrhythmia Detection with Comparative An...
IRJET Journal



cture

- The heart is a muscular organ about the size of a closed fist that functions as the body's circulatory pump.
- The heart contains 4 chambers: the right atrium, left atrium, right ventricle, and left ventricle.





Classification of ECG-signals using Artificial Neural Networks

Prateek A. Madne
S.B.Jain Institute of Technology Management and Research, Dept of ETC, Nagpur
Email: prateekmadne1305@gmail.com

Gaurav D. Upadhyay
S.B.Jain Institute of Technology Management and Research, Dept of ETC, Nagpur
Email: Upadhyay.gaurav1212@gmail.com

Sumit M. Pali
S.B.Jain Institute of Technology Management and Research, Dept of ETC, Nagpur
Email: sumitpali786@gmail.com

Akshay S. Thaware
S.B.Jain Institute of Technology Management and Research, Dept of ETC, Nagpur
Email: akshaythaware0109@gmail.com

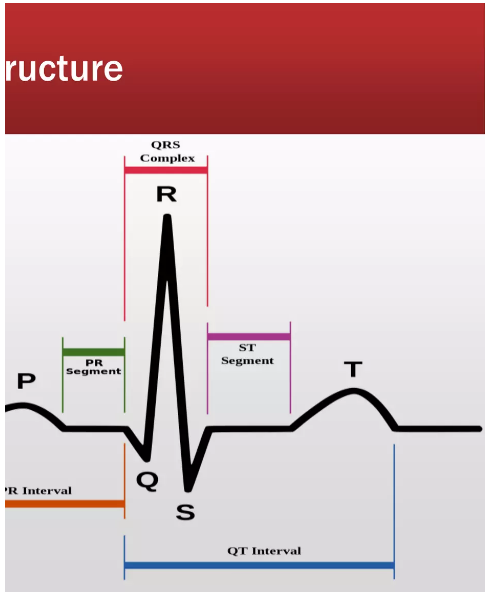
Abstract – *An electrocardiogram (ECG) is a bio-electrical signal which is used to record the heart's electrical activity with respect to time. Early and accurate detection is important in detecting heart diseases and choosing appropriate treatment for a patient. ECG signals are used as the parameter for detection of Cardiac diseases and most of the data comes from PhysioDataNet and MIT-BIH database. The pre-processing of ECG signal is performed with help of Wavelet toolbox and also used for feature extraction of ECG signal. The complete project is implemented on MATLAB platform. The performance of the algorithm is evaluated on MIT-BIH Database. This paper presents the application of Probabilistic Neural Networks (PNN) for the classification and detection of Electrocardiogram (ECG).*

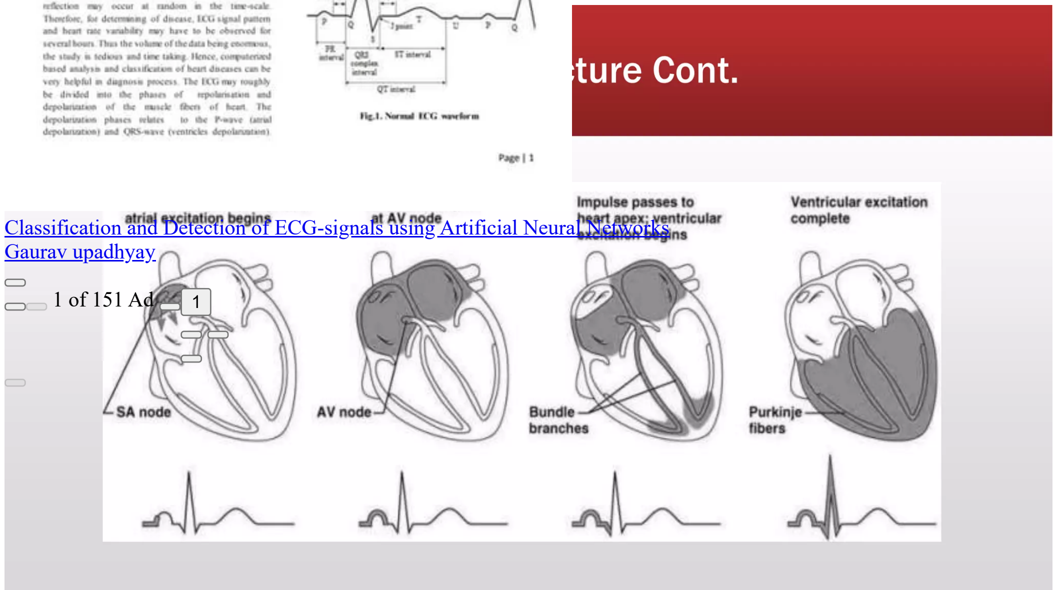
Keywords: *Electrocardiogram (ECG), MIT-BIH database, Probabilistic Neural Networks (PNN), Wavelet toolbox.*

I. INTRODUCTION

Electrocardiography deals with the electrical activity of the heart beat. Bio-signals are a non-stationary signals, the reflection may occur at random in the time-scale. Therefore, for determining of disease, ECG signal pattern and heart rate variability may have to be observed for several hours. Thus the volume of the data being enormous, the study is tedious and time taking. Hence, computerized based analysis and classification of heart diseases can be very helpful in diagnosis process. The ECG may roughly be divided into the phases of repolarisation and depolarization of the muscle fibers of heart. The depolarization phases relates to the P-wave (atrial depolarization) and QRS-wave (ventricles depolarization). The re-polarization phases correspond to the T-wave. Arrhythmia is a heart disorder representing itself as an irregular heartbeat due to malfunction in the electrical system cells in the heart. It causes the heart to pump blood less effectively and causing disorders in the heart conduction process. Early detection of heart disease is very helpful for living a long life and increase the improvement of our technique detection of arrhythmias. The technique used in ECG pattern recognition comprises: ECG signal pre-processing, QRS detection, feature extraction and neural network for signal classification. Probabilistic Neural Network (PNN) is used as a classifier to detect QRS and non-QRS regions. Most of the QRS detection algorithms reported in literature detects R-peak and separate rules are applied to locate the onsets and offsets of the QRS complexes.

Fig.1. Normal ECG waveform





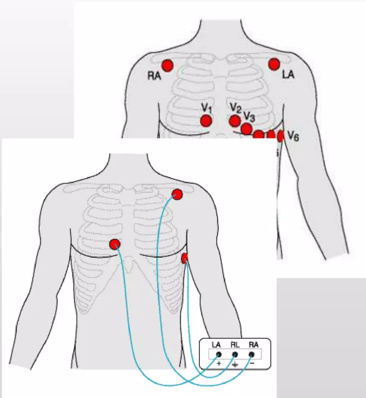
[Classification and Detection of ECG-signals using Artificial Neural Networks](#)
[Gaurav upadhyay](#)

1 of 151 Ad 1

Electrodes placement

Electrode	Placement
RA	On the right arm, avoiding thick muscle
LA	In the same location where RA was placed, but on the left arm
LL	In the same location where RL was placed, but on the left leg
RL	On the right leg, lateral calf muscle

MLII

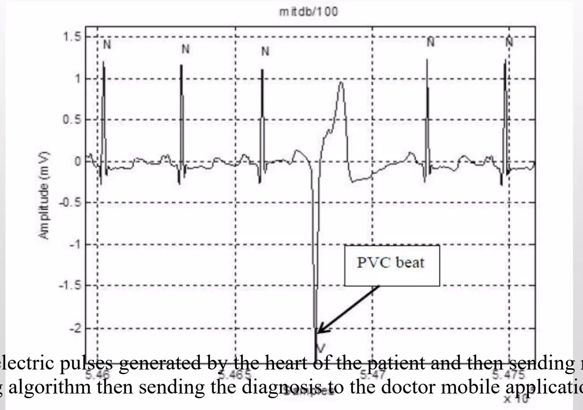


Arrhythmia

- An arrhythmia is a problem with the rate or rhythm of your heartbeat.
- When the heart beats faster than normal, it is called tachycardia. When the heart beats too slowly, it is called bradycardia.

Arrhythmia Cont.

- Premature Ventricular Contraction (PVC)
  - Broad QRS Complex
  - Lengthened RR interval
  - ST depression or T wave inversion or ST elevation with upright T wave

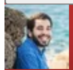


Project

Nov. 04, 2019

Engineering

An ECG module (Arduino shield) monitor the electric pulses generated by the heart of the patient and then sending readings using Bluetooth low energy to the mobile application of the patient then uploading these readings to the cloud to get processed and diagnosed using machine learning algorithm then sending the diagnosis to the doctor mobile application to monitor the state of his patient letting him to response quickly in an urgent state.

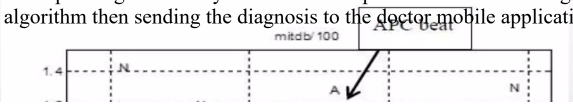


mina medhat

Arrhythmia Cont.

An ECG module (Arduino shield) monitor the electric pulses generated by the heart of the patient and then sending readings using Bluetooth low energy to the mobile application of the patient then uploading these readings to the cloud to get processed and diagnosed using machine learning algorithm then sending the diagnosis to the doctor mobile application to monitor the state of his patient letting him to response quickly in an urgent state.

- Atrial Premature Contraction (APC)



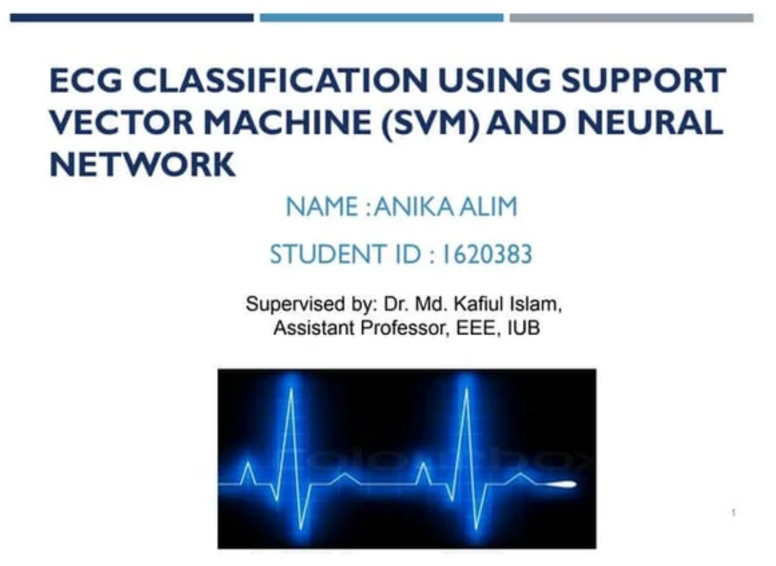
Engineering

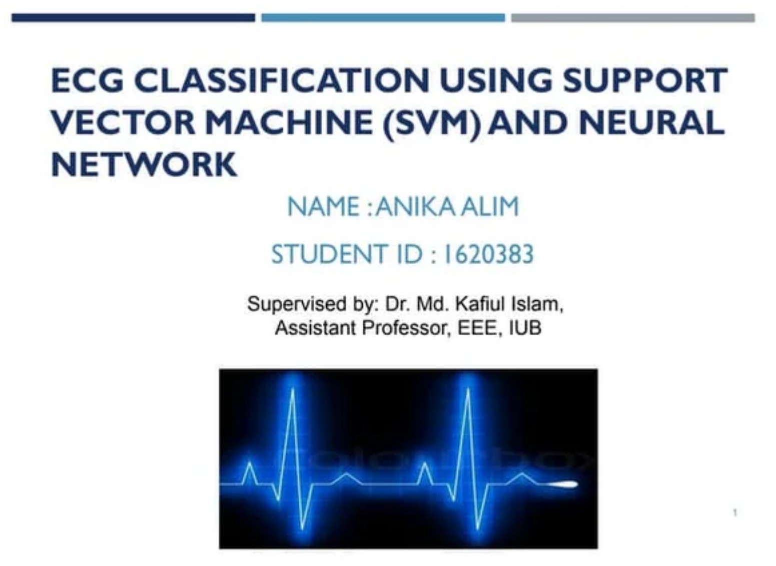
Recommended

ECG Hidden P wave
Mehran University Of Engineering And Technology Jamshoro.

ECG BASED REPORT.
Mehran University Of Engineering And Technology Jamshoro.

RESULTS!!





Dimension Reduction

CLOUD-BASED ECG CLASSIFICATION WITH MOBILE INTERFACE

Epperson, Joseph David (jde160530@utdallas.edu)
Hoff, Jason (jxj143230@utdallas.edu)
Noor Shoudha, Shamman (sxn170028@utdallas.edu)

THE UNIVERSITY OF TEXAS AT DALLAS
Erik Jonsson School of Engineering and Computer Science

CLOUD-BASED ECG CLASSIFICATION WITH MOBILE INTERFACE

Epperson, Joseph David (jde160530@utdallas.edu)
Hoff, Jason (jxj143230@utdallas.edu)
Noor Shoudha, Shamman (sxn170028@utdallas.edu)

THE UNIVERSITY OF TEXAS AT DALLAS
Erik Jonsson School of Engineering and Computer Science

performance on the ECG waveforms of different patients.

upraventricular arrhythmia databases are

and pass filter at 0.1–100 Hz and sampled

AAMI class	MIT-BIH heart beat types				
Normal beat (N)	Normal beat (N)	Left bundle branch block beat (L)	Right bundle branch block beat (R)	Atrial escape beat (e)	Nodal (junctional) escape beat (j)
Supraventricular ectopic beat (S)	Atrial premature beat (A)	Aberrated atrial premature beat (a)	Nodal (junctional) premature beat (J)	Supraventricular premature beat (S)	
Ventricular ectopic beat (V)	Premature ventricular contraction (V)	Ventricular escape beat (E)			
Fusion beat (F)	Fusion of ventricular and normal beat (F)				
Unknown beat (Q)	Paced beat (/)	Fusion of paced and normal beat (f)	Unclassified beat (Q)		

Seminar on...

ECG FEATURE EXTRACTION AND CLASSIFICATION USING BPN ALGORITHM

K.Senthil Kumar

Associate Professor
Department of Electronics and Communication Engineering
Rajalakshmi Institute of Technology
Chennai-600124.

Seminar on...

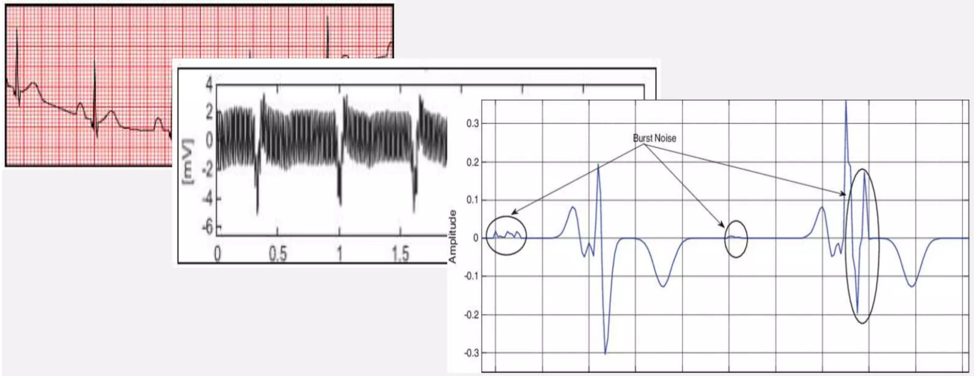
ECG FEATURE EXTRACTION AND CLASSIFICATION USING BPN ALGORITHM

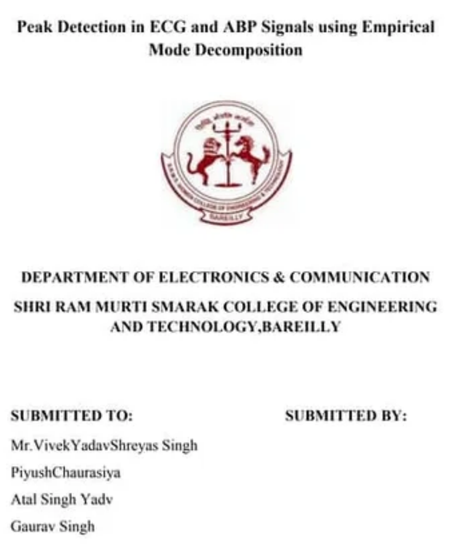
K.Senthil Kumar

Associate Professor
Department of Electronics and Communication Engineering
Rajalakshmi Institute of Technology
Chennai-600124.

Preprocessing Cont.

Baseline wander **Powerline interference** **Burst noise**





Peak Detection in ECG and ABP Signals using Empirical Mode Decomposition

DEPARTMENT OF ELECTRONICS & COMMUNICATION

SHRI RAM MURTI SMARAK COLLEGE OF ENGINEERING AND TECHNOLOGY,BAREILLY

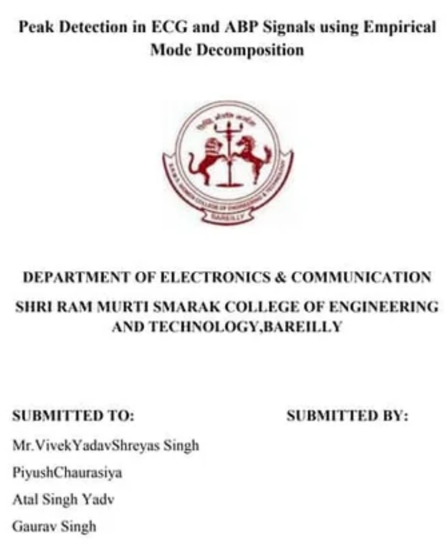
SUBMITTED TO: SUBMITTED BY:

Mr.VivekYadavShreyas Singh

PiyushChaurasiya

Atal Singh Yadv

Gaurav Singh



Peak Detection in ECG and ABP Signals using Empirical Mode Decomposition

DEPARTMENT OF ELECTRONICS & COMMUNICATION

SHRI RAM MURTI SMARAK COLLEGE OF ENGINEERING AND TECHNOLOGY,BAREILLY

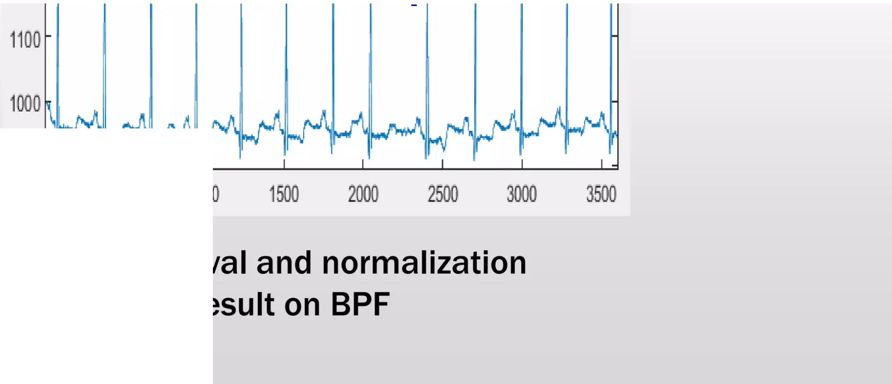
SUBMITTED TO: SUBMITTED BY:

Mr.VivekYadavShreyas Singh

PiyushChaurasiya

Atal Singh Yadv

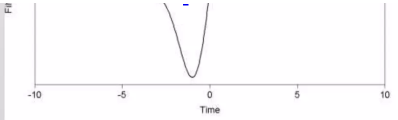
Gaurav Singh



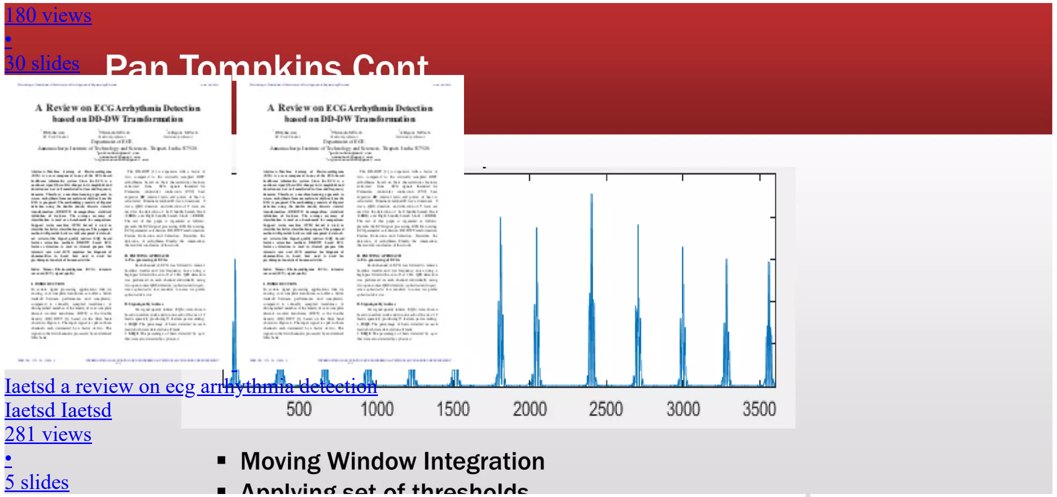
Recommended

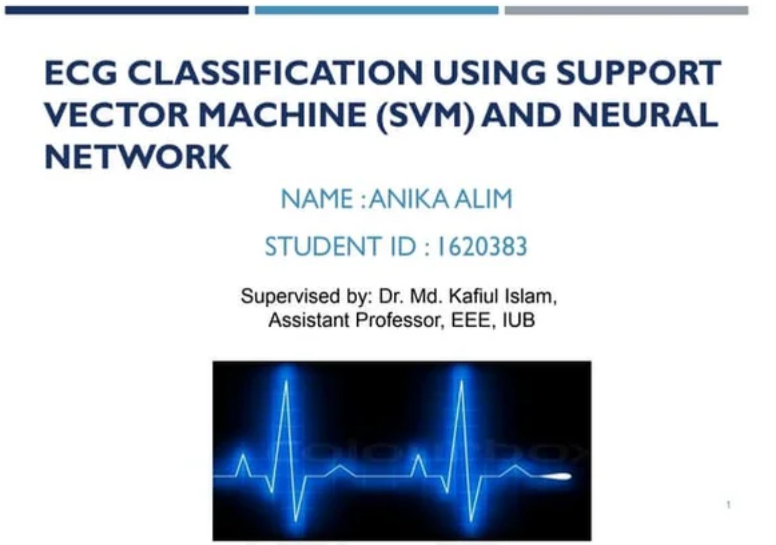
[ECG](#)
[Mehran University Of Engineering And Technology Jamshoro.](#)
[701 views](#)
[•](#)
[17 slides](#)

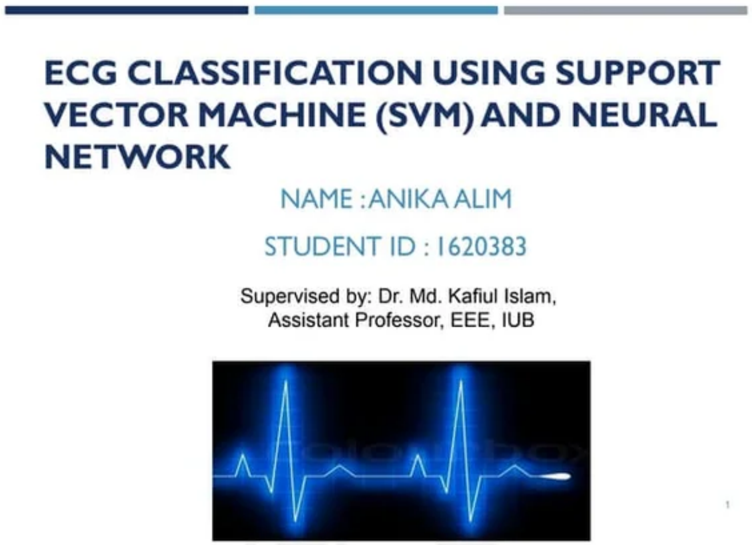
▪ Derivative Filter

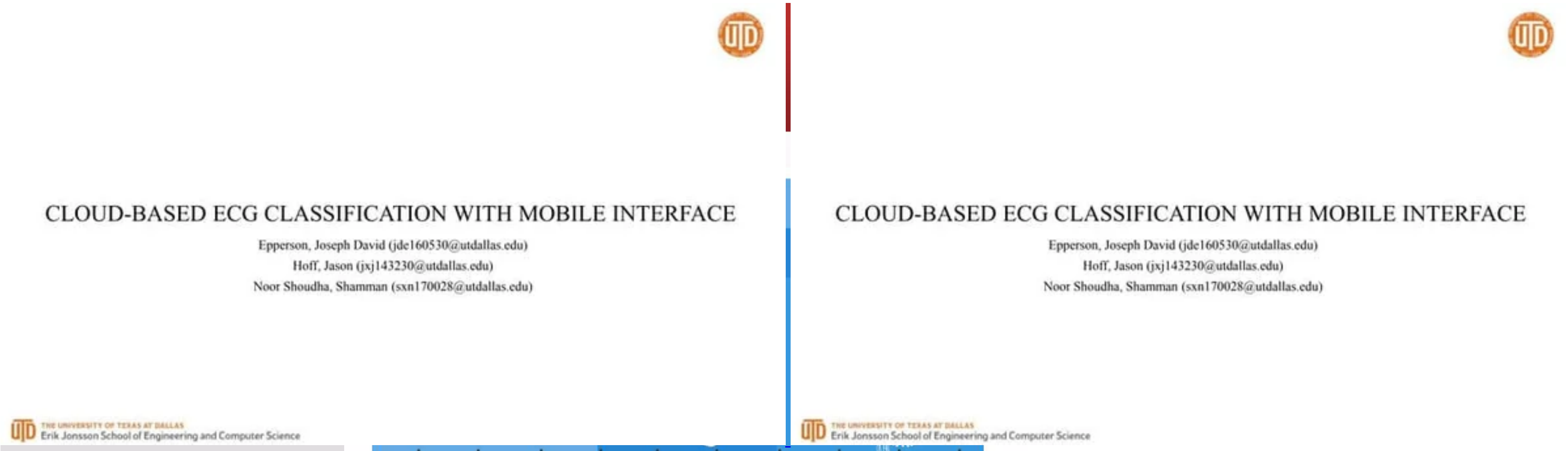


[ECG BASED REPORT.](#)
[Mehran University Of Engineering And Technology Jamshoro.](#)

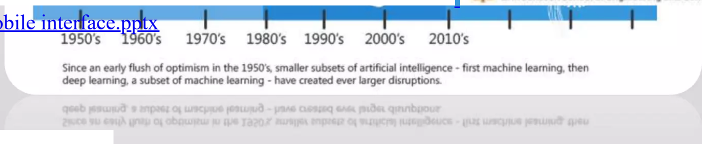

Pan Tompkins Cont
A Review on ECG Arrhythmia Detection based on DD-DW Transformation
500
1000
1500
2000
2500
3000
3500
Moving Window Integration
Applying set of thresholds


ECG CLASSIFICATION USING SUPPORT VECTOR MACHINE (SVM) AND NEURAL NETWORK
NAME : ANIKA ALIM
STUDENT ID : 1620383
Supervised by: Dr. Md. Kafiul Islam,
Assistant Professor, EEE, IUB


ECG CLASSIFICATION USING SUPPORT VECTOR MACHINE (SVM) AND NEURAL NETWORK
NAME : ANIKA ALIM
STUDENT ID : 1620383
Supervised by: Dr. Md. Kafiul Islam,
Assistant Professor, EEE, IUB



driven decisions.



[Cloud-based ECG classification with mobile interface.pptx]
[Shamman Noor Shoudha]
[48 views]
•
[22 slides]

[IRJET- Arrhythmia Detection using One Dimensional Convolutional Neural Network]
[IRJET Journal]
[23 views]
•
[11 slides]

Seminar on...

ECG FEATURE EXTRACTION AND CLASSIFICATION USING BPN ALGORITHM

K.Senthil Kumar

Associate Professor
Department of Electronics and Communication Engineering
Rajalakshmi Institute of Technology
Chennai-600124.

Seminar on...

ECG FEATURE EXTRACTION AND CLASSIFICATION USING BPN ALGORITHM

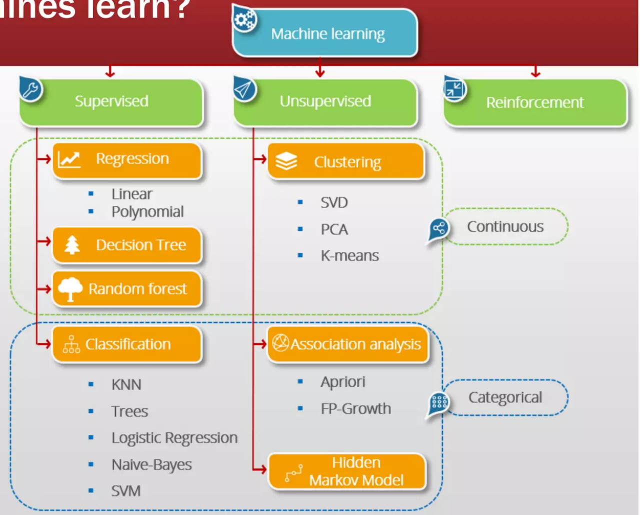
K.Senthil Kumar

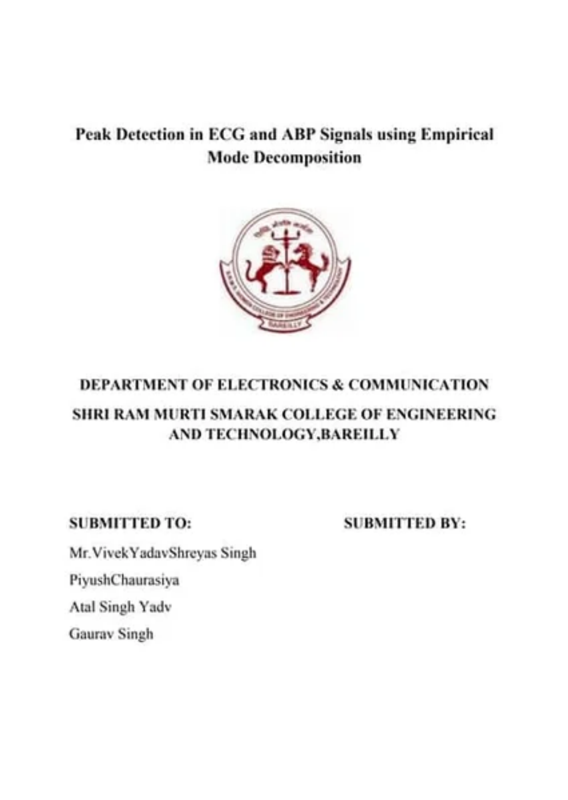
Associate Professor
Department of Electronics and Communication Engineering
Rajalakshmi Institute of Technology
Chennai-600124.

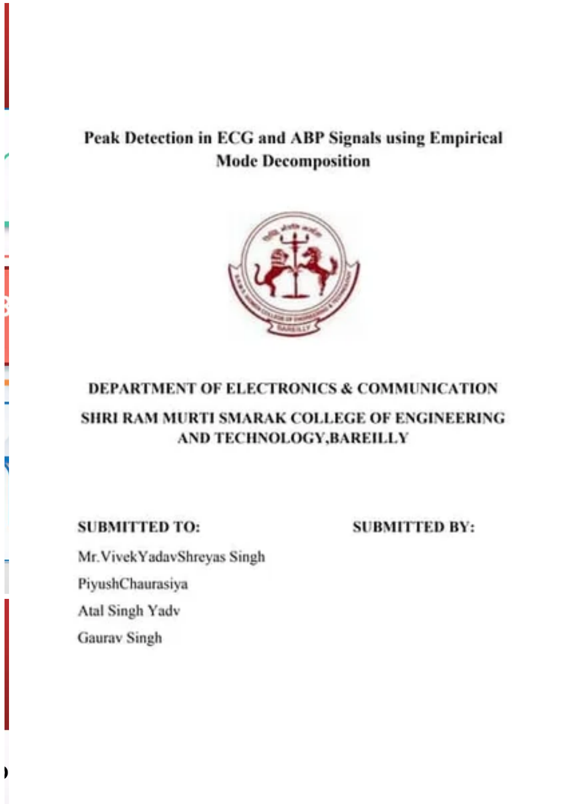
How exactly do machines learn?

- **Unsupervised Learning:** Group and interpret data based only on input data.

- **Supervised Learning:** Develop predictive model based on both input and output data.







More Related Content

Similar to Project (20)

Extraction Cont.

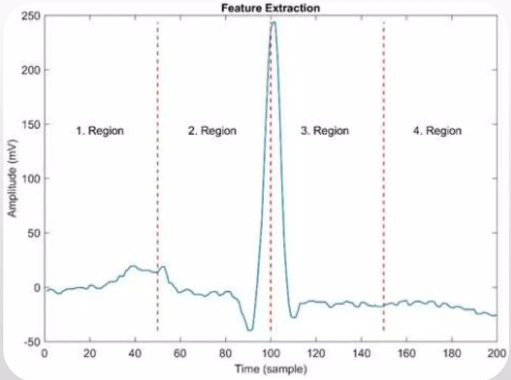
atures

ne beat and its sections.

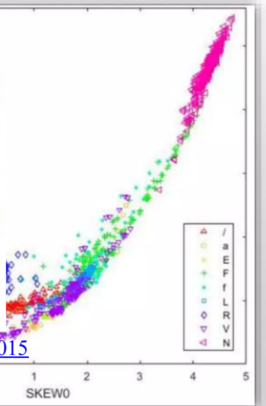
$$\frac{\sum_{i=1}^{n}(x_i-\bar{x})^3}{\sum_{i=1}^{n}(x-\bar{x}))^3}$$

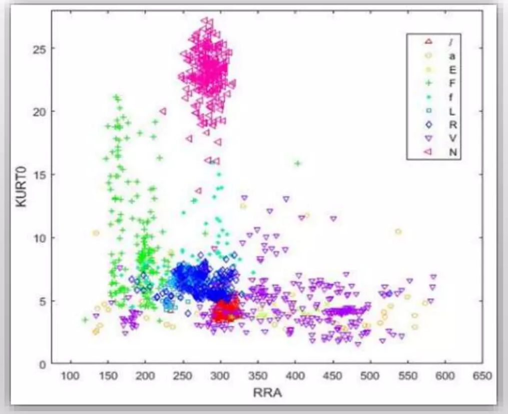
$$\frac{\sum_{i=1}^{n}(x_i-\bar{x})^4}{\sum_{i=1}^{n}(x-\bar{x}))^4}$$

$$\frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n}$$



Extraction Cont.





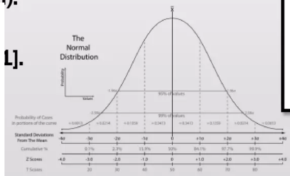
Extraction Cont.

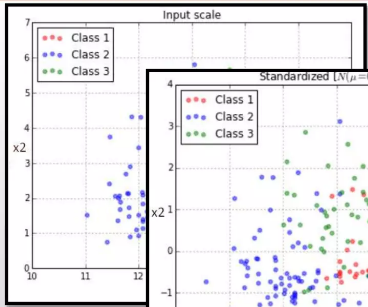
ormalization

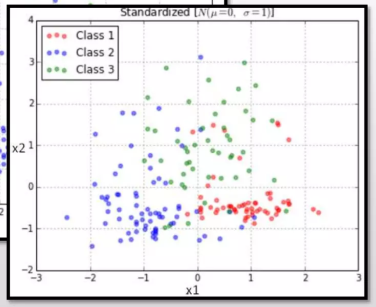
e effect of different
; features .

on (Z-score
normalization).

1].







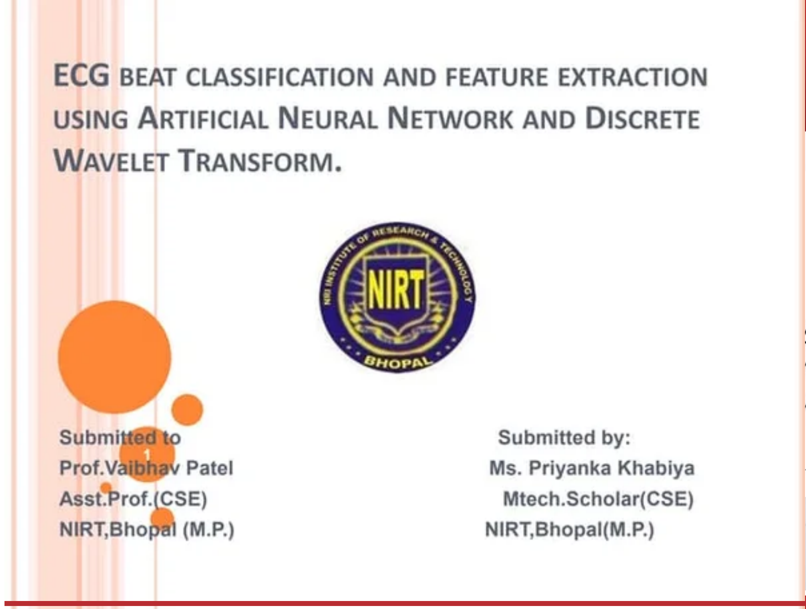
, μ=0 and σ=1

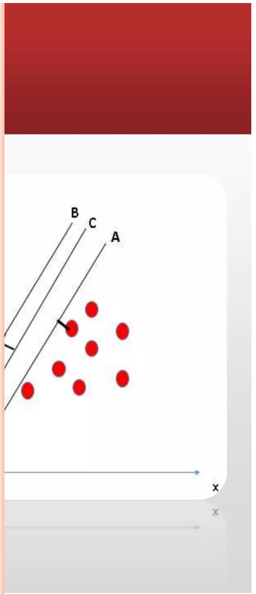
Feature Selection

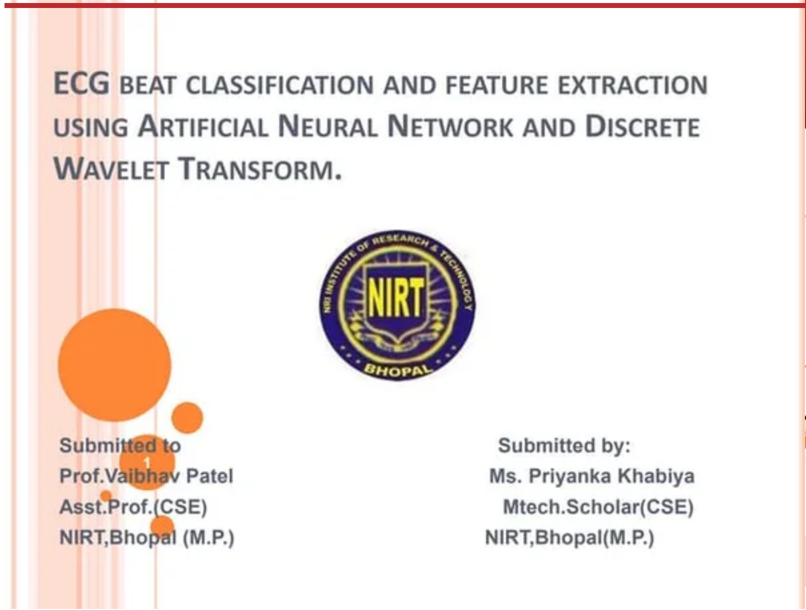
- Feature selection is a process where you automatically select those features in your data that contribute most to the prediction variable or output in which you are interested.
- Having irrelevant features in your data can decrease the accuracy of many models.
- **Benefits:**
  - Reduces Overfitting
  - Improves Accuracy
  - Reduces Training Time

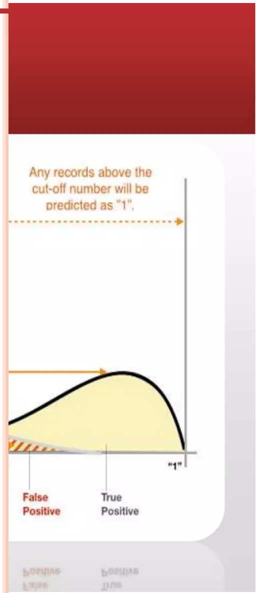
Methods:

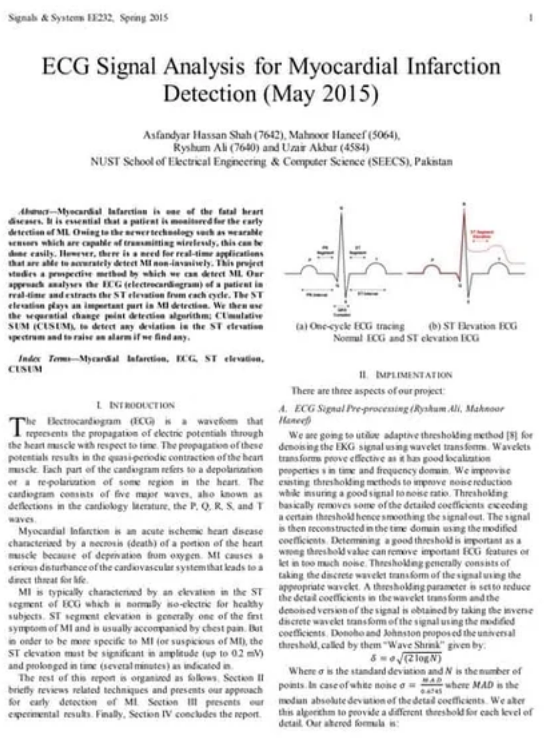
1) Univariate Selection
2) Principal Component Analysis.
3) Independent Component Analysis


ECG BEAT CLASSIFICATION AND FEATURE EXTRACTION USING ARTIFICIAL NEURAL NETWORK AND DISCRETE WAVELET TRANSFORM.
NIRT
BHOPAL
Submitted to
Prof.Vaibhav Patel
Asst.Prof.(CSE)
NIRT,Bhopal (M.P.)
Submitted by:
Ms. Priyanka Khabiya
Mtech.Scholar(CSE)
NIRT,Bhopal(M.P.)


B
C
A
x


ECG BEAT CLASSIFICATION AND FEATURE EXTRACTION USING ARTIFICIAL NEURAL NETWORK AND DISCRETE WAVELET TRANSFORM.
NIRT
BHOPAL
Submitted to
Prof.Vaibhav Patel
Asst.Prof.(CSE)
NIRT,Bhopal (M.P.)
Submitted by:
Ms. Priyanka Khabiya
Mtech.Scholar(CSE)
NIRT,Bhopal(M.P.)


Any records above the cut-off number will be predicted as "1".
"1"
False Positive
True Positive



Signals & Systems EE232, Spring 2015 1

ECG Signal Analysis for Myocardial Infarction Detection (May 2015)

Asfandyar Hassan Shah (7642), Mahnoor Haneef (5064),
Ryshum Ali (7640) and Uzair Akbar (4584)
NUST School of Electrical Engineering & Computer Science (SEECS), Pakistan

Abstract—Myocardial Infarction is one of the fatal heart diseases. It is essential that a patient is monitored for the early detection of MI. Owing to the newer technology such as wearable sensors which are capable of transmitting wirelessly, this can be done easily. However, there is a need for real-time applications that are able to accurately detect MI non-invasively. This project studies a prospective method by which we can detect MI. Our approach analyses the ECG (electrocardiogram) of a patient in real-time and extracts the ST elevation from each cycle. The ST elevation plays an important part in MI detection. We then use the sequential change point detection algorithm; CUmulative SUM (CUSUM), to detect any deviation in the ST elevation spectrum and to raise an alarm if we find any.

Index Terms—Mycardial Infarction, ECG, ST elevation, CUSUM

I. INTRODUCTION

The Electrocardiogram (ECG) is a waveform that represents the propagation of electric potentials through the heart muscle with respect to time. The propagation of these potentials results in the quasi-periodic contraction of the heart muscle. Each part of the cardiogram refers to a depolarization or a re-polarization of some region in the heart. The cardiogram consists of five major waves, also known as deflections in the cardiology literature, the P, Q, R, S, and T waves.

Myocardial Infarction is an acute ischemic heart disease characterized by a necrosis (death) of a portion of the heart muscle because of deprivation from oxygen. MI causes a serious disturbance of the cardiovascular system that leads to a direct threat for life.

MI is typically characterized by an elevation in the ST segment of ECG which is normally iso-electric for healthy subjects. ST segment elevation is generally one of the first symptom of MI and is usually accompanied by chest pain. But in order to be more specific to MI (or suspicious of MI), the ST elevation must be significant in amplitude (up to 0.2 mV) and prolonged in time (several minutes) as indicated in.

The rest of this report is organized as follows. Section II briefly reviews related techniques and presents our approach for early detection of MI. Section III presents our experimental results. Finally, Section IV concludes the report.

(a) One-cycle ECG tracing (b) ST Elevation ECG
Normal ECG and ST elevation ECG

II. IMPLIMENTATION

There are three aspects of our project:

A. ECG Signal Pre-processing (Ryshum Ali, Mahnoor Haneef)

We are going to utilize adaptive thresholding method [8] for denoising the EKG signal using wavelet transforms. Wavelets transforms prove effective as it has good localization properties s in time and frequency domain. We improvise existing thresholding methods to improve noise reduction while insuring a good signal to noise ratio. Thresholding basically removes some of the detailed coefficients exceeding a certain threshold hence smoothing the signal out. The signal is then reconstructed in the time domain using the modified coefficients. Determining a good threshold is important as a wrong threshold value can remove important ECG features or let in too much noise. Thresholding generally consists of taking the discrete wavelet transform of the signal using the appropriate wavelet. A thresholding parameter is set to reduce the detail coefficients in the wavelet transform and the denoised version of the signal is obtained by taking the inverse discrete wavelet transform of the signal using the modified coefficients. Donoho and Johnston proposed the universal threshold, called by them "Wave Shrink" given by:

$$\delta = \sigma\sqrt{(2\log N)}$$

Where σ is the standard deviation and N is the number of points. In case of white noise $\sigma = \frac{MAD}{0.6745}$ where MAD is the median absolute deviation of the detail coefficients. We alter this algorithm to provide a different threshold for each level of detail. Our altered formula is:

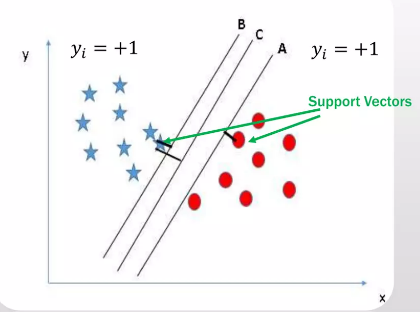
		Predicted class P	Predicted class N
tual lass	P	True Positives (TP)	False Negatives (FN)
	N	False Positives (FP)	True Negatives (TN)

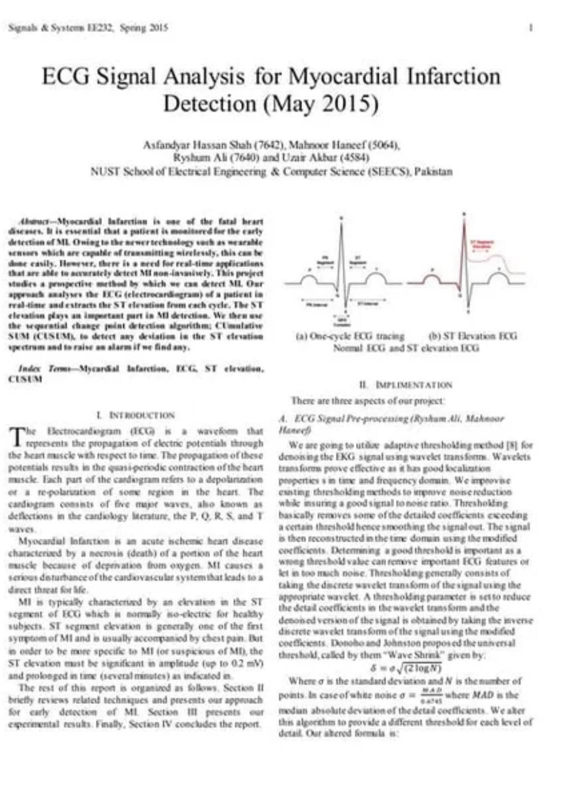
classification and regression.

1. Generalizes well.
2. Computationally efficient

- Classification is performed by finding the hyper-plane g(x) that differentiate the two classes very well.

$$g(x) = W^T X + b = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$$





Signals & Systems EE232, Spring 2015 1

ECG Signal Analysis for Myocardial Infarction Detection (May 2015)

Asfandyar Hassan Shah (7642), Mahnoor Haneef (5064), Rysham Ali (7640) and Uzair Akbar (4584)
NUST School of Electrical Engineering & Computer Science (SEECS), Pakistan

Abstract—Myocardial Infarction is one of the fatal heart diseases. It is essential that a patient is monitored for the early detection of MI. Owing to the newer technology such as wearable sensors which are capable of transmitting wirelessly, this can be done easily. However, there is a need for real-time applications that are able to accurately detect MI non-invasively. This project studies a prospective method by which we can detect MI. Our approach analyses the ECG (electrocardiogram) of a patient in real-time and extracts the ST elevation from each cycle. The ST elevation plays an important part in MI detection. We then use the sequential change point detection algorithm; CUmulative SUM (CUSUM), to detect any deviation in the ST elevation spectrum and to raise an alarm if we find any.

Index Terms—Mycardial Infarction, ECG, ST elevation, CUSUM

I. INTRODUCTION

The Electrocardiogram (ECG) is a waveform that represents the propagation of electric potentials through the heart muscle with respect to time. The propagation of these potentials results in the quasi-periodic contraction of the heart muscle. Each part of the cardiogram refers to a depolarization or a re-polarization of some region in the heart. The cardiogram consists of five major waves, also known as deflections in the cardiology literature, the P, Q, R, S, and T waves.

Myocardial Infarction is an acute ischemic heart disease characterized by a necrosis (death) of a portion of the heart muscle because of deprivation from oxygen. MI causes a serious disturbance of the cardiovascular system that leads to a direct threat for life.

MI is typically characterized by an elevation in the ST segment of ECG which is normally iso-electric for healthy subjects. ST segment elevation is generally one of the first symptom of MI and is usually accompanied by chest pain. But in order to be more specific to MI (or suspicious of MI), the ST elevation must be significant in amplitude (up to 0.2 mV) and prolonged in time (several minutes) as indicated in.

The rest of this report is organized as follows. Section II briefly reviews related techniques and presents our approach for early detection of MI. Section III presents our experimental results. Finally, Section IV concludes the report.

(a) One-cycle ECG tracing (b) ST Elevation ECG
Normal ECG and ST elevation ECG

II. IMPLIMENTATION

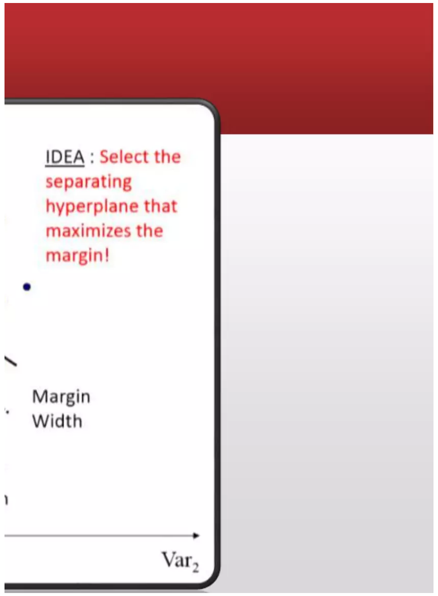
There are three aspects of our project:

A. ECG Signal Pre-processing (Rysham Ali, Mahnoor Haneef)

We are going to utilize adaptive thresholding method [8] for denoising the EKG signal using wavelet transforms. Wavelets transforms prove effective as it has good localization properties s in time and frequency domain. We improvise existing thresholding methods to improve noise reduction while insuring a good signal to noise ratio. Thresholding basically removes some of the detailed coefficients exceeding a certain threshold hence smoothing the signal out. The signal is then reconstructed in the time domain using the modified coefficients. Determining a good threshold is important as a wrong threshold value can remove important ECG features or let in too much noise. Thresholding generally consists of taking the discrete wavelet transform of the signal using the appropriate wavelet. A thresholding parameter is set to reduce the detail coefficients in the wavelet transform and the denoised version of the signal is obtained by taking the inverse discrete wavelet transform of the signal using the modified coefficients. Donoho and Johnston proposed the universal threshold, called by them "Wave Shrink" given by:

$$\delta = \sigma\sqrt{(2\log N)}$$

Where σ is the standard deviation and N is the number of points. In case of white noise $\sigma = \frac{MAD}{0.6745}$ where MAD is the median absolute deviation of the detail coefficients. We alter this algorithm to provide a different threshold for each level of detail. Our altered formula is:



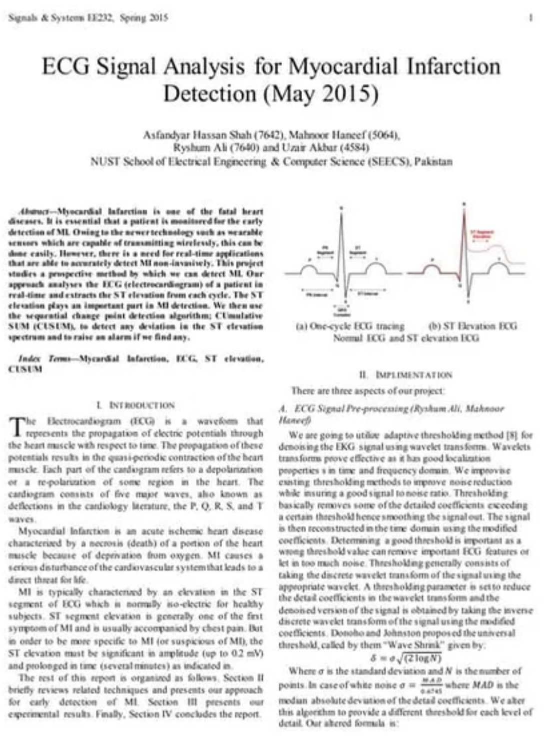
- SVM for each pair of *n classes.*

$$C(n,2)= \frac{n(n-1)}{2}$$

- We need $C(n,k)$ SVM's .
- Classe with most votes picked as a WINNER!

Predicted

True labels	A	B	C	
A	2	2	0	4
B	1	2	0	3
C	0	0	3	3
	3	4	3	Total



Signals & Systems EE232, Spring 2015 1

ECG Signal Analysis for Myocardial Infarction Detection (May 2015)

Asfandyar Hassan Shah (7642), Mahnoor Haneef (5064),
Rysham Ali (7640) and Uzair Akbar (4584)
NUST School of Electrical Engineering & Computer Science (SEECS), Pakistan

Abstract—**Myocardial Infarction is one of the fatal heart diseases. It is essential that a patient is monitored for the early detection of MI. Owing to the newer technology such as wearable sensors which are capable of transmitting wirelessly, this can be done easily. However, there is a need for real-time applications that are able to accurately detect MI non-invasively. This project studies a prospective method by which we can detect MI. Our approach analyses the ECG (electrocardiogram) of a patient in real-time and extracts the ST elevation from each cycle. The ST elevation plays an important part in MI detection. We then use the sequential change point detection algorithm; CUmulative SUM (CUSUM), to detect any deviation in the ST elevation spectrum and to raise an alarm if we find any.**

Index Terms—**Mycardial Infarction, ECG, ST elevation, CUSUM**

I. Introduction

The Electrocardiogram (ECG) is a waveform that repesents the propagation of electric potentials through the heart muscle with respect to time. The propagation of these potentials results in the quasi-periodic contraction of the heart muscle. Each part of the cardiogram refers to a depolarization or a re-polarization of some region in the heart. The cardiogram consists of five major waves, also known as deflections in the cardiology literature, the P, Q, R, S, and T waves.

Myocardial Infarction is an acute ischemic heart disease characterized by a necrosis (death) of a portion of the heart muscle because of deprivation from oxygen. MI causes a serious disturbance of the cardiovascular system that leads to a direct threat for life.

MI is typically characterized by an elevation in the ST segment of ECG which is normally iso-electric for healthy subjects. ST segment elevation is generally one of the first symptom of MI and is usually accompanied by chest pain. But in order to be more specific to MI (or suspicious of MI), the ST elevation must be significant in amplitude (up to 0.2 mV) and prolonged in time (several minutes) as indicated in.

The rest of this report is organized as follows. Section II briefly reviews related techniques and presents our approach for early detection of MI. Section III presents our experimental results. Finally, Section IV concludes the report.

(a) One-cycle ECG tracing (b) ST Elevation ECG
Normal ECG and ST elevation ECG

II. Implimentation

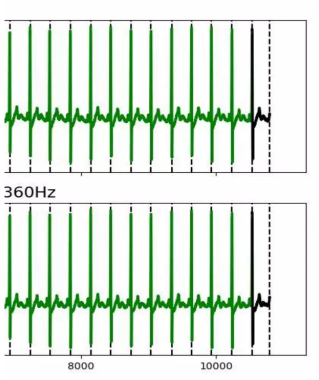
There are three aspects of our project:

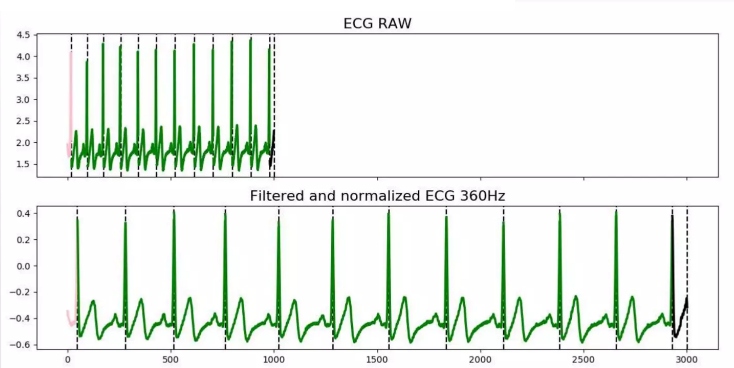
A. ECG Signal Pre-processing (Rysham Ali, Mahnoor Haneef)

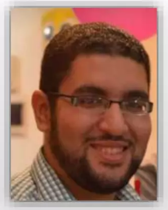
We are going to utilize adaptive thresholding method [8] for denoising the EKG signal using wavelet transforms. Wavelets transforms prove effective as it has good localization properties s in time and frequency domain. We improvise existing thresholding methods to improve noise reduction while insuring a good signal to noise ratio. Thresholding basically removes some of the detailed coefficients exceeding a certain threshold hence smoothing the signal out. The signal is then reconstructed in the time domain using the modified coefficients. Determining a good threshold is important as a wrong threshold value can remove important ECG features or let in too much noise. Thresholding generally consists of taking the discrete wavelet transform of the signal using the appropriate wavelet. A thresholding parameter is set to reduce the detail coefficients in the wavelet transform and the denoised version of the signal is obtained by taking the inverse discrete wavelet transform of the signal using the modified coefficients. Donoho and Johnston proposed the universal threshold, called by them "Wave Shrink" given by:

$$\delta = \sigma\sqrt{(2\log N)}$$

Where σ is the standard deviation and N is the number of points. In case of white noise $\sigma = \frac{MAD}{0.6745}$ where MAD is the median absolute deviation of the detail coefficients. We alter this algorithm to provide a different threshold for each level of detail. Our altered formula is:







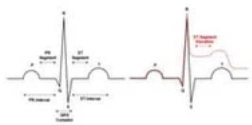
Signals & Systems EE232, Spring 2015 1

ECG Signal Analysis for Myocardial Infarction Detection (May 2015)

Asfandyar Hassan Shah (7642), Mahnoor Haneef (5064),
Ryshum Ali (7640) and Uzair Akbar (4584)
NUST School of Electrical Engineering & Computer Science (SEECS), Pakistan

Abstract—Myocardial Infarction is one of the fatal heart diseases. It is essential that a patient is monitored for the early detection of MI. Owing to the newer technology such as wearable sensors which are capable of transmitting wirelessly, this can be done easily. However, there is a need for real-time applications that are able to accurately detect MI non-invasively. This project studies a prospective method by which we can detect MI. Our approach analyses the ECG (electrocardiogram) of a patient in real-time and extracts the ST elevation from each cycle. The ST elevation plays an important part in MI detection. We then use the sequential change point detection algorithm; CUmulative SUM (CUSUM), to detect any deviation in the ST elevation spectrum and to raise an alarm if we find any.

Index Terms—Mycardial Infarction, ECG, ST elevation, CUSUM



(a) One-cycle ECG tracing (b) ST Elevation ECG
Normal ECG and ST elevation ECG

I. Introduction

The Electrocardiogram (ECG) is a waveform that repesents the propagation of electric potentials through the heart muscle with respect to time. The propagation of these potentials results in the quasi-periodic contraction of the heart muscle. Each part of the cardiogram refers to a depolarization or a re-polarization of some region in the heart. The cardiogram consists of five major waves, also known as deflections in the cardiology literature, the P, Q, R, S, and T waves.

Myocardial Infarction is an acute ischemic heart disease characterized by a necrosis (death) of a portion of the heart muscle because of deprivation from oxygen. MI causes a serious disturbance of the cardiovascular system that leads to a direct threat for life.

MI is typically characterized by an elevation in the ST segment of ECG which is normally iso-electric for healthy subjects. ST segment elevation is generally one of the first symptom of MI and is usually accompanied by chest pain. But in order to be more specific to MI (or suspicious of MI), the ST elevation must be significant in amplitude (up to 0.2 mV) and prolonged in time (several minutes) as indicated in.

The rest of this report is organized as follows. Section II briefly reviews related techniques and presents our approach for early detection of MI. Section III presents our experimental results. Finally, Section IV concludes the report.

II. Implimentation

There are three aspects of our project:

A. ECG Signal Pre-processing (Ryshum Ali, Mahnoor Haneef)

We are going to utilize adaptive thresholding method [8] for denoising the EKG signal using wavelet transforms. Wavelets transforms prove effective as it has good localization properties s in time and frequency domain. We improvise existing thresholding methods to improve noise reduction while insuring a good signal to noise ratio. Thresholding basically removes some of the detailed coefficients exceeding a certain threshold hence smoothing the signal out. The signal is then reconstructed in the time domain using the modified coefficients. Determining a good threshold is important as a wrong threshold value can remove important ECG features or let in too much noise. Thresholding generally consists of taking the discrete wavelet transform of the signal using the appropriate wavelet. A thresholding parameter is set to reduce the detail coefficients in the wavelet transform and the denoised version of the signal is obtained by taking the inverse discrete wavelet transform of the signal using the modified coefficients. Donoho and Johnston proposed the universal threshold, called by them "Wave Shrink" given by:

$$\delta = \sigma\sqrt{(2\log N)}$$

Where σ is the standard deviation and N is the number of points. In case of white noise $\sigma = \frac{MAD}{0.6745}$ where MAD is the median absolute deviation of the detail coefficients. We alter this algorithm to provide a different threshold for each level of detail. Our altered formula is:

Predicted Value

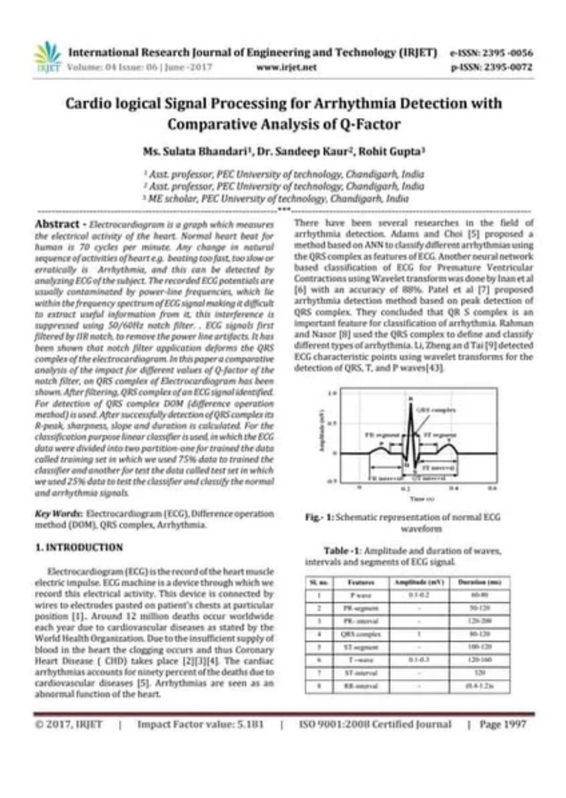
	Normal	SVEB	VEB	
	9	2	1	12
	3	7	2	12
	4	0	8	12
	16	9	11	36

Calculations	Results
9/12	75%
16/21	76.2%
17/22	77.3%
8/12	66.7%
7/12	58.3%
9/12	75%
15/22	68.2%
17/19	89.5%
16/19	84.2%

Predicted Values

		ed Negative	Predicted Positive	
True Values	True Negative	16	2	18
	True Positive	4	14	18
		21	16	36

Confusion Matrix Parameters	Calculations	Results
Accuracy	30/36	83.3 %
(True Positive Rate) "Sensitivity"	14 / 18	77.8 %
Specificity	16 / 18	88.9 %



International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 04 Issue: 06 | June -2017 www.irjet.net p-ISSN: 2395-0072

Cardio logical Signal Processing for Arrhythmia Detection with Comparative Analysis of Q-Factor

Ms. Sulata Bhandari[1], Dr. Sandeep Kaur[2], Rohit Gupta[3]

[1] Asst. professor, PEC University of technology, Chandigarh, India
[2] Asst. professor, PEC University of technology, Chandigarh, India
[3] ME scholar, PEC University of technology, Chandigarh, India

Abstract - *Electrocardiogram is a graph which measures the electrical activity of the heart. Normal heart beat for human is 70 cycles per minute. Any change in natural sequence of activities of heart e.g. beating too fast, too slow or erratically is Arrhythmia, and this can be detected by analyzing ECG of the subject. The recorded ECG potentials are usually contaminated by power-line frequencies, which lie within the frequency spectrum of ECG signal making it difficult to extract useful information from it, this interference is suppressed using 50/60Hz notch filter. . ECG signals first filtered by IIR notch, to remove the power line artifacts. It has been shown that notch filter application deforms the QRS complex of the electrocardiogram. In this paper a comparative analysis of the impact for different values of Q-factor of the notch filter, on QRS complex of Electrocardiogram has been shown. After filtering, QRS complex of an ECG signal identified. For detection of QRS complex DOM (difference operation method) is used. After successfully detection of QRS complex its R-peak, sharpness, slope and duration is calculated. For the classification purpose linear classifier is used, in which the ECG data were divided into two partition-one for trained the data called training set in which we used 75% data to trained the classifier and another for test the data called test set in which we used 25% data to test the classifier and classify the normal and arrhythmia signals.*

Key Words: Electrocardiogram (ECG), Difference operation method (DOM), QRS complex, Arrhythmia.

1. INTRODUCTION

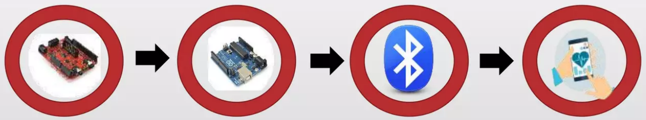
Electrocardiogram (ECG) is the record of the heart muscle electric impulse. ECG machine is a device through which we record this electrical activity. This device is connected by wires to electrodes pasted on patient's chests at particular position [1]. Around 12 million deaths occur worldwide each year due to cardiovascular diseases as stated by the World Health Organization. Due to the insufficient supply of blood in the heart the clogging occurs and thus Coronary Heart Disease (CHD) takes place [2][3][4]. The cardiac arrhythmias accounts for ninety percent of the deaths due to cardiovascular diseases [5]. Arrhythmias are seen as an abnormal function of the heart.

There have been several researches in the field of arrhythmia detection. Adams and Choi [5] proposed a method based on ANN to classify different arrhythmias using the QRS complex as features of ECG. Another neural network based classification of ECG for Premature Ventricular Contractions using Wavelet transform was done by Inan et al [6] with an accuracy of 88%. Patel et al [7] proposed arrhythmia detection method based on peak detection of QRS complex. They concluded that QR S complex is an important feature for classification of arrhythmia. Rahman and Nasor [8] used the QRS complex to define and classify different types of arrhythmia. Li, Zheng an d Tai [9] detected ECG characteristic points using wavelet transforms for the detection of QRS, T, and P waves[43].

Fig.- 1: Schematic representation of normal ECG waveform

Table -1: Amplitude and duration of waves, intervals and segments of ECG signal

Sl. no.	Features	Amplitude (mV)	Duration (ms)
1	P wave	0.1-0.2	60-80
2	PR-segment	-	50-120
3	PR- interval	-	120-200
4	QRS complex	1	80-120
5	ST segment	-	100-120
6	T –wave	0.1-0.3	120-160
7	ST-interval	-	320
8	RR-interval	-	(0.6-1.2)s



International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395 -0056
Volume: 04 Issue: 06 | June -2017 www.irjet.net p-ISSN: 2395-0072

Cardio logical Signal Processing for Arrhythmia Detection with Comparative Analysis of Q-Factor

Ms. Sulata Bhandari[1], Dr. Sandeep Kaur[2], Rohit Gupta[3]

[1] Asst. professor, PEC University of technology, Chandigarh, India
[2] Asst. professor, PEC University of technology, Chandigarh, India
[3] ME scholar, PEC University of technology, Chandigarh, India

Abstract - *Electrocardiogram is a graph which measures the electrical activity of the heart. Normal heart beat for human is 70 cycles per minute. Any change in natural sequence of activities of heart e.g. beating too fast, too slow or erratically is Arrhythmia, and this can be detected by analyzing ECG of the subject. The recorded ECG potentials are usually contaminated by power-line frequencies, which lie within the frequency spectrum of ECG signal making it difficult to extract useful information from it, this interference is suppressed using 50/60Hz notch filter. . ECG signals first filtered by IIR notch, to remove the power line artifacts. It has been shown that notch filter application deforms the QRS complex of the electrocardiogram. In this paper a comparative analysis of the impact for different values of Q-factor of the notch filter, on QRS complex of Electrocardiogram has been shown. After filtering, QRS complex of an ECG signal identified. For detection of QRS complex DOM (difference operation method) is used. After successfully detection of QRS complex its R-peak, sharpness, slope and duration is calculated. For the classification purpose linear classifier is used, in which the ECG data were divided into two partition-one for trained the data called training set in which we used 75% data to trained the classifier and another for test the data called test set in which we used 25% data to test the classifier and classify the normal and arrhythmia signals.*

Key Words: Electrocardiogram (ECG), Difference operation method (DOM), QRS complex, Arrhythmia.

1. INTRODUCTION

Electrocardiogram (ECG) is the record of the heart muscle electric impulse. ECG machine is a device through which we record this electrical activity. This device is connected by wires to electrodes pasted on patient's chests at particular position [1]. Around 12 million deaths occur worldwide each year due to cardiovascular diseases as stated by the World Health Organization. Due to the insufficient supply of blood in the heart the clogging occurs and thus Coronary Heart Disease (CHD) takes place [2][3][4]. The cardiac arrhythmias accounts for ninety percent of the deaths due to cardiovascular diseases [5]. Arrhythmias are seen as an abnormal function of the heart.

There have been several researches in the field of arrhythmia detection. Adams and Choi [5] proposed a method based on ANN to classify different arrhythmias using the QRS complex as features of ECG. Another neural network based classification of ECG for Premature Ventricular Contractions using Wavelet transform was done by Inan et al [6] with an accuracy of 88%. Patel et al [7] proposed arrhythmia detection method based on peak detection of QRS complex. They concluded that QR S complex is an important feature for classification of arrhythmia. Rahman and Nasor [8] used the QRS complex to define and classify different types of arrhythmia. Li, Zheng an d Tai [9] detected ECG characteristic points using wavelet transforms for the detection of QRS, T, and P waves[43].

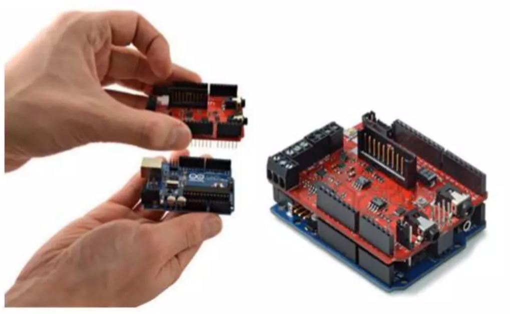
Fig.- 1: Schematic representation of normal ECG waveform

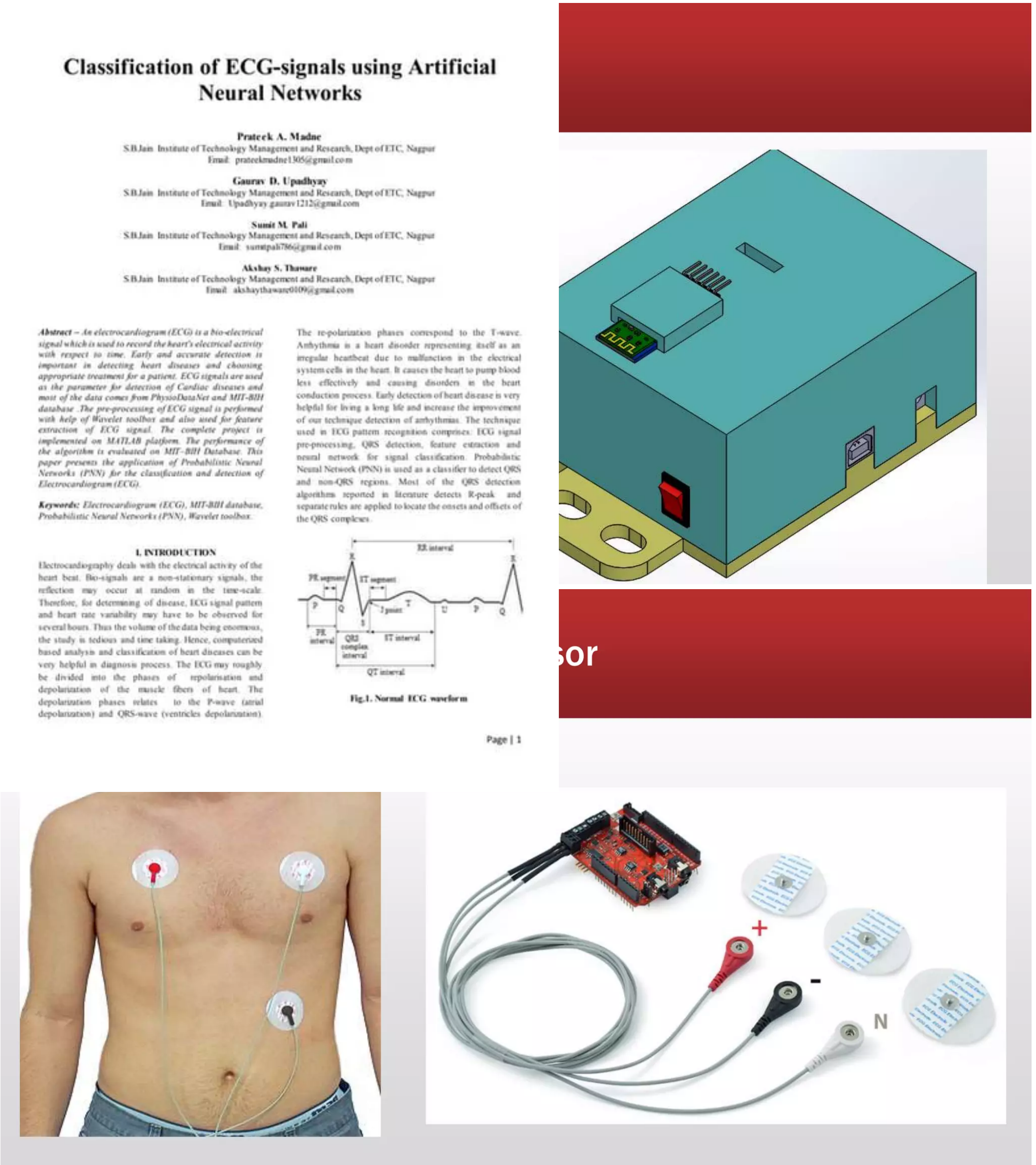
Table -1: Amplitude and duration of waves, intervals and segments of ECG signal.

Sl. no.	Features	Amplitude (mV)	Duration (ms)
1	P wave	0.1-0.2	60-80
2	PR-segment	-	50-120
3	PR- interval	-	120-200
4	QRS complex	1	80-120
5	ST-segment	-	100-120
6	T-wave	0.1-0.3	120-160
7	ST-interval	-	320
8	RR-interval	-	(0.4-1.2)s

Outlines

- **Feathers:**
  - This ECG returns an analogic value in volts (0 – 5) to represent the ECG wave form.
  - Variable sampling frequency.





Classification of ECG-signals using Artificial Neural Networks

Prateek A. Madne
S.B.Jain Institute of Technology Management and Research, Dept of ETC, Nagpur
Email: prateekmadne1305@gmail.com

Gaurav D. Upadhyay
S.B.Jain Institute of Technology Management and Research, Dept of ETC, Nagpur
Email: Upadhyay.gaurav1212@gmail.com

Sumit M. Pali
S.B.Jain Institute of Technology Management and Research, Dept of ETC, Nagpur
Email: sumitpali786@gmail.com

Akshay S. Thaware
S.B.Jain Institute of Technology Management and Research, Dept of ETC, Nagpur
Email: akshaythaware0109@gmail.com

Abstract – *An electrocardiogram (ECG) is a bio-electrical signal which is used to record the heart's electrical activity with respect to time. Early and accurate detection is important in detecting heart diseases and choosing appropriate treatment for a patient. ECG signals are used as the parameter for detection of Cardiac diseases and most of the data comes from PhysioDataNet and MIT-BIH database. The pre-processing of ECG signal is performed with help of Wavelet toolbox and also used for feature extraction of ECG signal. The complete project is implemented on MATLAB platform. The performance of the algorithm is evaluated on MIT-BIH Database. This paper presents the application of Probabilistic Neural Networks (PNN) for the classification and detection of Electrocardiogram (ECG).*

Keywords: *Electrocardiogram (ECG), MIT-BIH database, Probabilistic Neural Networks (PNN), Wavelet toolbox.*

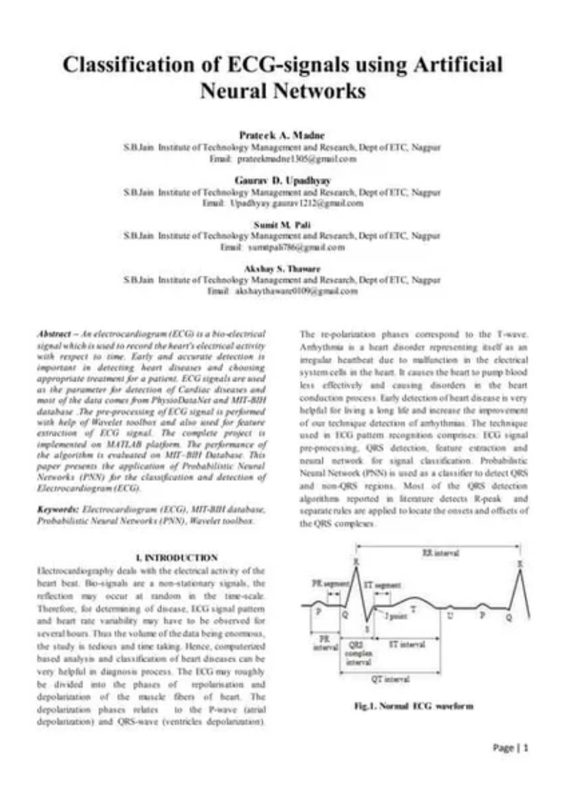
I. INTRODUCTION

Electrocardiography deals with the electrical activity of the heart beat. Bio-signals are a non-stationary signals, the reflection may occur at random in the time-scale. Therefore, for determining of disease, ECG signal pattern and heart rate variability may have to be observed for several hours. Thus the volume of the data being enormous, the study is tedious and time taking. Hence, computerized based analysis and classification of heart diseases can be very helpful in diagnosis process. The ECG may roughly be divided into the phases of repolarisation and depolarization of the muscle fibers of heart. The depolarization phases relates to the P-wave (atrial depolarization) and QRS-wave (ventricles depolarization). The re-polarization phases correspond to the T-wave. Arrhythmia is a heart disorder representing itself as an irregular heartbeat due to malfunction in the electrical system cells in the heart. It causes the heart to pump blood less effectively and causing disorders in the heart conduction process. Early detection of heart disease is very helpful for living a long life and increase the improvement of our technique detection of arrhythmias. The technique used in ECG pattern recognition comprises: ECG signal pre-processing, QRS detection, feature extraction and neural network for signal classification. Probabilistic Neural Network (PNN) is used as a classifier to detect QRS and non-QRS regions. Most of the QRS detection algorithms reported in literature detects R-peak and separate rules are applied to locate the onsets and offsets of the QRS complexes.

RR interval
R
R
PR segment
ST segment
P
Q
S
J point
T
U
P
Q
PR interval
QRS complex interval
ST interval
QT interval

Fig.1. Normal ECG waveform

Page | 1



Classification of ECG-signals using Artificial Neural Networks

Prateek A. Madne
S.B.Jain Institute of Technology Management and Research, Dept of ETC, Nagpur
Email: prateekmadne1305@gmail.com

Gaurav D. Upadhyay
S.B.Jain Institute of Technology Management and Research, Dept of ETC, Nagpur
Email: Upadhyay.gaurav1212@gmail.com

Sumit M. Pali
S.B.Jain Institute of Technology Management and Research, Dept of ETC, Nagpur
Email: sumitpali786@gmail.com

Akshay S. Thaware
S.B.Jain Institute of Technology Management and Research, Dept of ETC, Nagpur
Email: akshaythaware0109@gmail.com

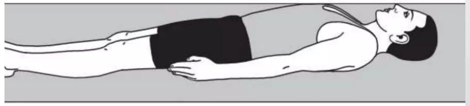
Abstract *– An electrocardiogram (ECG) is a bio-electrical signal which is used to record the heart's electrical activity with respect to time. Early and accurate detection is important in detecting heart diseases and choosing appropriate treatment for a patient. ECG signals are used as the parameter for detection of Cardiac diseases and most of the data comes from PhysioDataNet and MIT-BIH database .The pre-processing of ECG signal is performed with help of Wavelet toolbox and also used for feature extraction of ECG signal. The complete project is implemented on MATLAB platform. The performance of the algorithm is evaluated on MIT-BIH Database. This paper presents the application of Probabilistic Neural Networks (PNN) for the classification and detection of Electrocardiogram (ECG).*

Keywords: *Electrocardiogram (ECG), MIT-BIH database, Probabilistic Neural Networks (PNN), Wavelet toolbox.*

I. INTRODUCTION

Electrocardiography deals with the electrical activity of the heart beat. Bio-signals are a non-stationary signals, the reflection may occur at random in the time-scale. Therefore, for determining of disease, ECG signal pattern and heart rate variability may have to be observed for several hours. Thus the volume of the data being enormous, the study is tedious and time taking. Hence, computerized based analysis and classification of heart diseases can be very helpful in diagnosis process. The ECG may roughly be divided into the phases of repolarisation and depolarization of the muscle fibers of heart. The depolarization phases relates to the P-wave (atrial depolarization) and QRS-wave (ventricles depolarization). The re-polarization phases correspond to the T-wave. Arrhythmia is a heart disorder representing itself as an irregular heartbeat due to malfunction in the electrical system cells in the heart. It causes the heart to pump blood less effectively and causing disorders in the heart conduction process. Early detection of heart disease is very helpful for living a long life and increase the improvement of our technique detection of arrhythmias. The technique used in ECG pattern recognition comprises: ECG signal pre-processing, QRS detection, feature extraction and neural network for signal classification. Probabilistic Neural Network (PNN) is used as a classifier to detect QRS and non-QRS regions. Most of the QRS detection algorithms reported in literature detects R-peak and separate rules are applied to locate the onsets and offsets of the QRS complexes.

Fig.1. Normal ECG waveform



The patient should use sterilizer on his skin.

IOSR Journal of Engineering (IOSRJEN) www.iosrjen.org
ISSN (e): 2250-3021, ISSN (p): 2278-8719
Vol. 04, Issue 12 (December 2014), ||V1|| PP 53-58

Automation of ECG heart beat detection using Morphological filtering and Daubechies wavelet transform

Gayani K.S[1], Vinodkumar Jacob[2], Kavitha N Nair[3]
[1] (PG Scholar, Department of ECE, University College of Engineering, Thodupuzha, Kerala, India.)
[2] (Professor,Department of ECE, Mar Athanasius College of Engineering, Kothamangalam, Kerala, India)
[3] (Asst.Professor,Department of ECE, University College of Engineering, Thodupuzha, Kerala, India.)

Abstract: - The most specific diagnostic test for heart diseases is the Electrocardiogram (ECG). ECG is a graphical representation of the electrical activity of the heart. Analysis of an ECG signal starts with the detection of QRS complex. Detection of QRS complex is a difficult task as the signal is frequently corrupted by powerline interference, baseline drift, motion artifact and electromyographic interference. Therefore, reliable and accurate detection of QRS complex is gaining momentum nowadays.
A novel QRS detection algorithm based on Mathematical Morphological (MM) filtering and Daubechies wavelet transform has been developed in this work. MM uses its hybrid opening-closing operations for impulsive noise suppression and baseline wander removal. Daubechies3 WT is used for signal analysis since it has a shape similar to the ECG signal. R peak is extracted as a first in the feature extraction since it is having highest amplitude, followed by Q peak and S peak extraction. Heart beat rate was calculated from the R-R peak interval. From the heart rate and R-R peak interval the diagnosis of the cardiac ailments is done.

Keywords: - *Baseline wander, Daubechies wavelet transform, ECG, Mathematical Morphology, QRS complex*

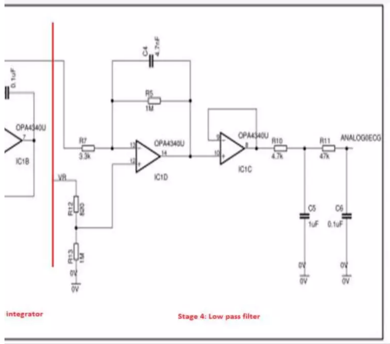
I. INTRODUCTION

Heart diseases are reported to have a major share in human death all over the world. Early diagnoses and medical treatment of heart diseases can prevent sudden death of the patient. The simplest and the most specific diagnostic test for cardiac ailments is the Electrocardiogram (ECG) test. ECG signals are generated by the ECG machine and these signals are analyzed for the presence of any heart abnormalities. Different computational tools and algorithms are being developed for the computer based analysis of the ECG to reduce time consumption and improve the accuracy of the extraction. The ECG heart beat detection involves the issue of extracting the QRS Complex, which is the main parameter that enables patient monitoring and further diagnosis of cardiac ailments.

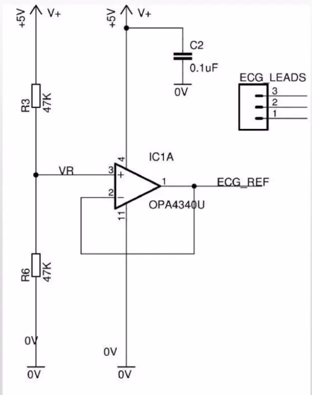
An ECG signal is a bioelectric signal, which records the heart's electrical activity versus time. It is characterized by a series of waves whose morphology and timing provide information used for diagnosing diseases reflected by disturbances of the electrical activity of the heart. This activity is recorded on graph sheets or some kinds of monitors by placing the electrodes on specific locations of the body of a person. The recorded waves have peaks and valleys and are normally represented by the letters P, Q, R, S, T and U waves. Figure.1 shows a standard ECG waveform.

Fig.1 A standard ECG waveform

Computer based heart beat detection has mainly two challenges-Noise and the non-stationary nature of the ECG signal. Some of the noise and interferences affecting the ECG signal are baseline wandering, electromyographic noise, power line interference, motion artifacts. Baseline Wandering is a low frequency activity in the ECG which shifts the isoelectric line position of the signal. Electromyographic noise overlaps with the ECG signal which makes its filtering difficult. Power line interference is caused by data cables carrying



- Provides electrical impedance transformation
- Optimized for low voltage, single supply operation
- Reduces power consumption in the source and distortion
- Removes high frequencies



IOSR Journal of Engineering (IOSRJEN) www.iosrjen.org
ISSN (e): 2250-3021, ISSN (p): 2278-8719
Vol. 04, Issue 12 (December 2014), ||V1|| PP 53-58

Automation of ECG heart beat detection using Morphological filtering and Daubechies wavelet transform

Gayani K.S[1], Vinodkumar Jacob[2], Kavitha N Nair[3]
[1] (PG Scholar, Department of ECE, University College of Engineering, Thodupuzha, Kerala, India.)
[2] (Professor,Department of ECE, Mar Athanasius College of Engineering, Kothamangalam, Kerala, India)
[3] (Asst.Professor,Department of ECE, University College of Engineering, Thodupuzha, Kerala, India.)

Abstract: - The most specific diagnostic test for heart diseases is the Electrocardiogram (ECG). ECG is a graphical representation of the electrical activity of the heart. Analysis of an ECG signal starts with the detection of QRS complex. Detection of QRS complex is a difficult task as the signal is frequently corrupted by powerline interference, baseline drift, motion artifact and electromyographic interference. Therefore, reliable and accurate detection of QRS complex is gaining momentum nowadays.

A novel QRS detection algorithm based on Mathematical Morphological (MM) filtering and Daubechies wavelet transform has been developed in this work. MM uses its hybrid opening-closing operations for impulsive noise suppression and baseline wander removal. Daubechies3 WT is used for signal analysis since it has a shape similar to the ECG signal. R peak is extracted as a first in the feature extraction since it is having highest amplitude, followed by Q peak and S peak extraction. Heart beat rate was calculated from the R-R peak interval. From the heart rate and R-R peak interval the diagnosis of the cardiac ailments is done.

Keywords: - *Baseline wander, Daubechies wavelet transform, ECG, Mathematical Morphology, QRS complex*

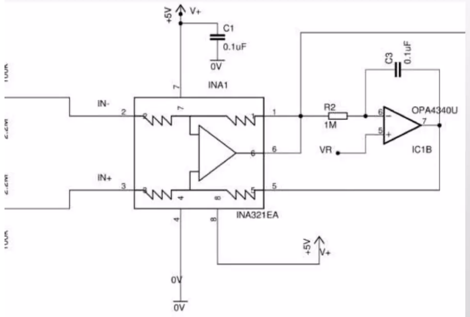
I. INTRODUCTION

Heart diseases are reported to have a major share in human death all over the world. Early diagnoses and medical treatment of heart diseases can prevent sudden death of the patient. The simplest and the most specific diagnostic test for cardiac ailments is the Electrocardiogram (ECG) test. ECG signals are generated by the ECG machine and these signals are analyzed for the presence of any heart abnormalities. Different computational tools and algorithms are being developed for the computer based analysis of the ECG to reduce time consumption and improve the accuracy of the extraction. The ECG heart beat detection involves the issue of extracting the QRS Complex, which is the main parameter that enables patient monitoring and further diagnosis of cardiac ailments.

An ECG signal is a bioelectric signal, which records the heart's electrical activity versus time. It is characterized by a series of waves whose morphology and timing provide information used for diagnosing diseases reflected by disturbances of the electrical activity of the heart. This activity is recorded on graph sheets or some kinds of monitors by placing the electrodes on specific locations of the body of a person. The recorded waves have peaks and valleys and are normally represented by the letters P, Q, R, S, T and U waves. Figure.1 shows a standard ECG waveform.

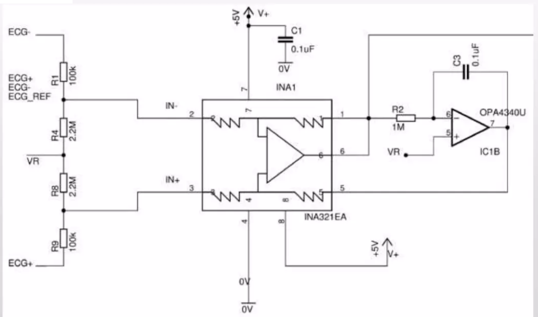
Fig.1 A standard ECG waveform

Computer based heart beat detection has mainly two challenges-Noise and the non-stationary nature of the ECG signal. Some of the noise and interferences affecting the ECG signal are baseline wandering, electromyographic noise, power line interference, motion artifacts. Baseline Wandering is a low frequency activity in the ECG which shifts the isoelectric line position of the signal. Electromyographic noise overlaps with the ECG signal which makes its filtering difficult. Power line interference is caused by data cables carrying



- Performs the mathematical operation of integration
- Output signal is determined by the length of time a voltage is present at its input

$$Vout = -\frac{1}{Rin\ C}\int_0^t Vin\, dt$$



"Classification of ECG-signals using Artificial Neural Networks"

Gaurav D.Upadhyay[1] Akshay S. Thaware[2] Sumit M. Pali[3] Prateek A. Madne[4]

Abstract *– An electrocardiogram (ECG) is a bioelectrical signal which records the heart's electrical activity with respect to time. Early and accurate detection is important in detecting heart diseases and choosing appropriate treatment for a patient. ECG signals are used as the parameter for detection of Cardiac diseases and most of the data comes from PhysioDataNet and MIT-BIH database .The pre-processing of ECG signal is performed with help of Wavelet toolbox and also used for feature extraction of ECG signal. The complete project is implemented on MATLAB platform. The performance of the algorithm is evaluated on MIT-BIH Database. This paper presents the application of Probabilistic Neural Networks (PNN) for the classification and detection of Electrocardiogram (ECG).*

Keywords: *Electrocardiogram (ECG), MIT-BIH database, Probabilistic Neural Networks (PNN), Wavelet toolbox.*

I. INTRODUCTION

Electrocardiography deals with the electrical activity of the heart. Bio-signals being non-stationary signals, the reflection may occur at random in the time-scale. Therefore, for effective diagnostic, ECG signal pattern and heart rate variability may have to be observed over several hours. Thus the volume of the data being enormous, the study is tedious and time consuming. Therefore, computer-based analysis and classification of cardiac diseases can be very helpful in diagnostic. The ECG may roughly be divided into the phases of depolarization and repolarisation of the muscle fibers making up the heart. The depolarization phases correspond to the P-wave (atrial depolarization) and QRS-wave (ventricles depolarization). The re-polarization phases correspond to the T-wave. Arrhythmia is a heart disorder representing itself as an irregular heartbeat due to malfunction in the electrical system cells in the heart. It causes the heart to pump blood less effectively and causing disorders in the heart conduction process. Early detection of heart disease is very helpful for living a long life and increase the improvement of our technique detection of arrhythmias. The technique used in ECG pattern recognition comprises: ECG signal pre-processing, QRS detection, feature extraction and neural network for signal classification. Probabilistic Neural Network (PNN) is used as a classifier to detect QRS and non-QRS regions. Most of the QRS detection algorithms reported in literature detects R-peak locations and separate rules are applied for the delineation of QRS i.e. to locate the onsets and offsets of the QRS complexes.

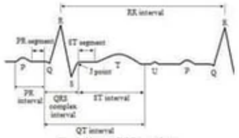


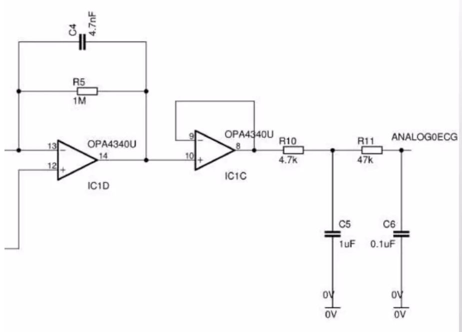
Fig. 1. Normal ECG waveform

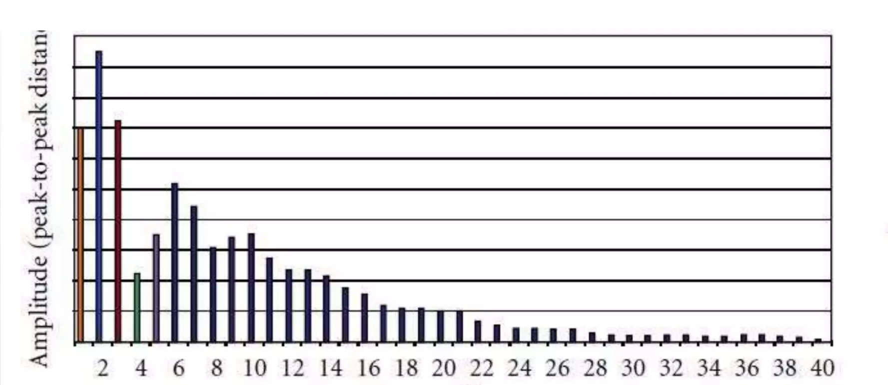
II. LITERATURE SURVEY

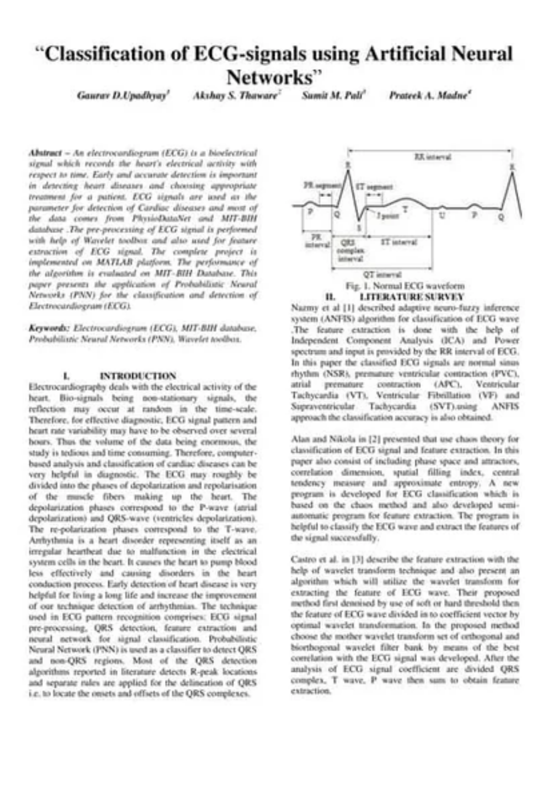
Nazmy et al [1] described adaptive neuro-fuzzy inference system (ANFIS) algorithm for classification of ECG wave .The feature extraction is done with the help of Independent Component Analysis (ICA) and Power spectrum and input is provided by the RR interval of ECG. In this paper the classified ECG signals are normal sinus rhythm (NSR), premature ventricular contraction (PVC), atrial premature contraction (APC), Ventricular Tachycardia (VT), Ventricular Fibrillation (VF) and Supraventricular Tachycardia (SVT).using ANFIS approach the classification accuracy is also obtained.

Alan and Nikola in [2] presented that use chaos theory for classification of ECG signal and feature extraction. In this paper also consist of including phase space and attractors, correlation dimension, spatial filling index, central tendency measure and approximate entropy. A new program is developed for ECG classification which is based on the chaos method and also developed semi-automatic program for feature extraction. The program is helpful to classify the ECG wave and extract the features of the signal successfully.

Castro et al. in [3] describe the feature extraction with the help of wavelet transform technique and also present an algorithm which will utilize the wavelet transform for extracting the feature of ECG wave. Their proposed method first denoised by use of soft or hard threshold then the feature of ECG wave divided in to coefficient vector by optimal wavelet transformation. In the proposed method choose the mother wavelet transform set of orthogonal and biorthogonal wavelet filter bank by means of the best correlation with the ECG signal was developed. After the analysis of ECG signal coefficient are divided QRS complex, T wave, P wave then sum to obtain feature extraction.







"Classification of ECG-signals using Artificial Neural Networks"

Gaurav D.Upadhyay[1] Akshay S. Thaware[2] Sumit M. Pali[3] Prateek A. Madne[4]

Abstract – An electrocardiogram (ECG) is a bioelectrical signal which records the heart's electrical activity with respect to time. Early and accurate detection is important in detecting heart diseases and choosing appropriate treatment for a patient. ECG signals are used as the parameter for detection of Cardiac diseases and most of the data comes from PhysioDataNet and MIT-BIH database .The pre-processing of ECG signal is performed with help of Wavelet toolbox and also used for feature extraction of ECG signal. The complete project is implemented on MATLAB platform. The performance of the algorithm is evaluated on MIT-BIH Database. This paper presents the application of Probabilistic Neural Networks (PNN) for the classification and detection of Electrocardiogram (ECG).

Keywords: Electrocardiogram (ECG), MIT-BIH database, Probabilistic Neural Networks (PNN), Wavelet toolbox.

I. INTRODUCTION

Electrocardiography deals with the electrical activity of the heart. Bio-signals being non-stationary signals, the reflection may occur at random in the time-scale. Therefore, for effective diagnostic, ECG signal pattern and heart rate variability may have to be observed over several hours. Thus the volume of the data being enormous, the study is tedious and time consuming. Therefore, computer-based analysis and classification of cardiac diseases can be very helpful in diagnostic. The ECG may roughly be divided into the phases of depolarization and repolarisation of the muscle fibers making up the heart. The depolarization phases correspond to the P-wave (atrial depolarization) and QRS-wave (ventricles depolarization). The re-polarization phases correspond to the T-wave. Arrhythmia is a heart disorder representing itself as an irregular heartbeat due to malfunction in the electrical system cells in the heart. It causes the heart to pump blood less effectively and causing disorders in the heart conduction process. Early detection of heart disease is very helpful for living a long life and increase the improvement of our technique detection of arrhythmias. The technique used in ECG pattern recognition comprises: ECG signal pre-processing, QRS detection, feature extraction and neural network for signal classification. Probabilistic Neural Network (PNN) is used as a classifier to detect QRS and non-QRS regions. Most of the QRS detection algorithms reported in literature detects R-peak locations and separate rules are applied for the delineation of QRS i.e. to locate the onsets and offsets of the QRS complexes.

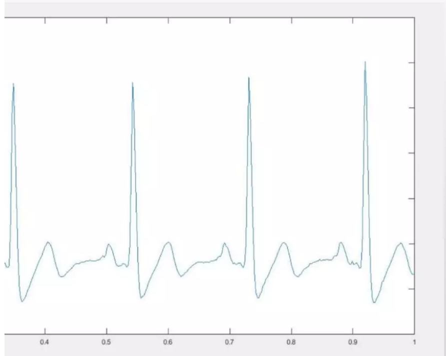
Fig. 1. Normal ECG waveform

II. LITERATURE SURVEY

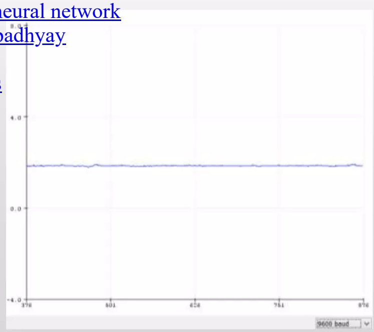
Nazmy et al [1] described adaptive neuro-fuzzy inference system (ANFIS) algorithm for classification of ECG wave .The feature extraction is done with the help of Independent Component Analysis (ICA) and Power spectrum and input is provided by the RR interval of ECG. In this paper the classified ECG signals are normal sinus rhythm (NSR), premature ventricular contraction (PVC), atrial premature contraction (APC), Ventricular Tachycardia (VT), Ventricular Fibrillation (VF) and Supraventricular Tachycardia (SVT).using ANFIS approach the classification accuracy is also obtained.

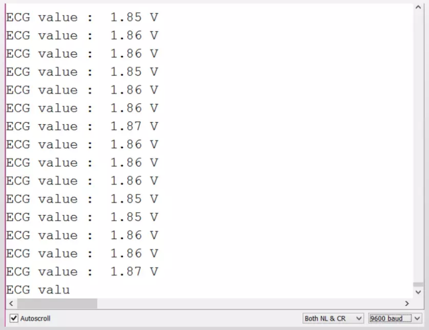
Alan and Nikola in [2] presented that use chaos theory for classification of ECG signal and feature extraction. In this paper also consist of including phase space and attractors, correlation dimension, spatial filling index, central tendency measure and approximate entropy. A new program is developed for ECG classification which is based on the chaos method and also developed semi-automatic program for feature extraction. The program is helpful to classify the ECG wave and extract the features of the signal successfully.

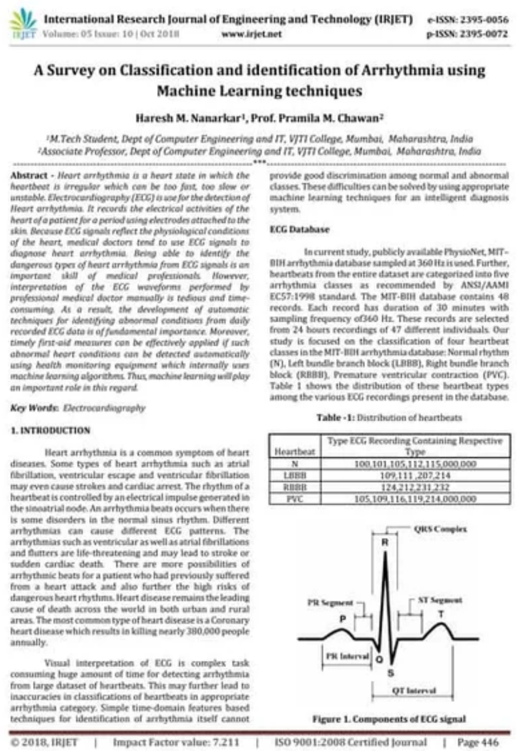
Castro et al. in [3] describe the feature extraction with the help of wavelet transform technique and also present an algorithm which will utilize the wavelet transform for extracting the feature of ECG wave. Their proposed method first denoised by use of soft or hard threshold then the feature of ECG wave divided in to coefficient vector by optimal wavelet transformation. In the proposed method choose the mother wavelet transform set of orthogonal and biorthogonal wavelet filter bank by means of the best correlation with the ECG signal was developed. After the analysis of ECG signal coefficient are divided QRS complex, T wave, P wave then sum to obtain feature extraction.



[Classification of ecg signal using artificial neural network](#)
[Gaurav upadhyay](#)
•







International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 05 Issue: 10 | Oct 2018 www.irjet.net p-ISSN: 2395-0072

A Survey on Classification and identification of Arrhythmia using Machine Learning techniques

Haresh M. Nanarkar[1], Prof. Pramila M. Chawan[2]

[1]M.Tech Student, Dept of Computer Engineering and IT, VJTI College, Mumbai, Maharashtra, India
[2]Associate Professor, Dept of Computer Engineering and IT, VJTI College, Mumbai, Maharashtra, India

Abstract - *Heart arrhythmia is a heart state in which the heartbeat is irregular which can be too fast, too slow or unstable. Electrocardiography (ECG) is use for the detection of Heart arrhythmia. It records the electrical activities of the heart of a patient for a period using electrodes attached to the skin. Because ECG signals reflect the physiological conditions of the heart, medical doctors tend to use ECG signals to diagnose heart arrhythmia. Being able to identify the dangerous types of heart arrhythmia from ECG signals is an important skill of medical professionals. However, interpretation of the ECG waveforms performed by professional medical doctor manually is tedious and time-consuming. As a result, the development of automatic techniques for identifying abnormal conditions from daily recorded ECG data is of fundamental importance. Moreover, timely first-aid measures can be effectively applied if such abnormal heart conditions can be detected automatically using health monitoring equipment which internally uses machine learning algorithms. Thus, machine learning will play an important role in this regard.*

Key Words: *Electrocardiography*

1. INTRODUCTION

Heart arrhythmia is a common symptom of heart diseases. Some types of heart arrhythmia such as atrial fibrillation, ventricular escape and ventricular fibrillation may even cause strokes and cardiac arrest. The rhythm of a heartbeat is controlled by an electrical impulse generated in the sinoatrial node. An arrhythmia beats occurs when there is some disorders in the normal sinus rhythm. Different arrhythmias can cause different ECG patterns. The arrhythmias such as ventricular as well as atrial fibrillations and flutters are life-threatening and may lead to stroke or sudden cardiac death. There are more possibilities of arrhythmic beats for a patient who had previously suffered from a heart attack and also further the high risks of dangerous heart rhythms. Heart disease remains the leading cause of death across the world in both urban and rural areas. The most common type of heart disease is a Coronary heart disease which results in killing nearly 380,000 people annually.

Visual interpretation of ECG is complex task consuming huge amount of time for detecting arrhythmia from large dataset of heartbeats. This may further lead to inaccuracies in classifications of heartbeats in appropriate arrhythmia category. Simple time-domain features based techniques for identification of arrhythmia itself cannot provide good discrimination among normal and abnormal classes. These difficulties can be solved by using appropriate machine learning techniques for an intelligent diagnosis system.

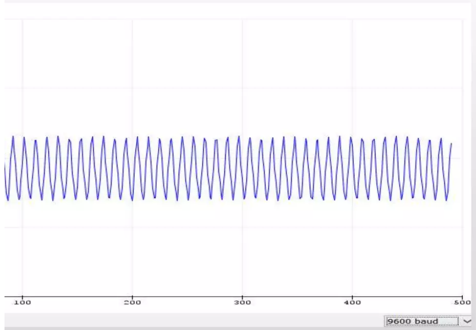
ECG Database

In current study, publicly available PhysioNet, MIT-BIH arrhythmia database sampled at 360 Hz is used. Further, heartbeats from the entire dataset are categorized into five arrhythmia classes as recommended by ANSI/AAMI EC57:1998 standard. The MIT-BIH database contains 48 records. Each record has duration of 30 minutes with sampling frequency of360 Hz. These records are selected from 24 hours recordings of 47 different individuals. Our study is focused on the classification of four heartbeat classes in the MIT-BIH arrhythmia database: Normal rhythm (N), Left bundle branch block (LBBB), Right bundle branch block (RBBB), Premature ventricular contraction (PVC). Table 1 shows the distribution of these heartbeat types among the various ECG recordings present in the database.

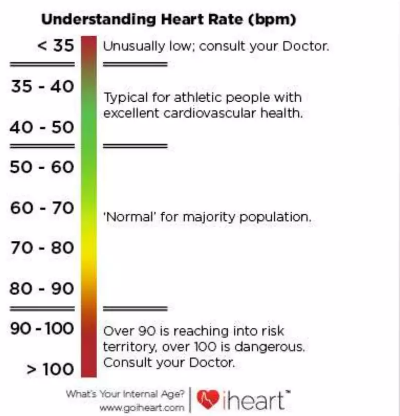
Table -1: Distribution of heartbeats

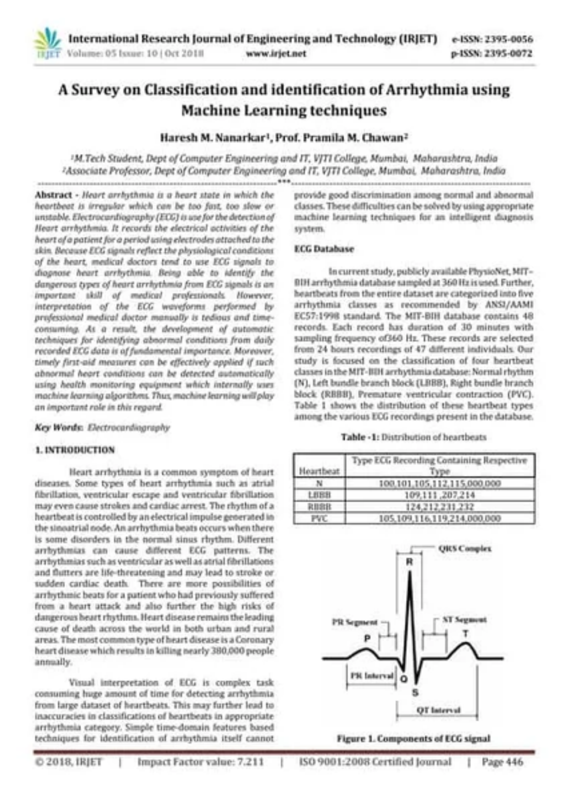
Heartbeat	Type ECG Recording Containing Respective Type
N	100,101,105,112,115,000,000
LBBB	109,111 ,207,214
RBBB	124,212,231,232
PVC	105,109,116,119,214,000,000

Figure 1. Components of ECG signal



$$Heart\ Rate = \frac{Pulses\ Count}{Time\ (Minute)}$$




International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 05 Issue: 10 | Oct 2018 www.irjet.net p-ISSN: 2395-0072

A Survey on Classification and identification of Arrhythmia using Machine Learning techniques

Haresh M. Nanarkar[1], Prof. Pramila M. Chawan[2]

[1]M.Tech Student, Dept of Computer Engineering and IT, VJTI College, Mumbai, Maharashtra, India
[2]Associate Professor, Dept of Computer Engineering and IT, VJTI College, Mumbai, Maharashtra, India

Abstract - *Heart arrhythmia is a heart state in which the heartbeat is irregular which can be too fast, too slow or unstable. Electrocardiography (ECG) is use for the detection of Heart arrhythmia. It records the electrical activities of the heart of a patient for a period using electrodes attached to the skin. Because ECG signals reflect the physiological conditions of the heart, medical doctors tend to use ECG signals to diagnose heart arrhythmia. Being able to identify the dangerous types of heart arrhythmia from ECG signals is an important skill of medical professionals. However, interpretation of the ECG waveforms performed by professional medical doctor manually is tedious and time-consuming. As a result, the development of automatic techniques for identifying abnormal conditions from daily recorded ECG data is of fundamental importance. Moreover, timely first-aid measures can be effectively applied if such abnormal heart conditions can be detected automatically using health monitoring equipment which internally uses machine learning algorithms. Thus, machine learning will play an important role in this regard.*

Key Words: *Electrocardiography*

1. INTRODUCTION

Heart arrhythmia is a common symptom of heart diseases. Some types of heart arrhythmia such as atrial fibrillation, ventricular escape and ventricular fibrillation may even cause strokes and cardiac arrest. The rhythm of a heartbeat is controlled by an electrical impulse generated in the sinoatrial node. An arrhythmia beats occurs when there is some disorders in the normal sinus rhythm. Different arrhythmias can cause different ECG patterns. The arrhythmias such as ventricular as well as atrial fibrillations and flutters are life-threatening and may lead to stroke or sudden cardiac death. There are more possibilities of arrhythmic beats for a patient who had previously suffered from a heart attack and also further the high risks of dangerous heart rhythms. Heart disease remains the leading cause of death across the world in both urban and rural areas. The most common type of heart disease is a Coronary heart disease which results in killing nearly 380,000 people annually.

Visual interpretation of ECG is complex task consuming huge amount of time for detecting arrhythmia from large dataset of heartbeats. This may further lead to inaccuracies in classifications of heartbeats in appropriate arrhythmia category. Simple time-domain features based techniques for identification of arrhythmia itself cannot provide good discrimination among normal and abnormal classes. These difficulties can be solved by using appropriate machine learning techniques for an intelligent diagnosis system.

ECG Database

In current study, publicly available PhysioNet, MIT-BIH arrhythmia database sampled at 360 Hz is used. Further, heartbeats from the entire dataset are categorized into five arrhythmia classes as recommended by ANSI/AAMI EC57:1998 standard. The MIT-BIH database contains 48 records. Each record has duration of 30 minutes with sampling frequency of360 Hz. These records are selected from 24 hours recordings of 47 different individuals. Our study is focused on the classification of four heartbeat classes in the MIT-BIH arrhythmia database: Normal rhythm (N), Left bundle branch block (LBBB), Right bundle branch block (RBBB), Premature ventricular contraction (PVC). Table 1 shows the distribution of these heartbeat types among the various ECG recordings present in the database.

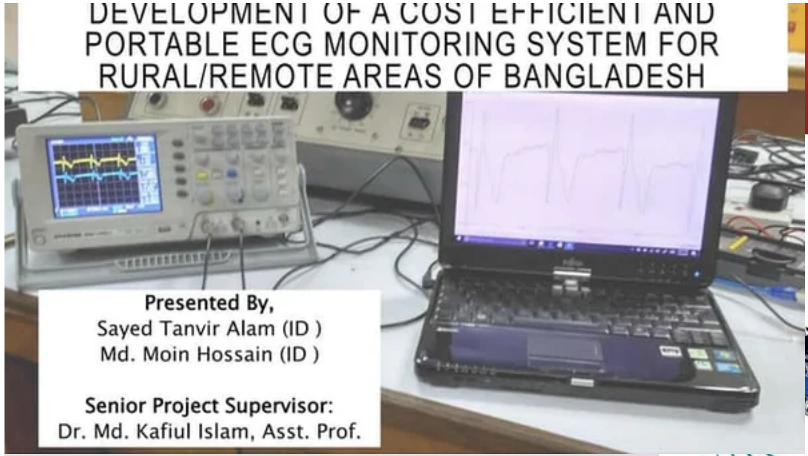
Table -1: Distribution of heartbeats

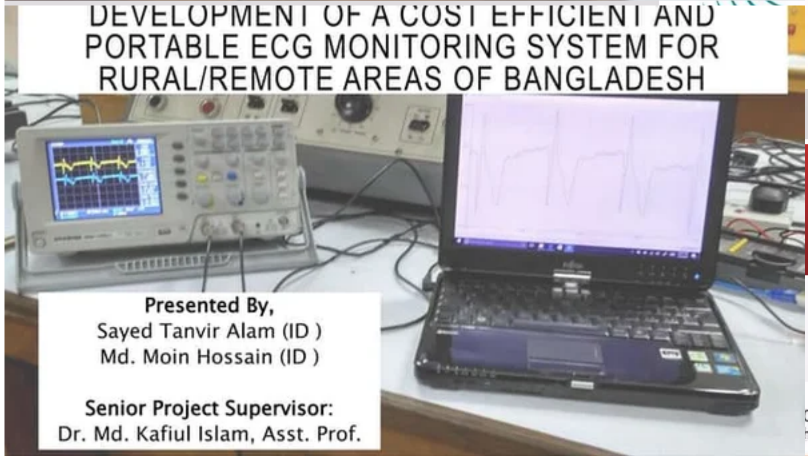
Heartbeat	Type ECG Recording Containing Respective Type
N	100,101,105,112,115,000,000
LBBB	109,111 ,207,214
RBBB	124,212,231,232
PVC	105,109,116,119,214,000,000

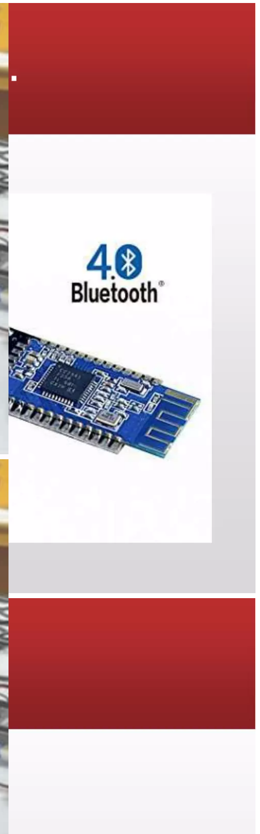
Figure 1. Components of ECG signal

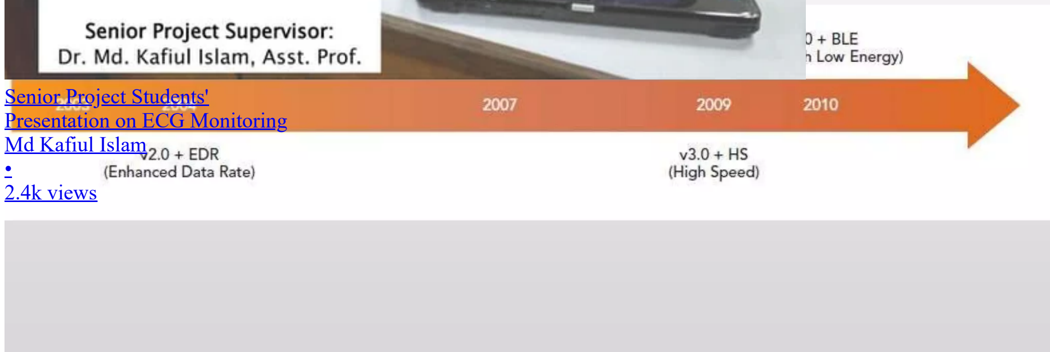
le (BLE)

BLE) Cont.









Senior Project Students' Presentation on ECG Monitoring
Md Kafiul Islam
•
2.4k views


XAI MEDICA
Presents
Medical Diagnostic Systems and Technologies
Electrocardiography
Assessment of the ANS
ECG/ECG+BP Holter Monitor
Electroencephalography
Rheography
Spirography
Telemedical Devices
Fetal ECG monitoring
4.0
Bluetooth


XAI MEDICA
Presents
Medical Diagnostic Systems and Technologies
Electrocardiography
Assessment of the ANS
ECG/ECG+BP Holter Monitor
Electroencephalography
Rheography
Spirography
Telemedical Devices
Fetal ECG monitoring

th Low Energy Module (BLE) Cont.

letails:

equency band.

rate.

d for.

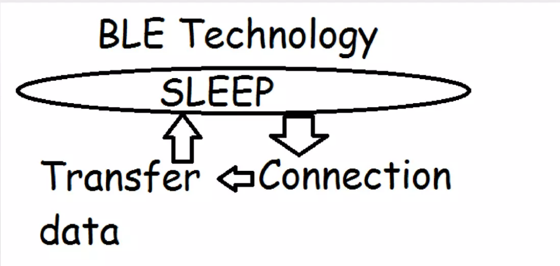
entication and (128-bit AES) .

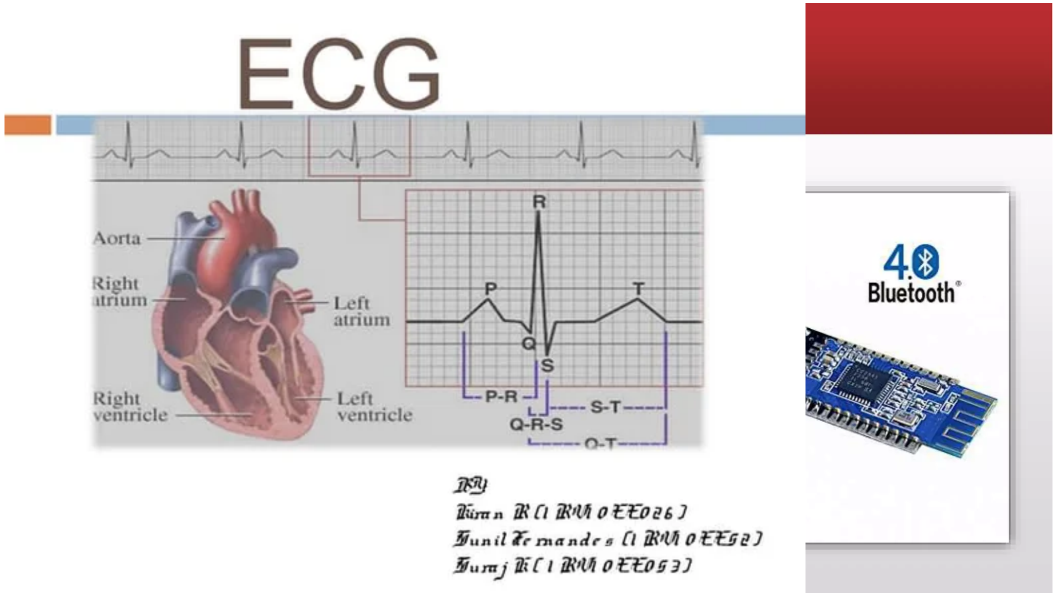
ethod : GFSK .

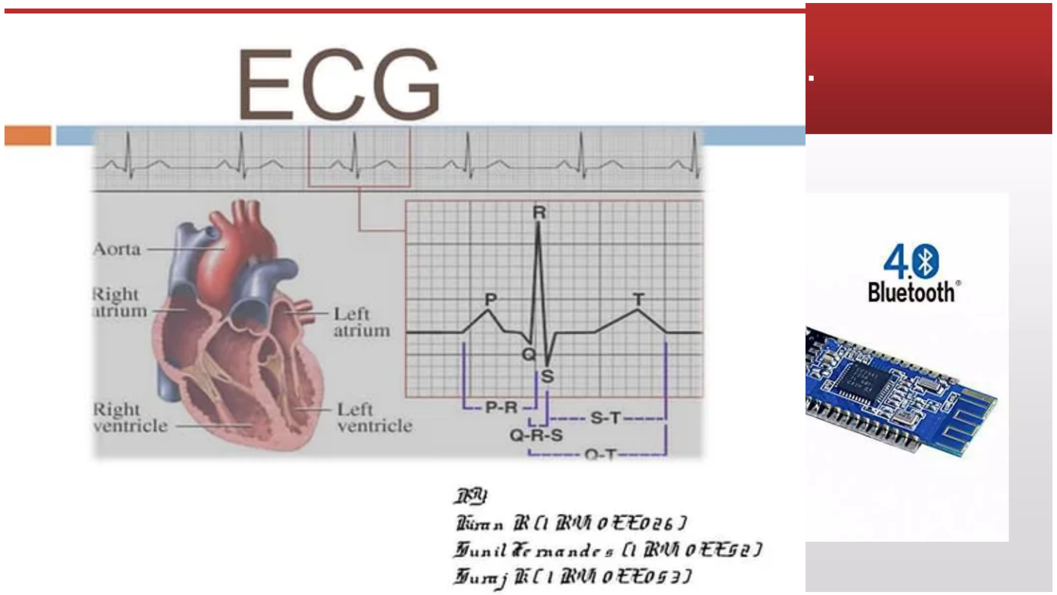
on index 0.5

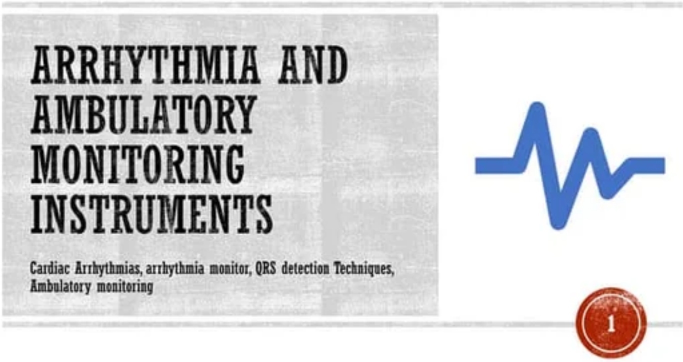
Bluetooth Low Energy Module (BLE) Cont.

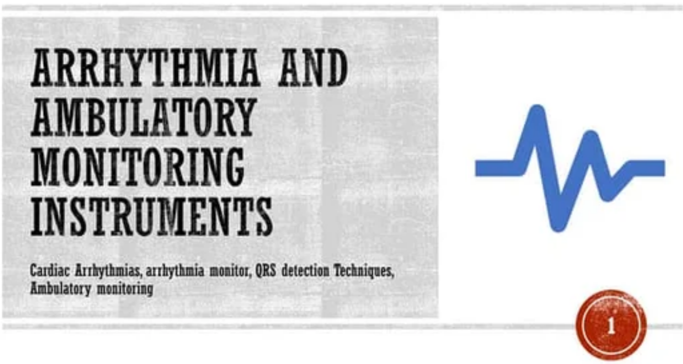
- **Channel Bandwidth : 2 MHz .**
- **Number of Channels : 40 .**
- Low power consumption.

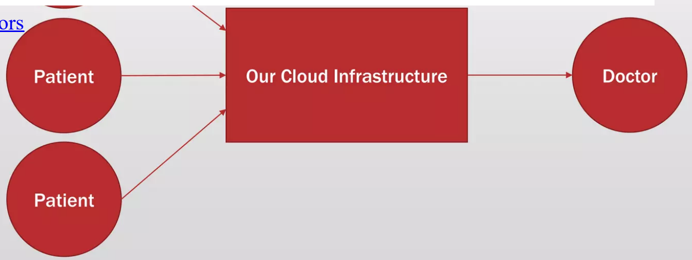


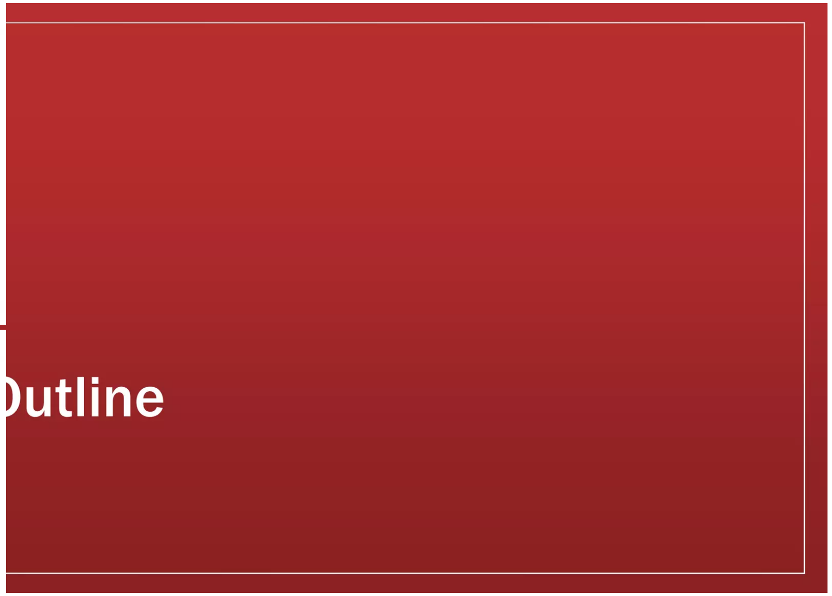

ECG
Aorta
Right atrium
Left atrium
Right ventricle
Left ventricle
R
P
T
Q
S
P-R
S-T
Q-R-S
Q-T
4.0
Bluetooth

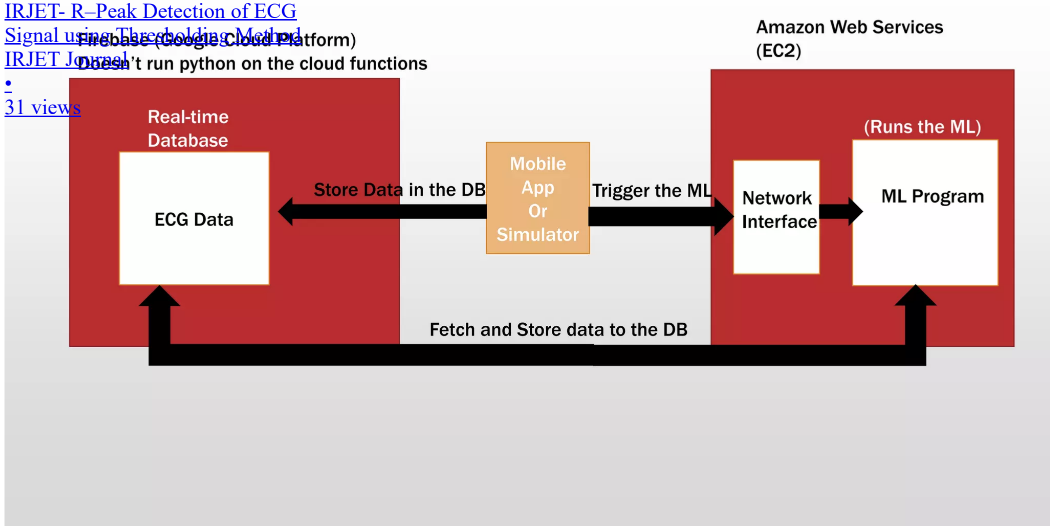

ECG
Aorta
Right atrium
Left atrium
Right ventricle
Left ventricle
R
P
T
Q
S
P-R
S-T
Q-R-S
Q-T
4.0
Bluetooth

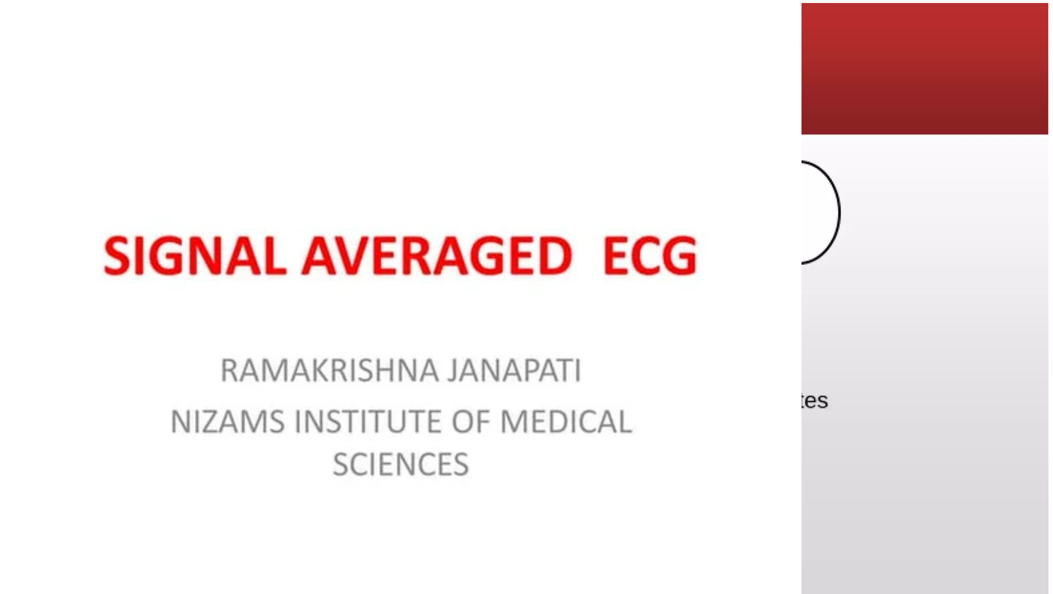

ARRHYTHMIA AND AMBULATORY MONITORING INSTRUMENTS
Cardiac Arrhythmias, arrhythmia monitor, QRS detection Techniques, Ambulatory monitoring
1

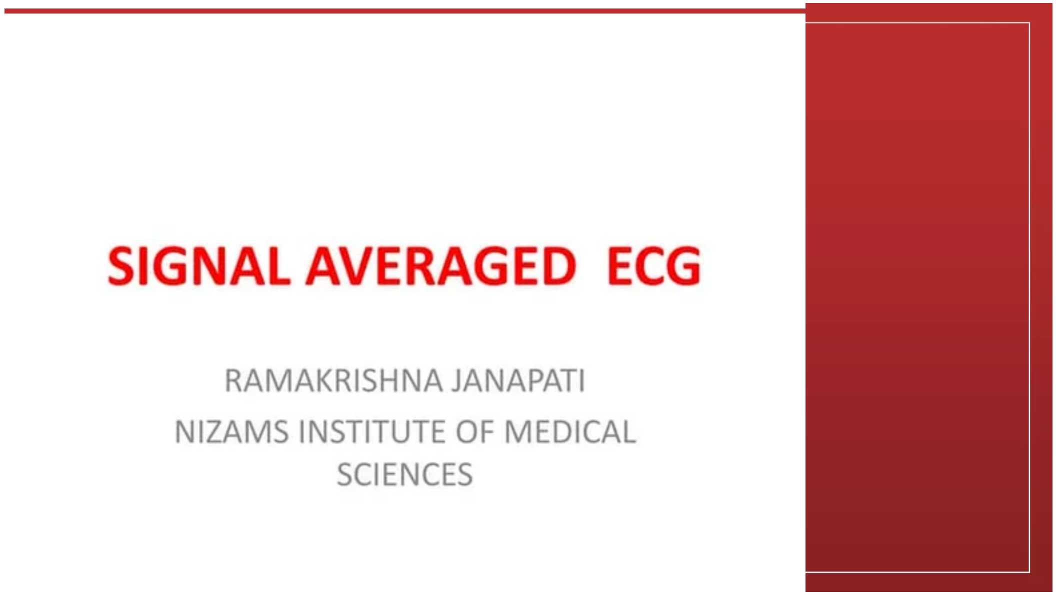

ARRHYTHMIA AND AMBULATORY MONITORING INSTRUMENTS
Cardiac Arrhythmias, arrhythmia monitor, QRS detection Techniques, Ambulatory monitoring
1

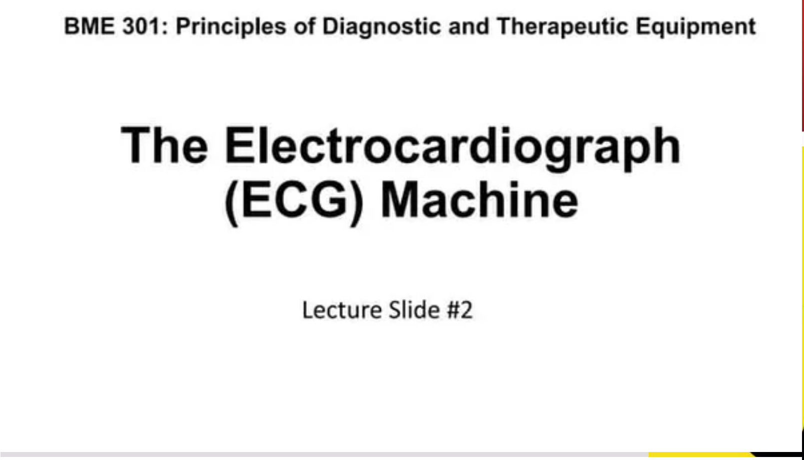

Patient
Our Cloud Infrastructure
Doctor
Patient


Outline

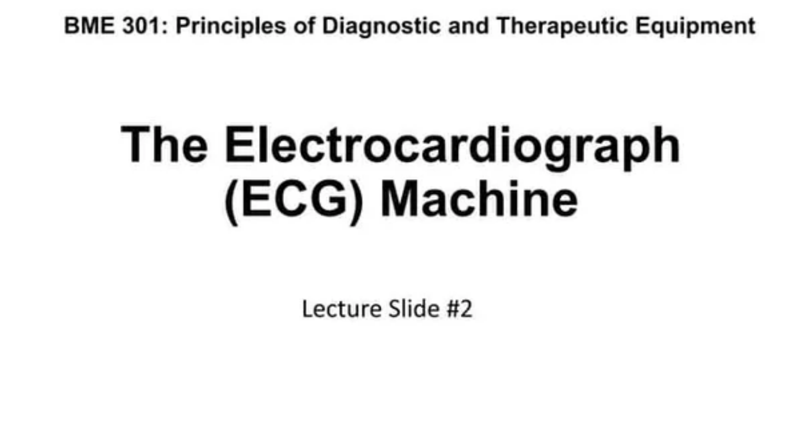

Firebase (Google Cloud Platform)
Doesn't run python on the cloud functions
Amazon Web Services (EC2)
Real-time Database
ECG Data
Store Data in the DB
Mobile App Or Simulator
Trigger the ML
Network Interface
(Runs the ML)
ML Program
Fetch and Store data to the DB

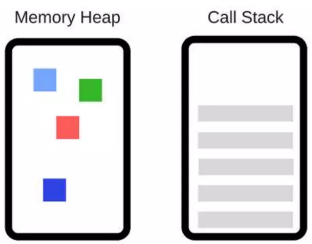

SIGNAL AVERAGED ECG
RAMAKRISHNA JANAPATI
NIZAMS INSTITUTE OF MEDICAL SCIENCES
tes


SIGNAL AVERAGED ECG
RAMAKRISHNA JANAPATI
NIZAMS INSTITUTE OF MEDICAL SCIENCES


BME 301: Principles of Diagnostic and Therapeutic Equipment
The Electrocardiograph (ECG) Machine
Lecture Slide #2


JS


BME 301: Principles of Diagnostic and Therapeutic Equipment
The Electrocardiograph (ECG) Machine
Lecture Slide #2


Memory Heap
Call Stack

IJRET: International Journal of Research in Engineering and Technology eISSN: 2319-1163 | pISSN: 2321-7308

HEART RATE DETECTION USING HILBERT TRANSFORM

S. Thulasi Prasad[1], Dr. S. Varadarajan[2]

[1]Associate Professor, Dept. of ECE, CVSE, Andhra Pradesh, India, stprasad123@yahoo.co.in
[2]Professor, Dept. of ECE, SVUCE, Andhra Pradesh, India, varadasouri@gmail.com

Abstract

The electrocardiogram (ECG) is a well known method that can be used to measure Heart Rate Variability (HRV). This paper describes a procedure for processing electrocardiogram signals (ECG) to detect Heart Rate Variability (HRV). In recent years, there have been wide-ranging studies on Heart rate variability in ECG signals and analysis of Respiratory Sinus Arrhythmia (RSA). Normally the Heart rate variability is studied based on cycle length variability, heart period variability, RR variability and RR interval tachogram. The HRV provides information about the sympathetic-parasympathetic autonomic stability and consequently about the risk of unpredicted cardiac death. The heart beats in ECG signal are detected by detecting R-Peaks in ECG signals and used to determine useful information about the various cardiac abnormalities. The temporal locations of the R-wave are identified as the locations of the QRS complexes. In the presence of poor signal-to-noise ratios or pathological signals and wrong placement of ECG electrodes, the QRS complex may be missed or falsely detected and may lead to poor results in calculating heart beat in turn inter-beat intervals. We have studied the effects of number of common elements of QRS detection methods using MIT/BIH arrhythmia database and devised a simple and effective method. In this method, first the ECG signal is preprocessed using band-pass filter; later the Hilbert Transform is applied on filtered ECG signal to enhance the presence of QRS complexes, to detect R-Peaks by setting a threshold and finally the RR-intervals are calculated to determine Heart Rate. We have implemented our method using MATLAB on ECG signal which is obtained from MIT/BIH arrhythmia database. Our MATLAB implementation results in the detection of QRS complexes in ECG signal, locate the R-Peaks, computes Heart Rate (HR) by calculating RR-internal and plotting of HR signal to show the information about HRV.

Index Terms: *ECG, QRS complex, R-Peaks, HRV, Heart Rate signal, RSA, Hilbert Transform, Arrhythmia, MIT/BIH, MATLAB and Lynn's filters*

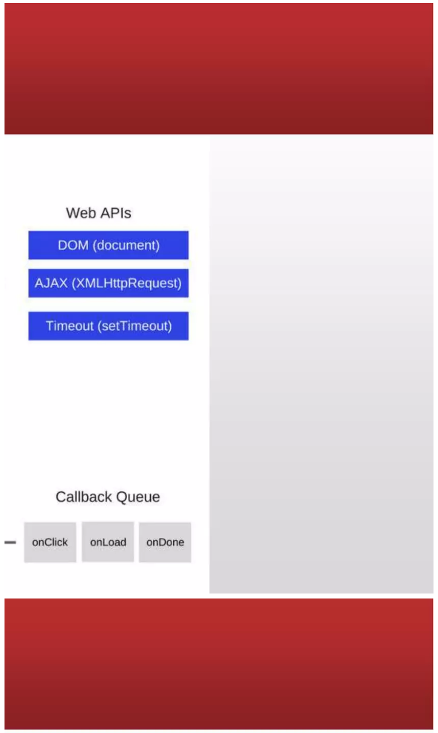
***

1. INTRODUCTION

The World Health Organization has discovered a fact that the most frequent cause of deaths worldwide is due to cardiac arrest [1]. Hence a strong focus has been laid on preventative, medicinal, and technological advances on cardiac health research which in turn made leading researchers to work on improving the conventional cardiovascular-diagnosis technologies used in hospitals, clinics and the home. The ECG analysis is most common clinical cardiac test used for screening various cardiac abnormalities. Therefore, the analysis of ECG signals has been extensively investigated over the past two decades using Digital Signal Processing [2][3].

A graphical record of bioelectrical signal generated by the human heart during the cardiac cycle [4] is called as ECG (Electro Cardio Gram). The electrocardiogram permits us to determine many electrical and mechanical defects of the heart such as the heart rate and other cardiac parameters regarding Auricular and ventricular hypertrophy, Myocardial Infarction (heart attack), Arrhythmias, Pericarditis, Generalized suffering affecting heart and blood pressure. The main parts of ECG waveform are the P wave, PR interval, QRS complex, ST segment, T wave and QT interval which represents polarization of atria and ventricles in a sequential manner. These parts are shown in the Fig-1. The frequency spectrum of ECG signal ranges from 0.05 Hz to 100 Hz with QRS complexes concentrating around 10 Hz. The power spectrum of ECG signal [5][6] is shown in the Fig-2. In addition to the ECG wave the noise due to power line interferences of 50-Hz, EMG from muscles, motion artifact from the electrode and skin interface, and possibly other interference from electro-surgical equipment in the operating room is also picked up by electrodes, when the ECG signal is recorded. Fig-3 shows the baseline Wander due of Sudden Body Movements by elevating the effected part of the ECG signal. Analysis of ECG signals requires extracting the signal of interest, the QRS complex, from the noise sources and the P and T waves.

Volume: 02 Issue: 08 | Aug-2013, Available @ http://www.ijret.org 508



- Enables executing blocking code on a single-threaded architecture.
- It returns a promise before execution.

```
setTimeout( function() {
console.log(1);
}, 5000 );
```

IJRET: International Journal of Research in Engineering and Technology eISSN: 2319-1163 | pISSN: 2321-7308

HEART RATE DETECTION USING HILBERT TRANSFORM

S. Thulasi Prasad[1], Dr. S. Varadarajan[2]

[1]Associate Professor, Dept. of ECE, CVSE, Andhra Pradesh, India, stprasad123@yahoo.co.in
[2]Professor, Dept. of ECE, SVUCE, Andhra Pradesh, India, varadasouri@gmail.com

Abstract

The electrocardiogram (ECG) is a well known method that can be used to measure Heart Rate Variability (HRV). This paper describes a procedure for processing electrocardiogram signals (ECG) to detect Heart Rate Variability (HRV). In recent years, there have been wide-ranging studies on Heart rate variability in ECG signals and analysis of Respiratory Sinus Arrhythmia (RSA). Normally the Heart rate variability is studied based on cycle length variability, heart period variability, RR variability and RR interval tachogram. The HRV provides information about the sympathetic-parasympathetic autonomic stability and consequently about the risk of unpredicted cardiac death. The heart beats in ECG signal are detected by detecting R-Peaks in ECG signals and used to determine useful information about the various cardiac abnormalities. The temporal locations of the R-wave are identified as the locations of the QRS complexes. In the presence of poor signal-to-noise ratios or pathological signals and wrong placement of ECG electrodes, the QRS complex may be missed or falsely detected and may lead to poor results in calculating heart beat in turn inter-beat intervals. We have studied the effects of number of common elements of QRS detection methods using MIT/BIH arrhythmia database and devised a simple and effective method. In this method, first the ECG signal is preprocessed using band-pass filter; later the Hilbert Transform is applied on filtered ECG signal to enhance the presence of QRS complexes, to detect R-Peaks by setting a threshold and finally the RR-intervals are calculated to determine Heart Rate. We have implemented our method using MATLAB on ECG signal which is obtained from MIT/BIH arrhythmia database. Our MATLAB implementation results in the detection of QRS complexes in ECG signal, locate the R-Peaks, computes Heart Rate (HR) by calculating RR-internal and plotting of HR signal to show the information about HRV.

Index Terms: *ECG, QRS complex, R-Peaks, HRV, Heart Rate signal, RSA, Hilbert Transform, Arrhythmia, MIT/BIH, MATLAB and Lynn's filters*

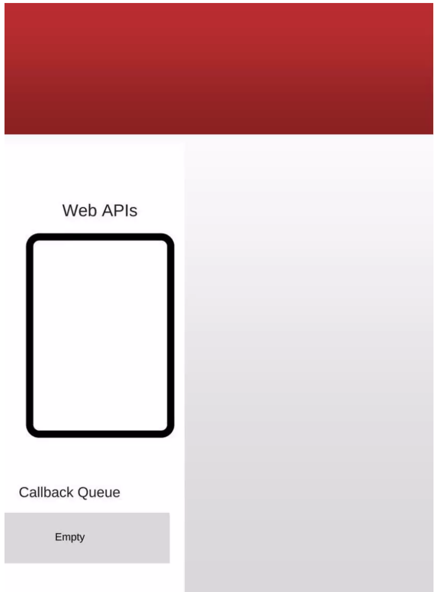
---***---

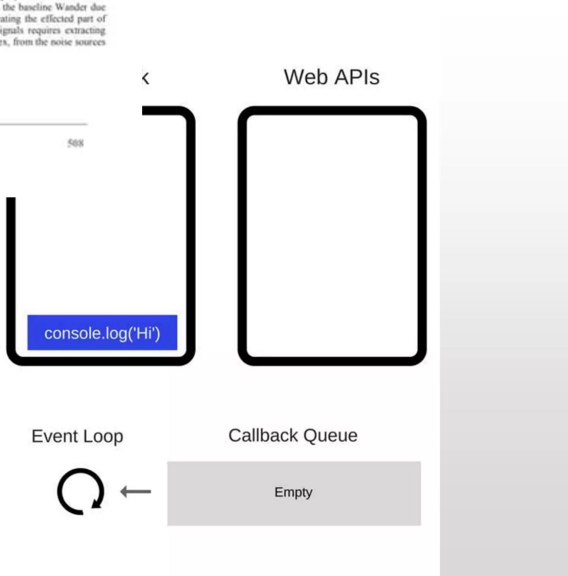
1. INTRODUCTION

The World Health Organization has discovered a fact that the most frequent cause of deaths worldwide is due to cardiac arrest [1]. Hence a strong focus has been laid on preventative, medicinal, and technological advances on cardiac health research which in turn made leading researchers to work on improving the conventional cardiovascular-diagnosis technologies used in hospitals, clinics and the home. The ECG analysis is most common clinical cardiac test used for screening various cardiac abnormalities. Therefore, the analysis of ECG signals has been extensively investigated over the past two decades using Digital Signal Processing [2][3].

A graphical record of bioelectrical signal generated by the human heart during the cardiac cycle [4] is called as ECG (Electro Cardio Gram). The electrocardiogram permits us to determine many electrical and mechanical defects of the heart such as the heart rate and other cardiac parameters regarding Auricular and ventricular hypertrophy, Myocardial Infarction (heart attack), Arrhythmias, Pericarditis, Generalized suffering affecting heart and blood pressure. The main parts of ECG waveform are the P wave, PR interval, QRS complex, ST segment, T wave and QT interval which represents polarization of atria and ventricles in a sequential manner. These parts are shown in the Fig-1. The frequency spectrum of ECG signal ranges from 0.05 Hz to 100 Hz with QRS complexes concentrating around 10 Hz. The power spectrum of ECG signal [5][6] is shown in the Fig-2. In addition to the ECG wave the noise due to power line interferences of 50-Hz, EMG from muscles, motion artifact from the electrode and skin interface, and possibly other interference from electro-surgical equipment in the operating room is also picked up by electrodes, when the ECG signal is recorded. Fig-3 shows the baseline Wander due of Sudden Body Movements by elevating the effected part of the ECG signal. Analysis of ECG signals requires extracting the signal of interest, the QRS complex, from the noise sources and the P and T waves.

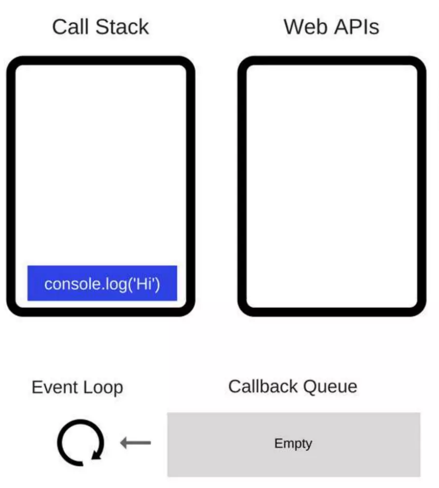
Volume: 02 Issue: 08 | Aug-2013, Available @ http://www.ijret.org 508





Matthew Gray Summer 2015 Presentation
Matthew Gray
438 views
•
14 slides

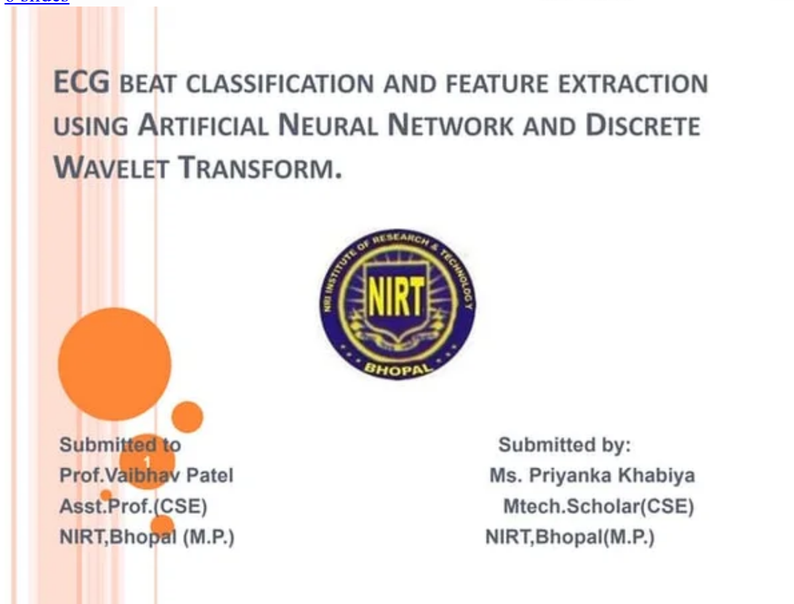
Hi

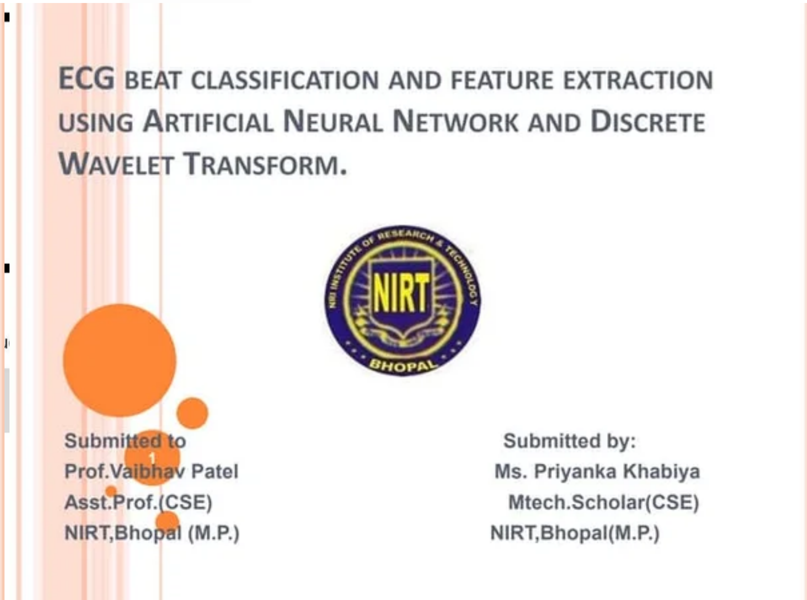


Jq3516631668
IJERA Editor
287 views
•
6 slides

4 / 16

Call Stack Web APIs





Ecg beat classification and feature extraction using artificial neural networ...
priyanka leenakhabiya
772 views
•
48 slides

ECG Signal Analysis for Myocardial Infarction Detection (May 2015)

Asfandyar Hassan Shah (7642), Mahnoor Haneef (5064),
Rysham Ali (7640) and Uzair Akbar (4584)
NUST School of Electrical Engineering & Computer Science (SEECS), Pakistan

***Abstract*—Myocardial Infarction is one of the fatal heart diseases. It is essential that a patient is monitored for the early detection of MI. Owing to the newer technology such as wearable sensors which are capable of transmitting wirelessly, this can be done easily. However, there is a need for real-time applications that are able to accurately detect MI non-invasively. This project studies a prospective method by which we can detect MI. Our approach analyses the ECG (electrocardiogram) of a patient in real-time and extracts the ST elevation from each cycle. The ST elevation plays an important part in MI detection. We then use the sequential change point detection algorithm; CUmulative SUM (CUSUM), to detect any deviation in the ST elevation spectrum and to raise an alarm if we find any.**

***Index Terms*—Mycardial Infarction, ECG, ST elevation, CUSUM**

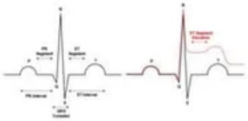
I. Introduction

The Electrocardiogram (ECG) is a waveform that represents the propagation of electric potentials through the heart muscle with respect to time. The propagation of these potentials results in the quasi-periodic contraction of the heart muscle. Each part of the cardiogram refers to a depolarization or a re-polarization of some region in the heart. The cardiogram consists of five major waves, also known as deflections in the cardiology literature, the P, Q, R, S, and T waves.

Myocardial Infarction is an acute ischemic heart disease characterized by a necrosis (death) of a portion of the heart muscle because of deprivation from oxygen. MI causes a serious disturbance of the cardiovascular system that leads to a direct threat for life.

MI is typically characterized by an elevation in the ST segment of ECG which is normally iso-electric for healthy subjects. ST segment elevation is generally one of the first symptom of MI and is usually accompanied by chest pain. But in order to be more specific to MI (or suspicious of MI), the ST elevation must be significant in amplitude (up to 0.2 mV) and prolonged in time (several minutes) as indicated in.

The rest of this report is organized as follows. Section II briefly reviews related techniques and presents our approach for early detection of MI. Section III presents our experimental results. Finally, Section IV concludes the report.



(a) One-cycle ECG tracing (b) ST Elevation ECG
Normal ECG and ST elevation ECG

II. Implimentation

There are three aspects of our project:

A. ECG Signal Pre-processing (Rysham Ali, Mahnoor Haneef)

We are going to utilize adaptive thresholding method [8] for denoising the EKG signal using wavelet transforms. Wavelets transforms prove effective as it has good localization properties s in time and frequency domain. We improvise existing thresholding methods to improve noise reduction while insuring a good signal to noise ratio. Thresholding basically removes some of the detailed coefficients exceeding a certain threshold hence smoothing the signal out. The signal is then reconstructed in the time domain using the modified coefficients. Determining a good threshold is important as a wrong threshold value can remove important ECG features or let in too much noise. Thresholding generally consists of taking the discrete wavelet transform of the signal using the appropriate wavelet. A thresholding parameter is set to reduce the detail coefficients in the wavelet transform and the denoised version of the signal is obtained by taking the inverse discrete wavelet transform of the signal using the modified coefficients. Donoho and Johnston proposed the universal threshold, called by them "Wave Shrink" given by:

$$\delta = \sigma\sqrt{(2\log N)}$$

Where σ is the standard deviation and N is the number of points. In case of white noise $\sigma = \frac{MAD}{0.6745}$ where MAD is the median absolute deviation of the detail coefficients. We alter this algorithm to provide a different threshold for each level of detail. Our altered formula is:

Signals & Systems EE232, Spring 2015 1

ECG Signal Analysis for Myocardial Infarction Detection (May 2015)

Asfandyar Hassan Shah (7642), Mahnoor Haneef (5064),
Rysham Ali (7640) and Uzair Akbar (4584)
NUST School of Electrical Engineering & Computer Science (SEECS), Pakistan

Abstract—Myocardial Infarction is one of the fatal heart diseases. It is essential that a patient is monitored for the early detection of MI. Owing to the newer technology such as wearable sensors which are capable of transmitting wirelessly, this can be done easily. However, there is a need for real-time applications that are able to accurately detect MI non-invasively. This project studies a prospective method by which we can detect MI. Our approach analyses the ECG (electrocardiogram) of a patient in real-time and extracts the ST elevation from each cycle. The ST elevation plays an important part in MI detection. We then use the sequential change point detection algorithm; CUmulative SUM (CUSUM), to detect any deviation in the ST elevation spectrum and to raise an alarm if we find any.

Index Terms—Mycardial Infarction, ECG, ST elevation, CUSUM

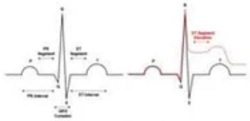
I. Introduction

The Electrocardiogram (ECG) is a waveform that represents the propagation of electric potentials through the heart muscle with respect to time. The propagation of these potentials results in the quasi-periodic contraction of the heart muscle. Each part of the cardiogram refers to a depolarization or a re-polarization of some region in the heart. The cardiogram consists of five major waves, also known as deflections in the cardiology literature, the P, Q, R, S, and T waves.

Myocardial Infarction is an acute ischemic heart disease characterized by a necrosis (death) of a portion of the heart muscle because of deprivation from oxygen. MI causes a serious disturbance of the cardiovascular system that leads to a direct threat for life.

MI is typically characterized by an elevation in the ST segment of ECG which is normally iso-electric for healthy subjects. ST segment elevation is generally one of the first symptom of MI and is usually accompanied by chest pain. But in order to be more specific to MI (or suspicious of MI), the ST elevation must be significant in amplitude (up to 0.2 mV) and prolonged in time (several minutes) as indicated in.

The rest of this report is organized as follows. Section II briefly reviews related techniques and presents our approach for early detection of MI. Section III presents our experimental results. Finally, Section IV concludes the report.



(a) One-cycle ECG tracing (b) ST Elevation ECG
Normal ECG and ST elevation ECG

II. Implimentation

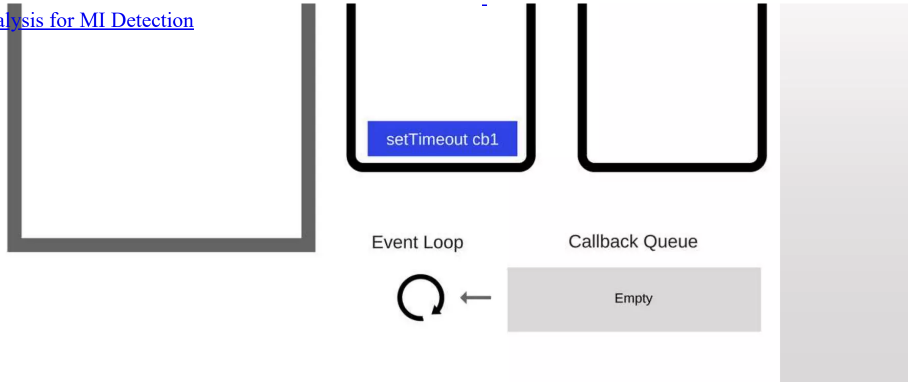
There are three aspects of our project:

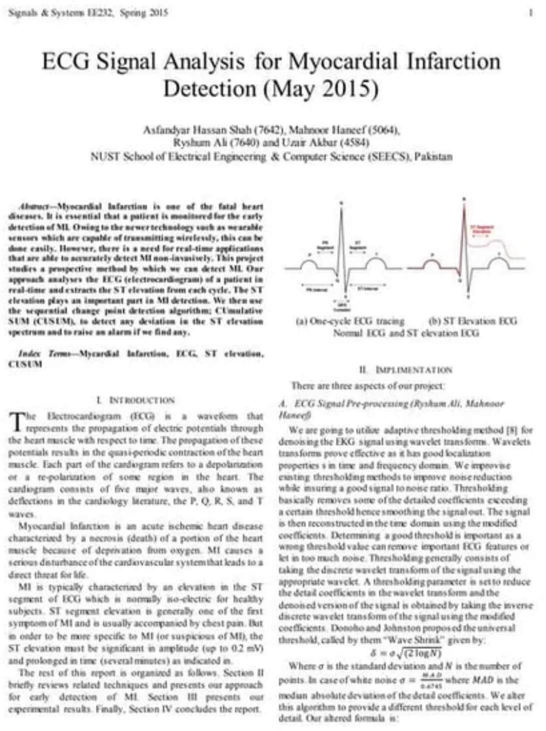
A. ECG Signal Pre-processing (Rysham Ali, Mahnoor Haneef)

We are going to utilize adaptive thresholding method [8] for denoising the EKG signal using wavelet transforms. Wavelets transforms prove effective as it has good localization properties s in time and frequency domain. We improvise existing thresholding methods to improve noise reduction while insuring a good signal to noise ratio. Thresholding basically removes some of the detailed coefficients exceeding a certain threshold hence smoothing the signal out. The signal is then reconstructed in the time domain using the modified coefficients. Determining a good threshold is important as a wrong threshold value can remove important ECG features or let in too much noise. Thresholding generally consists of taking the discrete wavelet transform of the signal using the appropriate wavelet. A thresholding parameter is set to reduce the detail coefficients in the wavelet transform and the denoised version of the signal is obtained by taking the inverse discrete wavelet transform of the signal using the modified coefficients. Donoho and Johnston proposed the universal threshold, called by them "Wave Shrink" given by:

$$\delta = \sigma\sqrt{(2\log N)}$$

Where σ is the standard deviation and N is the number of points. In case of white noise $\sigma = \frac{MAD}{0.6745}$ where MAD is the median absolute deviation of the detail coefficients. We alter this algorithm to provide a different threshold for each level of detail. Our altered formula is:





Signals & Systems EE232, Spring 2015 1

ECG Signal Analysis for Myocardial Infarction Detection (May 2015)

Asfandyar Hassan Shah (7642), Mahnoor Haneef (5064),
Rysham Ali (7640) and Uzair Akbar (4584)
NUST School of Electrical Engineering & Computer Science (SEECS), Pakistan

Abstract—Myocardial Infarction is one of the fatal heart diseases. It is essential that a patient is monitored for the early detection of MI. Owing to the newer technology such as wearable sensors which are capable of transmitting wirelessly, this can be done easily. However, there is a need for real-time applications that are able to accurately detect MI non-invasively. This project studies a prospective method by which we can detect MI. Our approach analyses the ECG (electrocardiogram) of a patient in real-time and extracts the ST elevation from each cycle. The ST elevation plays an important part in MI detection. We then use the sequential change point detection algorithm; CUmulative SUM (CUSUM), to detect any deviation in the ST elevation spectrum and to raise an alarm if we find any.

***Index Terms*—Myocardial Infarction, ECG, ST elevation, CUSUM**

I. INTRODUCTION

The Electrocardiogram (ECG) is a waveform that represents the propagation of electric potentials through the heart muscle with respect to time. The propagation of these potentials results in the quasi-periodic contraction of the heart muscle. Each part of the cardiogram refers to a depolarization or a re-polarization of some region in the heart. The cardiogram consists of five major waves, also known as deflections in the cardiology literature, the P, Q, R, S, and T waves.

Myocardial Infarction is an acute ischemic heart disease characterized by a necrosis (death) of a portion of the heart muscle because of deprivation from oxygen. MI causes a serious disturbance of the cardiovascular system that leads to a direct threat for life.

MI is typically characterized by an elevation in the ST segment of ECG which is normally iso-electric for healthy subjects. ST segment elevation is generally one of the first symptom of MI and is usually accompanied by chest pain. But in order to be more specific to MI (or suspicious of MI), the ST elevation must be significant in amplitude (up to 0.2 mV) and prolonged in time (several minutes) as indicated in.

The rest of this report is organized as follows. Section II briefly reviews related techniques and presents our approach for early detection of MI. Section III presents our experimental results. Finally, Section IV concludes the report.

(a) One-cycle ECG tracing (b) ST Elevation ECG
Normal ECG and ST elevation ECG

II. IMPLIMENTATION

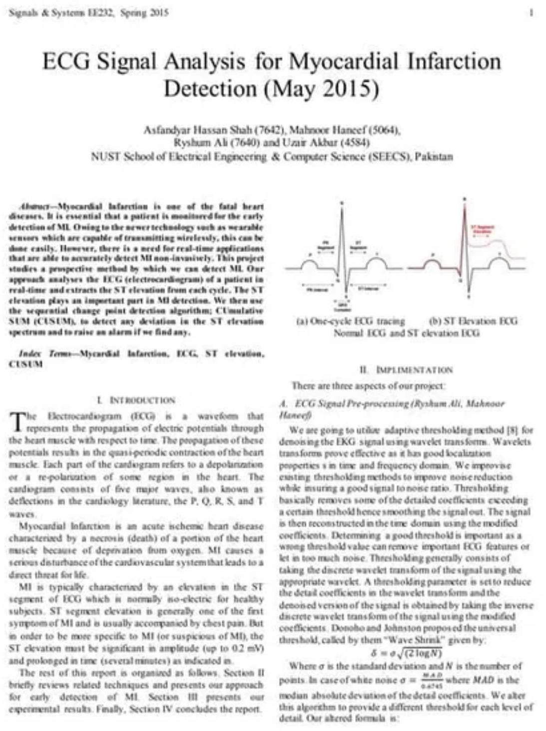
There are three aspects of our project:

A. ECG Signal Pre-processing (Rysham Ali, Mahnoor Haneef)

We are going to utilize adaptive thresholding method [8] for denoising the EKG signal using wavelet transforms. Wavelets transforms prove effective as it has good localization properties s in time and frequency domain. We improvise existing thresholding methods to improve noise reduction while insuring a good signal to noise ratio. Thresholding basically removes some of the detailed coefficients exceeding a certain threshold hence smoothing the signal out. The signal is then reconstructed in the time domain using the modified coefficients. Determining a good threshold is important as a wrong threshold value can remove important ECG features or let in too much noise. Thresholding generally consists of taking the discrete wavelet transform of the signal using the appropriate wavelet. A thresholding parameter is set to reduce the detail coefficients in the wavelet transform and the denoised version of the signal is obtained by taking the inverse discrete wavelet transform of the signal using the modified coefficients. Donoho and Johnston proposed the universal threshold, called by them "Wave Shrink" given by:

$$\delta = \sigma\sqrt{(2\log N)}$$

Where σ is the standard deviation and N is the number of points. In case of white noise $\sigma = \frac{MAD}{0.6745}$ where MAD is the median absolute deviation of the detail coefficients. We alter this algorithm to provide a different threshold for each level of detail. Our altered formula is:



Signals & Systems EE232, Spring 2015 1

ECG Signal Analysis for Myocardial Infarction Detection (May 2015)

Asfandyar Hassan Shah (7642), Mahnoor Haneef (5064),
Rysham Ali (7640) and Uzair Akbar (4584)
NUST School of Electrical Engineering & Computer Science (SEECS), Pakistan

Abstract—Myocardial Infarction is one of the fatal heart diseases. It is essential that a patient is monitored for the early detection of MI. Owing to the newer technology such as wearable sensors which are capable of transmitting wirelessly, this can be done easily. However, there is a need for real-time applications that are able to accurately detect MI non-invasively. This project studies a prospective method by which we can detect MI. Our approach analyses the ECG (electrocardiogram) of a patient in real-time and extracts the ST elevation from each cycle. The ST elevation plays an important part in MI detection. We then use the sequential change point detection algorithm; CUmulative SUM (CUSUM), to detect any deviation in the ST elevation spectrum and to raise an alarm if we find any.

Index Terms—Myocardial Infarction, ECG, ST elevation, CUSUM

I. INTRODUCTION

The Electrocardiogram (ECG) is a waveform that represents the propagation of electric potentials through the heart muscle with respect to time. The propagation of these potentials results in the quasi-periodic contraction of the heart muscle. Each part of the cardiogram refers to a depolarization or a re-polarization of some region in the heart. The cardiogram consists of five major waves, also known as deflections in the cardiology literature, the P, Q, R, S, and T waves.

Myocardial Infarction is an acute ischemic heart disease characterized by a necrosis (death) of a portion of the heart muscle because of deprivation from oxygen. MI causes a serious disturbance of the cardiovascular system that leads to a direct threat for life.

MI is typically characterized by an elevation in the ST segment of ECG which is normally iso-electric for healthy subjects. ST segment elevation is generally one of the first symptom of MI and is usually accompanied by chest pain. But in order to be more specific to MI (or suspicious of MI), the ST elevation must be significant in amplitude (up to 0.2 mV) and prolonged in time (several minutes) as indicated in.

The rest of this report is organized as follows. Section II briefly reviews related techniques and presents our approach for early detection of MI. Section III presents our experimental results. Finally, Section IV concludes the report.

(a) One-cycle ECG tracing (b) ST Elevation ECG
Normal ECG and ST elevation ECG

II. IMPLIMENTATION

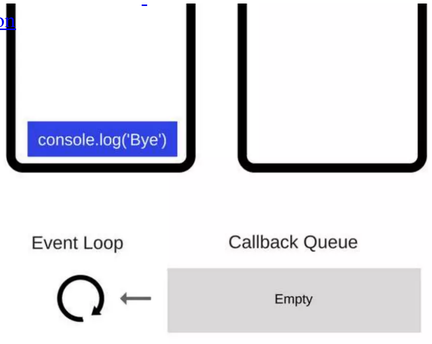
There are three aspects of our project:

A. ECG Signal Pre-processing (Rysham Ali, Mahnoor Haneef)

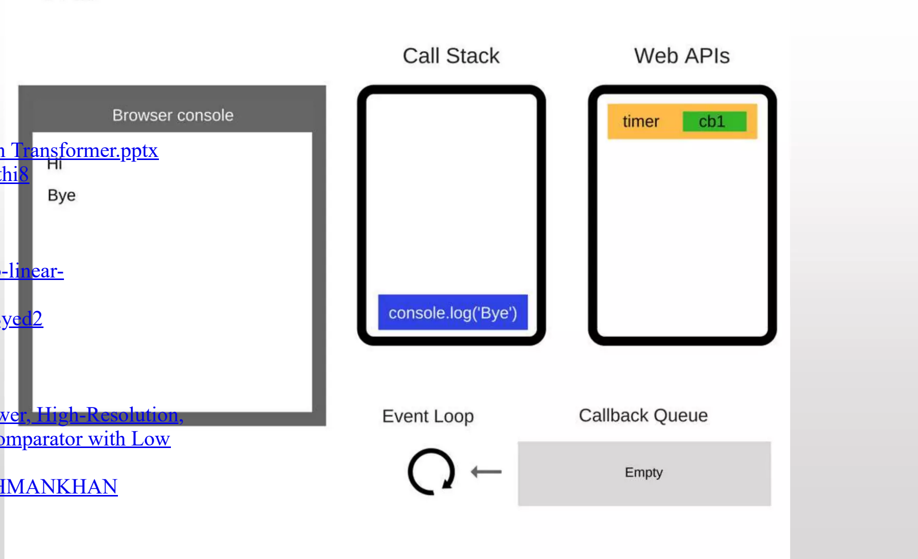
We are going to utilize adaptive thresholding method [8] for denoising the EKG signal using wavelet transforms. Wavelets transforms prove effective as it has good localization properties s in time and frequency domain. We improvise existing thresholding methods to improve noise reduction while insuring a good signal to noise ratio. Thresholding basically removes some of the detailed coefficients exceeding a certain threshold hence smoothing the signal out. The signal is then reconstructed in the time domain using the modified coefficients. Determining a good threshold is important as a wrong threshold value can remove important ECG features or let in too much noise. Thresholding generally consists of taking the discrete wavelet transform of the signal using the appropriate wavelet. A thresholding parameter is set to reduce the detail coefficients in the wavelet transform and the denoised version of the signal is obtained by taking the inverse discrete wavelet transform of the signal using the modified coefficients. Donoho and Johnston proposed the universal threshold, called by them "Wave Shrink" given by:

$$\delta = \sigma\sqrt{(2\log N)}$$

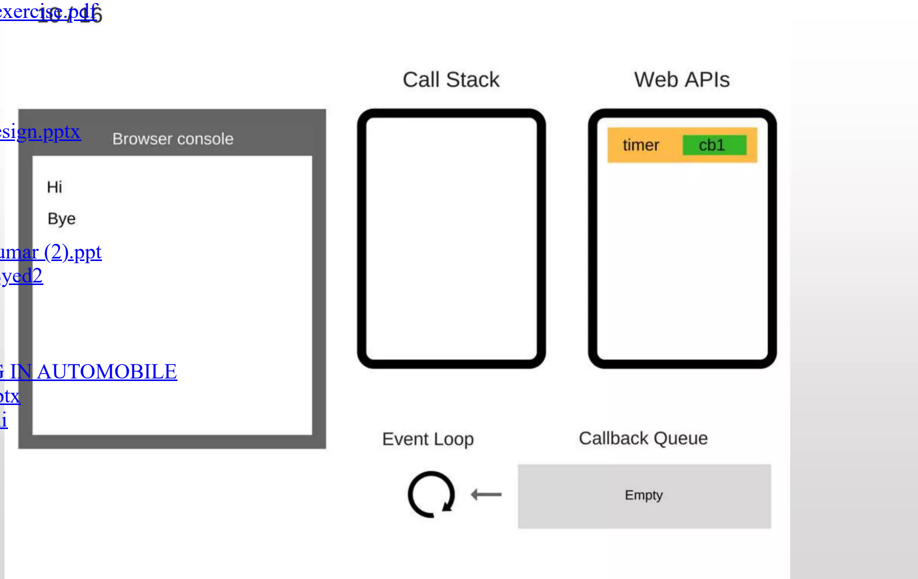
Where σ is the standard deviation and N is the number of points. In case of white noise $\sigma = \frac{MAD}{0.6745}$ where MAD is the median absolute deviation of the detail coefficients. We alter this algorithm to provide a different threshold for each level of detail. Our altered formula is:



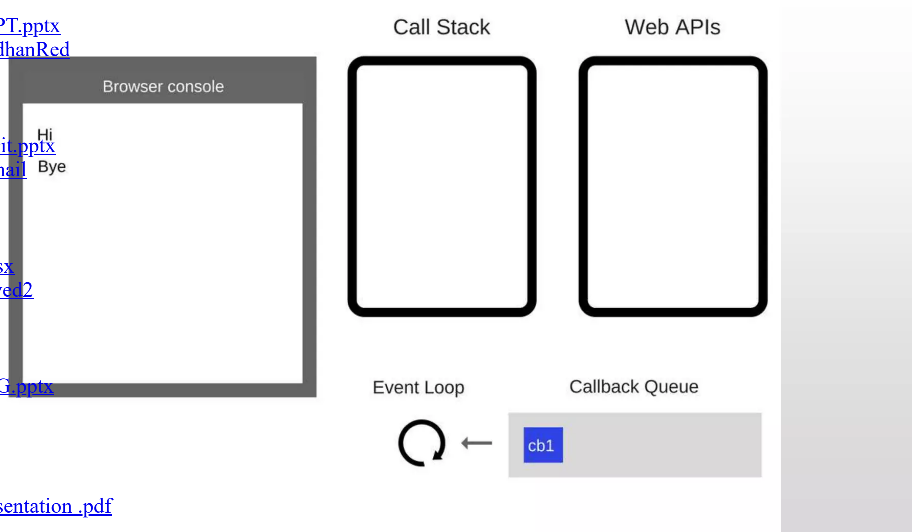
9 / 16


Call Stack
Web APIs
Browser console
Hi
Bye
console.log('Bye')
timer
cb1
Event Loop
Callback Queue
Empty

10 / 16

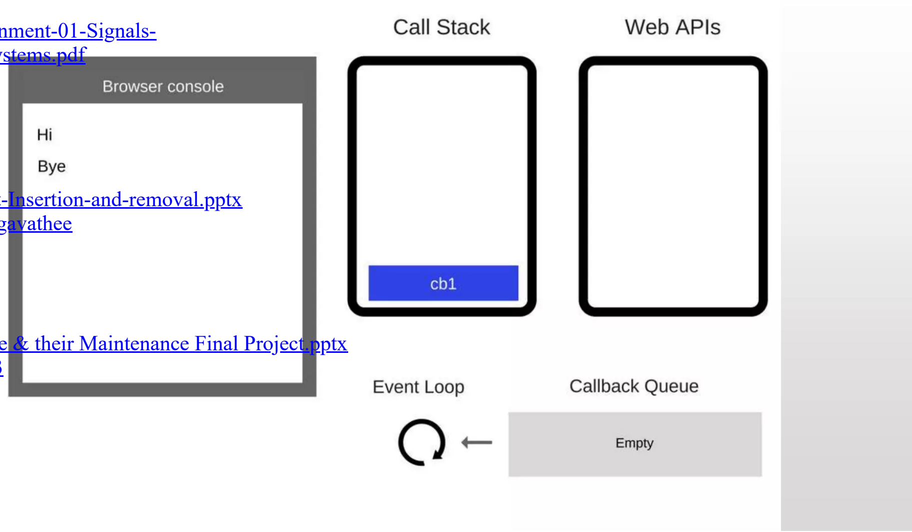

Call Stack
Web APIs
Browser console
Hi
Bye
timer
cb1
Event Loop
Callback Queue
Empty

11 / 16

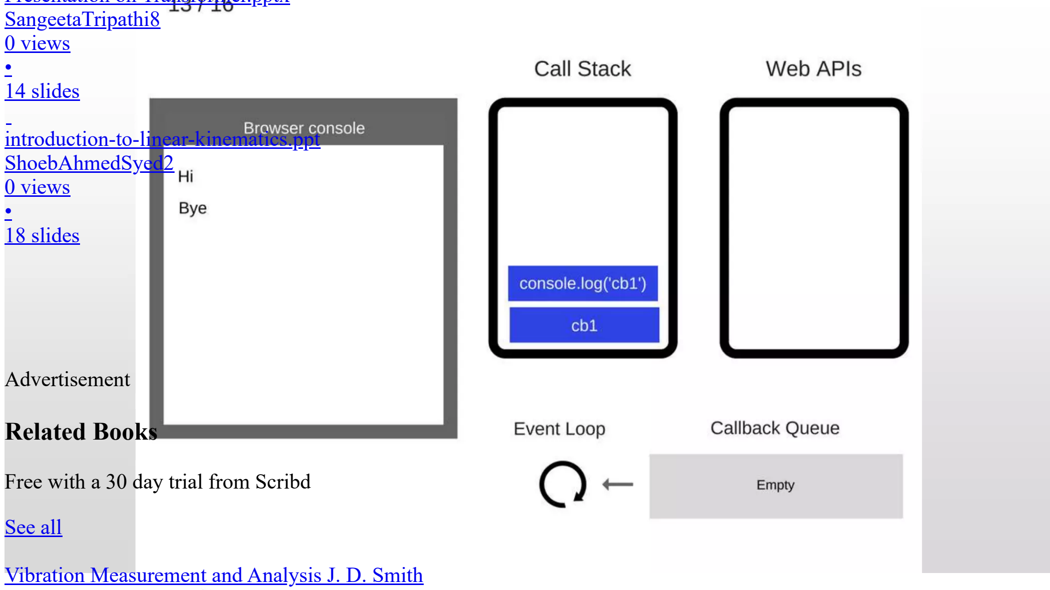


Call Stack
Web APIs
Browser console
Hi
Bye
Event Loop
Callback Queue
cb1

12 / 16



Call Stack
Web APIs
Browser console
Hi
Bye
cb1
Event Loop
Callback Queue
Empty

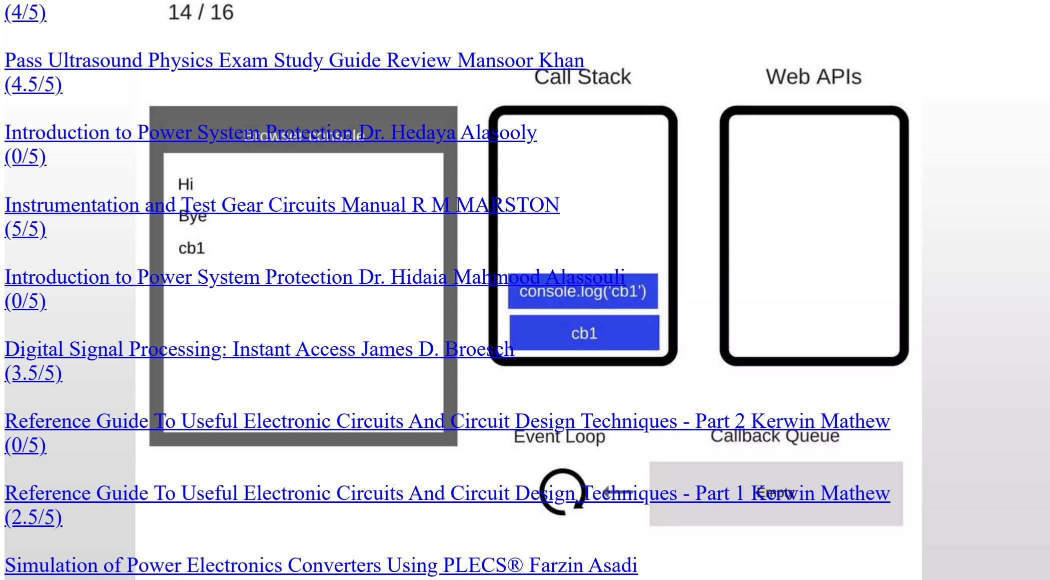


Related Books

Free with a 30 day trial from Scribd

[See all](#)

[Vibration Measurement and Analysis J. D. Smith](#)
[(4/5)](#)



[Pass Ultrasound Physics Exam Study Guide Review Mansoor Khan](#)
[(4.5/5)](#)

[Introduction to Power System Protection Dr. Hedaya Alasooly](#)
[(0/5)](#)

[Instrumentation and Test Gear Circuits Manual R M MARSTON](#)
[(5/5)](#)

[Introduction to Power System Protection Dr. Hidaia Mahmood Alassouli](#)
[(0/5)](#)

[Digital Signal Processing: Instant Access James D. Broesch](#)
[(3.5/5)](#)

[Reference Guide To Useful Electronic Circuits And Circuit Design Techniques - Part 2 Kerwin Mathew](#)
[(0/5)](#)

[Reference Guide To Useful Electronic Circuits And Circuit Design Techniques - Part 1 Kerwin Mathew](#)
[(2.5/5)](#)

[Simulation of Power Electronics Converters Using PLECS® Farzin Asadi](#)
[(0/5)](#)

[Analog Dialogue, Volume 47, Number 2 Analog Dialogue](#)
[(0/5)](#)

[PLC: Understanding a fitters guide Mitch Edwards](#)
[(0/5)](#)

[Brain-Computer Interfacing for Assistive Robotics: Electroencephalograms, Recurrent Quantum Neural Networks, and User-Centric Graphical Interfaces Vaibhav Gandhi](#)
[(5/5)](#)

[Analog Dialogue Volume 46, Number 1 Analog Dialogue](#)
(0/5)

[Simulation of Some Power Electronics Case Studies in Matlab Simpowersystem Blockset Dr. Hidaia Mahmood Alassouli](#)
(0/5)

[Electronic Systems: Study Topics in Physics Book 8 William Bolton](#)
(5/5)

[Power Electronics Applied to Industrial Systems and Transports: Volume 5: Measurement Circuits, Safeguards and Energy Storage Nicolas Patin](#)
(0/5)

[Analog Dialogue, Volume 45, Number 4 Analog Dialogue](#)
(0/5)

[Analog Dialogue, Volume 48, Number 2 Analog Dialogue](#)
(0/5)

[Nonlinear Electronics 1: Nonlinear Dipoles, Harmonic Oscillators and Switching Circuits Brahim Haraoubia](#)
(0/5)

[Simulation of Some Power Electronics Case Studies in Matlab Simpowersystem Blockset Dr. Hidaia Mamood Alassouli](#)
(0/5)

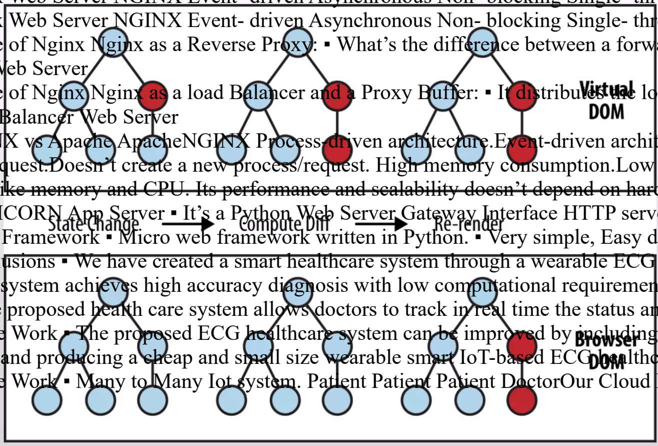
Project

1. 1. An IoT-cloud Based Wearable ECG Monitoring System for Smart Healthcare
2. 2. Outlines Introduction Biomedical and Machine Learning Hardware Internet Of Things (IOT) Live Demo
3. 3. Presented By ▪ Ahmed Ayman ▪ Ahmed Said ▪ Ahmed Mostafa ▪ Amr Mohamed ▪ Claudia Adly ▪ Latifa Mahmoud ▪ Marc Emad ▪ Mina Medhat ▪ Yaman Knan
4. 4. Introduction
5. 5. Problem
6. 6. Problem Cont. ▪ Elderly patients who live alone. ▪ Patients who don't know how to deal with mobiles or modern technologies. ▪ Patients with slow gait or even bed ridden. ▪ Ambulance late arrival.
7. 7. Solution
8. 8. Solution Cont.
9. 9. Electrocardiography
10. 10. Outlines Introduction Heart structure ECG wave structure Electrodes placement Arrhythmia
11. 11. Introduction ECG Periodic Rate and Rhythm Frequency range Aspects
12. 12. Heart structure The heart is a muscular organ about the size of a closed fist that functions as the body's circulatory pump. The heart contains 4 chambers: the right atrium, left atrium, right ventricle, and left ventricle.
13. 13. ECG wave structure 1. P wave 2. PR Interval 3. QRS Complex 4. J Point & ST Segment 5. QT Interval 6. T wave 7. U wave
14. 14. ECG wave structure Cont.
15. 15. Electrodes placement Electrode Placement RA On the right arm, avoiding thick muscle LA In the same location where RA was placed, but on the left arm LL In the same location where RL was placed, but on the left leg RL On the right leg, lateral calf muscle MLII
16. 16. Arrhythmia An arrhythmia is a problem with the rate or rhythm of your heartbeat. When the heart beats faster than normal, it is called tachycardia. When the heart beats too slowly, it is called bradycardia. Symptoms Fast or slow heart beat Skipping beats Lighthead edness or dizziness Chest pain Shortness of breath Sweating
17. 17. Arrhythmia Cont. Premature Ventricular Contraction (PVC) Broad QRS Complex Lengthened RR interval ST depression or T wave inversion or ST elevation with upright T wave
18. 18. Arrhythmia Cont. Atrial Premature Contraction (APC) Narrow QRS Complex shortened RR interval
19. 19. Arrhythmia Cont. Supraventricular Arrhythmia Narrow QRS Complex Shortened RR interval Hidden P wave
20. 20. Biomedical and Machine Learning
21. 21. Outlines HRV Analysis 1. Preprocessing 2. QRS detection 3. Feature Extraction 4. Feature Selection 5. Classifier RESULTS!!
22. 22. HRV Analysis Raw ECG Preprocessing & QRS detection Feature Extraction Dimension Reduction Classification (SVM) Results
23. 23. ECG Classification ▪ It is very difficult for doctors to analyze long ECG records in the short period of time and also human eye is poorly suited to detect the morphological variation of ECG signal, hence imposing the need for CAD. ▪ The ECG waveforms may differ for the same patient at different time and similar for different patients having different types of beats. For this reason, most of the ECG beats classification methods perform well on the training data but provide poor performance on the ECG waveforms of different patients.
24. 24. Database ECG data of MIT-BIH arrhythmia and Supraventricular arrhythmia databases are used. Each ECG signal is passed through a band pass filter at 0.1–100 Hz and sampled at 360 Hz
25. 25. Preprocessing The preprocessing of ECG signal is performed to remove the base line wander, motion artifacts and other interruptions of original recorded signal. ▪ Types of artifacts ▪ Baseline wander ▪ Powerline interference ▪ Muscle interference ▪ Burst noise
26. 26. Preprocessing Cont. Baseline wander Powerline interference Burst noise
27. 27. QRS detection ▪ The Pan-Tompkins algorithm, detects the QRS complexes based upon digital analyses of slope, amplitude, and width. Adv.?! Disadv.?

28. [28.] Pan Tompkins Dc drift removal and normalization Passing the result on BPF
29. [29.] Pan Tompkins Cont. Derivative Filter
30. [30.] Pan Tompkins Cont. Squaring Function
31. [31.] Pan Tompkins Cont. Moving Window Integration Applying set of thresholds
32. [32.] Pan Tompkins Cont.
33. [33.] What is ML? ▪ Subset of artificial intelligence which focuses mainly on ML from their experience and making predictions based on its experience. ▪ It enables the computers or the machines to make data- driven decisions.
34. [34.] What is ML? Cont.
35. [35.] Why ML? Problem Solution Can machines do what we (as thinking entities) do? ML uses algorithms that can learn from and make predictions on data Can even outperform human
36. [36.] How exactly do machines learn? Unsupervised Learning: Group and interpret data based only on input data. Supervised Learning: Develop predictive model based on both input and output data.
37. [37.] Uses of ML
38. [38.] Feature Extraction ▪ In order to describe the beats for classification purpose, we employ the following features: ▪ Morphological Features Discrete Wavelet Transform "DWT" Higher Order Statistics "HOS" ▪ Temporal-based features: R-R previous(RRP). R-R after(RAA) ▪ Normalized RR intervals
39. [39.] Feature Extraction Cont. Statistics-based features ▪ Calculated features from one beat and its sections. Range. Skewness distribution . i=1 n $(xi-x)3$ (i=1 n $(x-x))3$ Kurtosis distribution. i=1 n $(xi-x)4$ (i=1 n $(x-x))4$ Standard deviation. i=1 n $(xi-x)2$ n Mean. x = i=1 n x i n
40. [40.] Feature Extraction Cont.
41. [41.] Feature Extraction Cont. ▪ Features Normalization ▪ neutralize the effect of different scales across features . ▪ Standardization (Z-score normalization). ▪ Scaling to [0,1]. $\boldsymbol{z} = \boldsymbol{x}$−μ σ , μ=0 and σ=1
42. [42.] Feature Selection ▪ Feature selection is a process where you automatically select those features in your data that contribute most to the prediction variable or output in which you are interested. ▪ Having irrelevant features in your data can decrease the accuracy of many models. ▪ Benefits: ▪ Reduces Overfitting ▪ Improves Accuracy ▪ Reduces Training Time Methods: 1) Univariate Selection 2) Principal Component Analysis. 3) Independent Component Analysis
43. [43.] Classifier (SVM) ▪ "Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for both classification and regression challenges. ▪ Classification is performed by finding the hyper- plane that differentiate the two classes very well.
44. [44.] Binary Classification ▪ The predictions now fall into four groups based on the actual known answer and the predicted answer: ▪ correct positive predictions (TP). ▪ correct negative predictions (TN). ▪ incorrect positive predictions (FP). ▪ incorrect negative predictions (FN).
45. [45.] Confusion Matrix The confusion matrix is a table that shows each class in the evaluation data and the number or percentage of correct predictions and incorrect predictions. Accuracy = $\boldsymbol{TP+TN}$ $\boldsymbol{TP+TN+FP+FN}$ Sensitivity = $\boldsymbol{TP}$ $\boldsymbol{TP+FN}$ Specificity = $\boldsymbol{TN}$ $\boldsymbol{TN+FP}$
46. [46.] Classifier (SVM) ▪ "Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for both classification and regression. 1. Generalizes well. 2. Computationally efficient ▪ Classification is performed by finding the hyper-plane g(x) that differentiate the two classes very well. g $x = W$ T $X + b = -1$ 0 1 Support Vectors $yi = +1$ $yi = +1$
47. [47.] SVM Cont.
48. [48.] Multiclass Classification ▪ The predicted answer is the class with the highest predicted score. ▪ SVM for each pair of n classes. C(n,2)= $n(n-1)$ 2 ▪ We need C(n,k) SVM's . ▪ Classe with most votes picked as a WINNER!
49. [49.] RESULTS!! ▪ Output screenshots from python.
50. [50.] RESULTS! Cont. ▪ ECG signal acquired from Ahmed Said.
51. [51.] RESULTS! Cont. ▪ Confusion Matrix 1- Multiclass Classification
52. [52.] RESULTS! Cont. 2- Binary Classification
53. [53.] Hardware
54. [54.] Hardware system
55. [55.] Outlines E-Health kit Packaging Case Using the e-Health ECG sensor Usage precautions ECG Circuit schematic Sources Of Artifacts Signal reading Average Voltage Reference Heart Rate Bluetooth Low Energy Module
56. [56.] E-Health kit Feathers: This ECG returns an analogic value in volts (0 – 5) to represent the ECG wave form. Variable sampling frequency.
57. [57.] Packaging Case Protects the core component of our project against shocks or falls. User friendly.
58. [58.] Using the e-Health ECG sensor
59. [59.] Usage precautions ▪ The patient should lie down on a horizontal bed. ▪ The patient's body should be completely at rest.
60. [60.] Usage precautions Cont. ▪ The patient's chest hair should be removed. ▪ The patient should use sterilizer on his skin.
61. [61.] ECG Circuit schematic
62. [62.] ECG Circuit schematic Cont. Stage 1: Buffer amplifier ▪ Provides electrical impedance transformation ▪ Optimized for low voltage, single supply operation ▪ Reduces power consumption in the source and distortion ▪ Removes high frequencies
63. [63.] ECG Circuit schematic Cont. Stage 2: Instrumentation amplifier ▪ Eliminates the need for input impedance matching ▪ Makes it suitable for use in measurement and test equipment ▪ Gets the difference between the two input voltages and multiplies the result with the gain which is 5 $G = 5 + 5$ $R2$ $R1$
64. [64.] ECG Circuit schematic Cont. Stage 3: Op-amp integrator Performs the mathematical operation of integration ▪ Output signal is determined by the length of time a voltage is present at its input $Vout = -1$ Rin C 0 t Vin dt
65. [65.] ECG Circuit schematic Cont. Stage 4: Low-pass filter ▪ Passes signals with a frequency lower than a certain cutoff frequency ▪ Attenuates signals with frequencies higher than the cutoff frequency ▪ Cutoff frequency of low-pass filter: $fc = 1$ $2\pi RC$
66. [66.] ECG Circuit schematic Cont.
67. [67.] Signal reading
68. [68.] Average Voltage Reference DC Biasing all to detect 'Q' and 'S' peaks.
69. [69.] Sources Of Artifacts ▪ Muscle: 5 – 50 Hz ▪ Respiratory "Baseline wander": 0.12 – 0.5 Hz (e.g. 8 – 30 bpm) ▪ >10 Hz (muscle stimulators, strong magnetic fields, pacemakers with impedance monitoring) ▪ 50 or 60 Hz (powerline frequency)
70. [70.] Heart Rate $Heart\ Rate = Pulses\ Count\ Time\ (Minute)$
71. [71.] Bluetooth Low Energy Module (BLE) General details Technical details HM 10 Specifications Applications
72. [72.] Bluetooth Low Energy Module (BLE) Cont.
73. [73.] Bluetooth Low Energy Module (BLE) Cont. General details Marketed as Bluetooth Smart.. Wireless technology standard. Small size and low cost. Mobile operating systems.

74. 74. Bluetooth History
75. 75. Bluetooth Low Energy Module (BLE) Cont. Technical details ▪ Wireless technology standard. ▪ marketed as Bluetooth Smart.. ▪ small size and low cost. ▪ Mobile operating systems. ▪ Bluetooth version 4.0 BLE.
76. 76. Bluetooth Low Energy Module (BLE) Cont.
77. 77. Bluetooth Low Energy Module (BLE) Cont. Technical details: ▪ ISM 2.4 GHz frequency band. ▪ Data transfer rate. ▪ Products suited for. ▪ Security: Authentication and Encryption (128-bit AES) . ▪ Modulation method : GFSK . modulation index 0.5
78. 78. Bluetooth Low Energy Module (BLE) Cont. ▪ Channel Bandwidth : 2 MHz . ▪ Number of Channels : 40 . ▪ Low power consumption.
79. 79. HM 10 Specifications ▪ +2.5v to +3.3v ▪ Uses around 9mA when in an active state ▪ Use 50-200uA when asleep ▪ RF power: -23dbm, -6dbm, 0dbm, 6dbm ▪ Supported baud rate: 1200, 2400, 4800, 9600 (default), 19200,38400, 57600, 115200, 230400. ▪ The data is sent from the BLE module to the patient's app at a speed of 6 K bytes/s. THIS IS THE BEST !!
80. 80. Bluetooth Low Energy Module (BLE) Cont. Applications ▪ Health care profiles. ▪ Sports and fitness profiles. ▪ Battery. ▪ Generic Sensors.
81. 81. IoT System
82. 82. Our IoT Infrastructure ▪ It's a Many-to-One IoT System. Patient Patient Patient DoctorOur Cloud Infrastructure
83. 83. The Outline
84. 84. Firebase (Google Cloud Platform) Doesn't run python on the cloud functions ECG Data Real-time Database Mobile App Or Simulator Amazon Web Services (EC2) ML ProgramNetwork Interface (Runs the ML) Store Data in the DB Trigger the ML Fetch and Store data to the DB
85. 85. Model–view–controller (MVC) Pattern
86. 86. The Apps' Logic (Controller)
87. 87. Javascript ▪ Uses Google's V8 Engine. ▪ Single-threaded language. ▪ Asynchronous Non-blocking language.
88. 88. V8 Engine
89. 89. The Runtime
90. 90. Callbacks ▪ Enables executing blocking code on a single-threaded architecture. ▪ It returns a promise before execution. setTimeout(function() { console.log(1); }, 5000);
91. 91. The Event Loop
92. 92. The Apps' Views
93. 93. Rendering HTML (The DOM Tree)
94. 94. How React.js Solved the problem
95. 95. React's Virtual DOM
96. 96. Why React Native? ▪ It's written in Javascript which we all know. ▪ It has huge community support. ▪ It uses iOS' and Android's Native UI Views. ▪ Its logic is run inside a JS Runtime environment that's directly bridged to the Native Platform.
97. 97. How it compares to Native in terms of CPU
98. 98. How it compares to Native in terms of GPU
99. 99. How it compares to Native in terms of Memory Usage
100. 100. The Patient's Mobile App
101. 101. Hardware Connectivity ▪ The ECG sampling rate is 125 HZ. ▪ Almost everyone has a smartphone. ▪ It's much easier for patients to pair a BLE device with their phone than connect a hardware device to their Wi-Fi at home. ▪ We wanted the system to be portable and useable outdoors too. ▪ BLE modules are very cheap compared to Wi-Fi or GSM modules.
102. 102. How BLE Works
103. 103. Getting data from the BLE ▪ Uses the BLE PLX library bindings. ▪ The user can select the BLE device. ▪ Connects to the default service and characteristic. ▪ Keeps monitoring the characteristic for any updates.
104. 104. Storing the data in Real-time ▪ The app collects the data. ▪ Sends the data to Firebase's Real-time DB.
105. 105. The Patient's Simulator ▪ Reads the CSV file. ▪ Pushes the data to the DB with a delay. ▪ Triggers the ML. >> node index.js SimulatorName ./data/path.csv
106. 106. Firebase's Cloud Functions - Run in the cloud. - Could be triggered automatically. - Can monitor the DB.
107. 107. Database &
108. 108. Key capabilities of Firebase Database ▪ Real-time Connected device receives updates within milliseconds. ▪ Offline Firebase Real-time Database SDK persists data to disk ▪ Accessible from Client Devices – Concurent connections Accessed directly from a mobile device or web browser ▪ Scale multiple databases instances Splitting your data across multiple database instances in the same Firebase project. Authenticate users across your database instances.
109. 109. How does Firebase work? ▪ Firebase Authentication developers can define who has access to what data, and how they can access it. ▪ Use NoSQL data storage. ▪ Use Web-sockets protocol. ▪ Data is stored as JSON objects.
110. 110. NoSQL cloud database. ▪ Stands for "NOT ONLY SQL" ▪ A Non Relational database (No Tables,columns) ▪ A flexiable DB used for big data & real-time web apps ▪ No predefined schema Tables, columns fields, datatype, unstructured ▪ Cheaper to manage less sysadmin ▪ Use Horizontal Scaling (Scale out)
111. 111. Add additional nodes form a cluster Add cluster Change components, resources. Expensive , Time consumption Scaling Out
112. 112. Relational vs Document DB
113. 113. Real-time Database Limits Data
114. 114. Reads
115. 115. More than that: fail and return an error reporting the limit that was hit
116. 116. Our Usage with Firebase
117. 117. Virtualization Technology ▪ Cloud is a model not the technology itself ▪ Cloud computing is a model for enabling on-demand network access to a shared pool of computing resources (e.g., networks, servers, storage, applications, and services)
118. 118. Disadvantage of physical server ▪ Purchasing time (time wasting) ▪ Cost of ownership is high ▪ Cost maintaining: - Spare Parts - Energy (Electricty and cooling) - Wasted Hardware resources - Maintenance down time ▪ Difficult Backup and recover ▪ Difficult Test & Dev operations
119. 119. Advantage of Cloud Computing with just a few clicks ▪ Work from anywhere ▪ Security ▪ Fast Deployment, Upgrade ▪ Pay only for how much you consume. ▪ Scale up and down as required
120. 120. AWS ▪ Secure cloud services platform ▪ Offers Compute power Database storage Analytics Management tools Developer tools Networking
121. 121. Amazon EC2 (Elastic Compute Cloud) ▪ Secure and resizable compute capacity in the cloud. Reduces time required to obtain and boot new server instances to minutes Quickly scale capacity (EC2 Auto Scaling) Highly reliable environment where replacement instances can be rapidly and predictably commissioned.
122. 122. Our Usage to run machine learning code ▪ Single-Core machine ▪ 1 GB RAM ▪ Ubuntu 14.04 LTS ▪ Amazon Free Tier : Amazon EC2 750 Hours per month

123. 123. The need for NGINX and GUNICORN ML ProgramFlask (API) (Runs the ML) Nginx (Web Server) Acts as a Reverse Proxy Gunicorn (App Server) (New Process per Patient) ML ProgramFlask (API) (Runs the ML) (New Process per Patient) HTTP Request Dynamic Request
124. 124. The need for NGINX and GUNICORN ▪ Any sort of deployment has something upstream that will handle the requests that the app should not be handling. ▪ NGINX handles such requests if they are static (images/css/js). ▪ GUNICORN handles these requests if they are dynamic.
125. 125. Nginx Web Server ▪ NGINX is a free, open-source, high- performance HTTP server. ▪ The most popular web server among high- traffic websites.
126. 126. Nginx Web Server NGINX Event- driven Asynchronous Non- blocking Single- threaded Single-threaded: Traditional Web servers implemented thread based models. It was written to address the C10K problem.
127. 127. Nginx Web Server NGINX Event- driven Asynchronous Non- blocking Single- threaded Event-driven and non- blocking: Requests are executed concurrently without blocking. Has low memory usage.
128. 128. Usage of Nginx Nginx as a Reverse Proxy: ▪ What's the difference between a forward proxy and a reverse proxy? ▪ Used to pass requests to appropriate backend server. Nginx Proxy Server Reverse Proxy Proxy Buffer SSL Load Balancer Web Server
129. 129. Usage of Nginx Nginx as a load Balancer and a Proxy Buffer: ▪ It distributes the load onto other servers and manages the traffic. ▪ Nginx stores the responses in memory buffers. Nginx Proxy Server Reverse Proxy Proxy Buffer SSL Load Balancer Web Server
130. 130. NGINX vs Apache ApacheNGINX Process-driven architecture. Event-driven architecture. Easier configuration and better documentation. Only comes with core features. More Functionality. Less components. Creates a new process for each request. Doesn't create a new process/request. High memory consumption. Low memory consumption. Slower under same conditions. Faster than Apache under same condition. Performance and scalability depends on hardware resources like memory and CPU. Its performance and scalability doesn't depend on hardware resources.
131. 131. GUNICORN App Server ▪ It's a Python Web Server Gateway Interface HTTP server. ▪ Based on the worker model. ▪ We Used it to create multiple processes, one for each patient.
132. 132. Flask Framework ▪ Micro web framework written in Python. ▪ Very simple, Easy documentation. ▪ We Used it to extract the ID of patient and pass it on to the ML program.
133. 133. Conclusions ▪ We have created a smart healthcare system through a wearable ECG monitoring device connected to an IoT cloud using the best- fitted technologies and cost-effective options. ▪ The HRV analysis of the proposed healthcare system achieves high accuracy diagnosis with low computational requirements. ▪ The proposed IOT system including the patient's App, doctor's App, AWS, and EC2 cloud Web Service provides reliable performance in real time. ▪ The proposed health care system allows doctors to track in real time the status and diagnosis of their patients wherever they are.
134. 134. Future Work ▪ The proposed ECG healthcare system can be improved by including more ECG diseases using a robust HRV approach. ▪ The diagnosis performance can be enhanced using advanced machine learning techniques. ▪ Designing and producing a cheap and small size wearable smart IoT-based ECG healthcare system.
135. 135. Future Work ▪ Many to Many Iot system. Patient Patient Patient DoctorOur Cloud Infrastructure Doctor Doctor



- About
- Support
- Terms
- Privacy
- Copyright
- Cookie Preferences
- Do not sell or share my personal information

English
Current Language English
Español
Português
Français
Deutsch

×

Share Clipboard

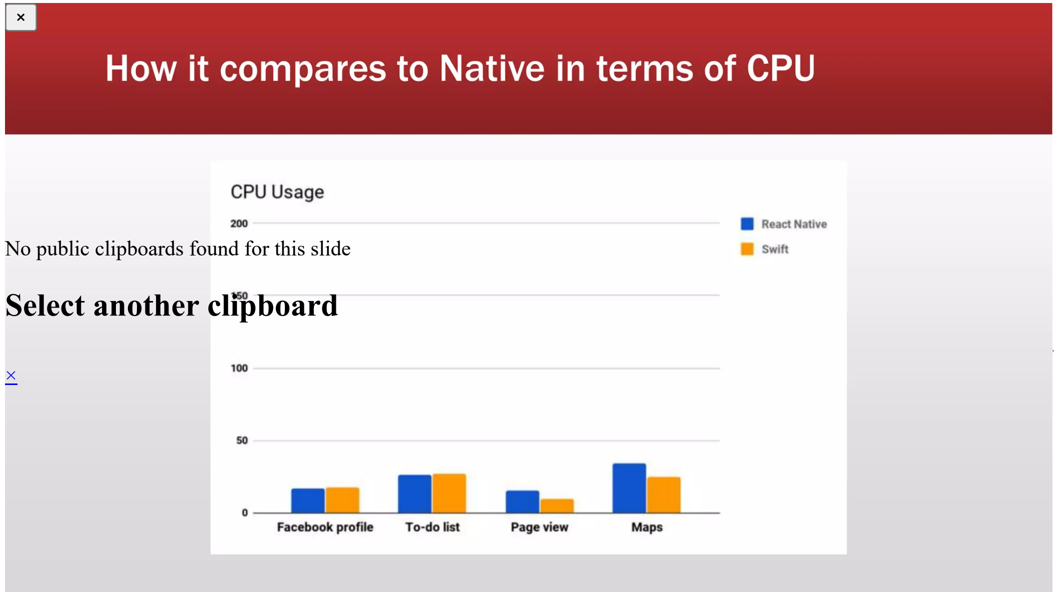
×

- Facebook
- Twitter
- LinkedIn

Link

Public clipboards featuring this slide

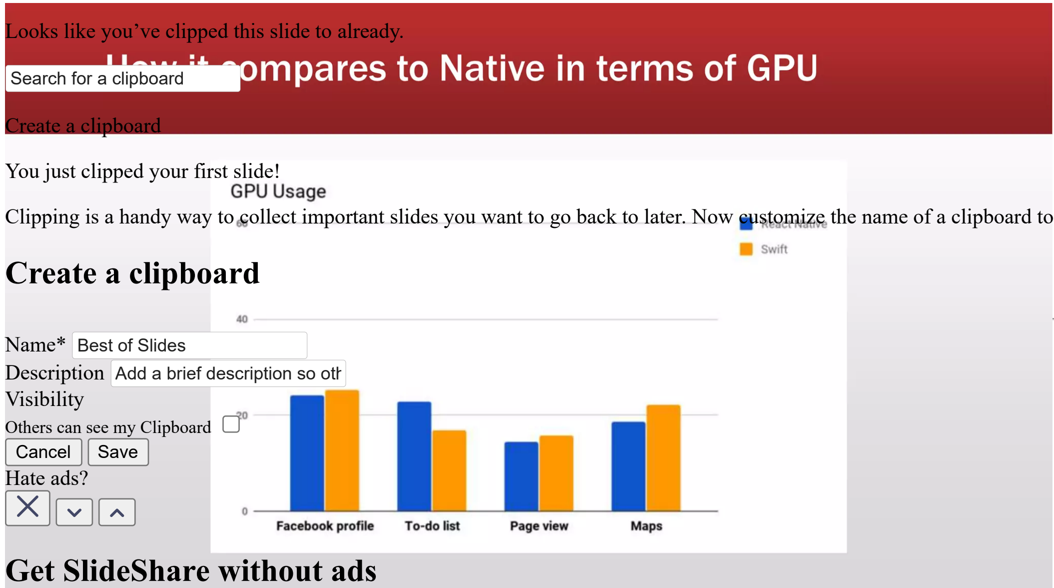
×



No public clipboards found for this slide

Select another clipboard

×



Looks like you've clipped this slide to already.

Search for a clipboard

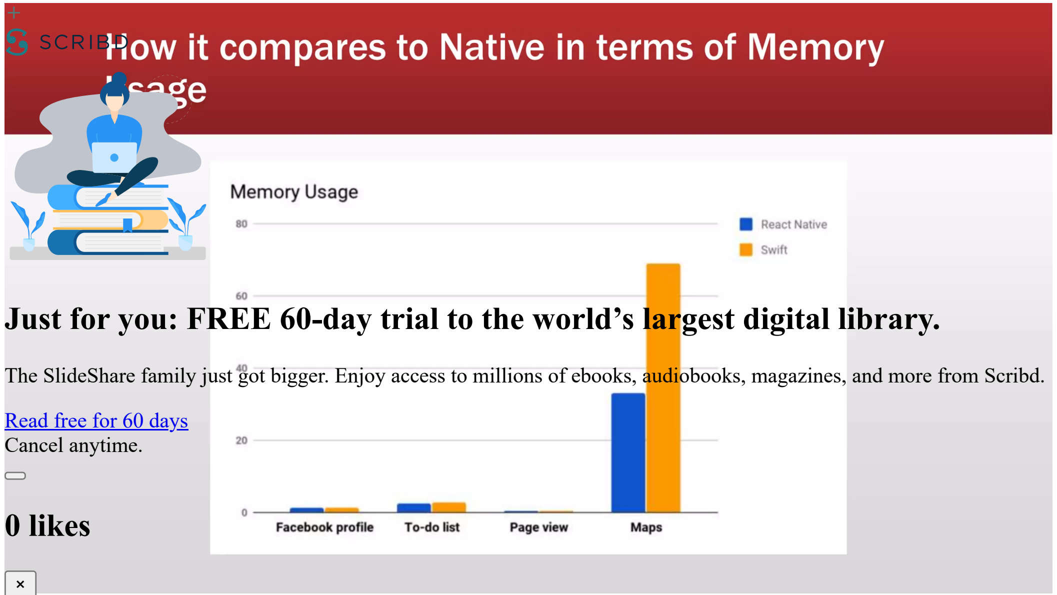
Create a clipboard

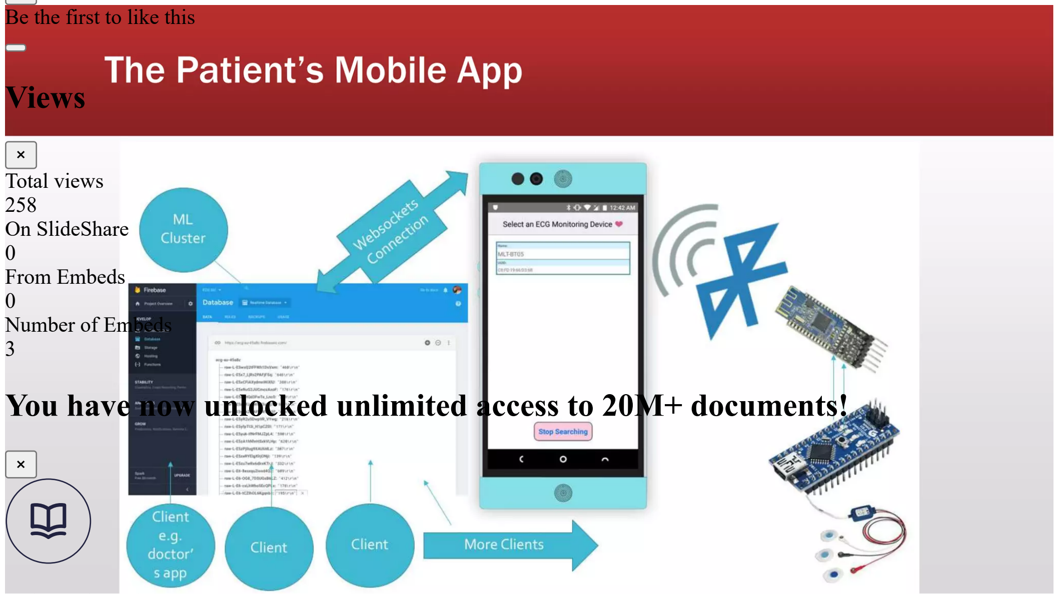
You just clipped your first slide!

Clipping is a handy way to collect important slides you want to go back to later. Now customize the name of a clipboard to store your clips.

Create a clipboard

Name* Best of Slides
Description Add a brief description so oth
Visibility
Others can see my Clipboard
Cancel Save

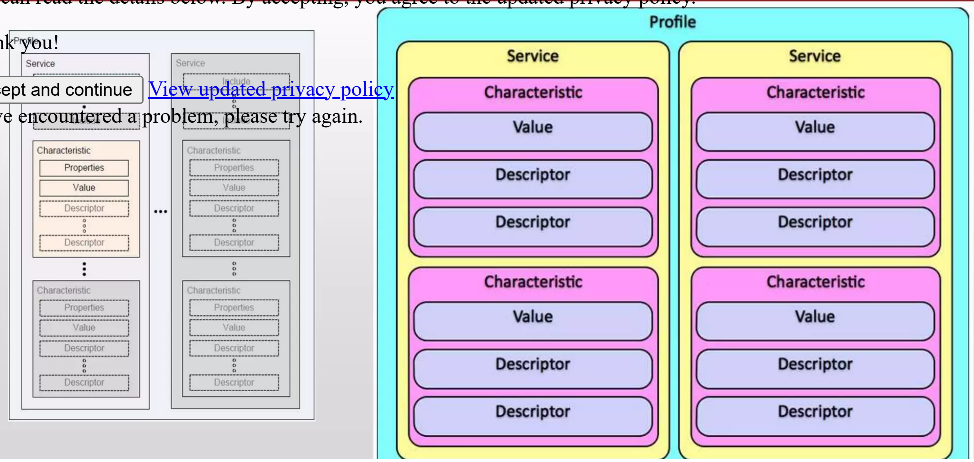

How it compares to Native in terms of Memory Usage
Memory Usage
React Native
Swift
80
60
40
20
0
Facebook profile
To-do list
Page view
Maps


The Patient's Mobile App
ML Cluster
Websockets Connection
Database
Select an ECG Monitoring Device
Stop Searching
Client e.g. doctor's app
Client
Client
More Clients

Hardware Connectivity

- The ECG sampling rate is 125 HZ.
- Almost everyone has a smartphone.
- It's much easier for patients to pair a BLE device with their phone than connect a hardware device to their Wi-Fi at home.
- We wanted the system to be portable and useable outdoors too.
- BLE modules are very cheap compared to Wi-Fi or GSM modules.

How BLE Works



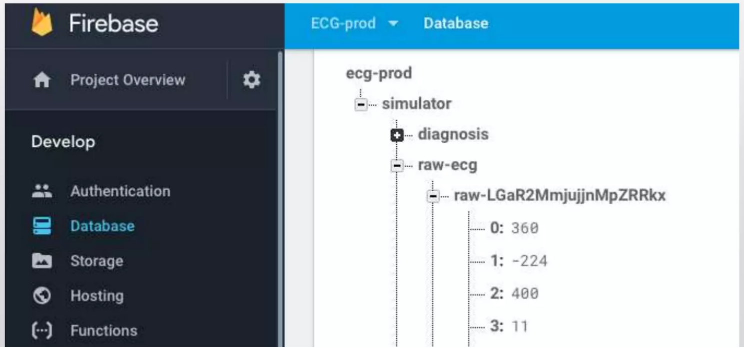
Getting data from the BLE

- Used the BLE PLX library bindings.
- The user can select the BLE device.
- Connects to the default service and characteristic.
- Keeps monitoring the characteristic for any updates.

```
componentDidMount() {
  const notify = () => {
    this.props.monitorCharacteristic(this.props.deviceId,
      // Service ID
      '0000ffe0-0000-1000-8000-00805f9b34fb',
      // Characteristic ID
      '0000ffe1-0000-1000-8000-00805f9b34fb',
      true);
  };
  notify();
```

Storing the data in Real-time

- The app collects the data.
- Sends the data to Firebase's Real-time DB.



The Patient's Simulator

- Reads the CSV file.
- Pushes the data to the DB with a delay.
- Triggers the ML.

>> node index.js SimulatorName ./data/path.csv

Firebase's Cloud Functions

- Run in the cloud. - Could be triggered automatically.

- Can monitor the DB.

```
exports.newData = functions.database
// Watch for any new diagnosis data that was returned form the ML
  .ref('/{patient}/diagnosis/{diagnosis-array}')
  .onCreate((snapshot, context) => {

    // console.log('Received new ECG Data for', context.params.patient);
    // the diagnosis object
    var rawDiagnosis = snapshot._data;
    // convert the diagnosis object to an array
    var diagnosisArray = Object.keys(rawDiagnosis).map(key => rawDiagnosis[key]);
    // after calculating the mode for the diagnosis
    var finalDiagnosis = calculateMode(diagnosisArray)[0];
    return admin.database().ref(context.params.patient + "/status").push
    (finalDiagnosis);
});
```

Key capabilities of Firebase Database

- Real-time
  Connected device receives updates within milliseconds.
- Offline
  Firebase Real-time Database SDK persists data to disk
- Accessible from Client Devices – Concurent connections
  Accessed directly from a mobile device or web browser
- Scale multiple databases instances
  Splitting your data across multiple database instances in the same Firebase project. Authenticate users across your database instances.

How does Firebase work?

- Firebase Authentication, developers can define who has access to what data, and how they can access it.
- Use NoSQL data storage.
- Use Web-sockets protocol.
- Data is stored as JSON objects.

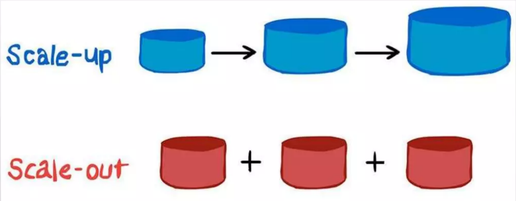
NoSQL cloud database.

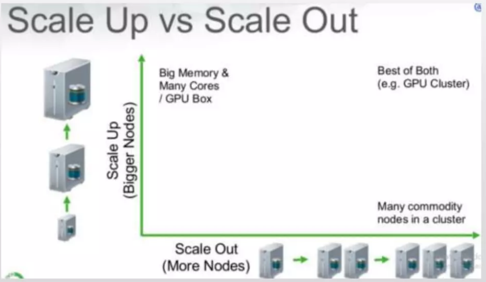
- Stands for "NOT ONLY SQL"
- A Non-Relational database (No Tables,columns)
- A flexiable DB used for **big data** & **real-time** web apps
- No predefined schema
  Tables, columns fields, datatype, unstructured data
- Cheaper to manage
  less system admin
- Use Horizontal Scaling (Scaling out)

Scaling Out

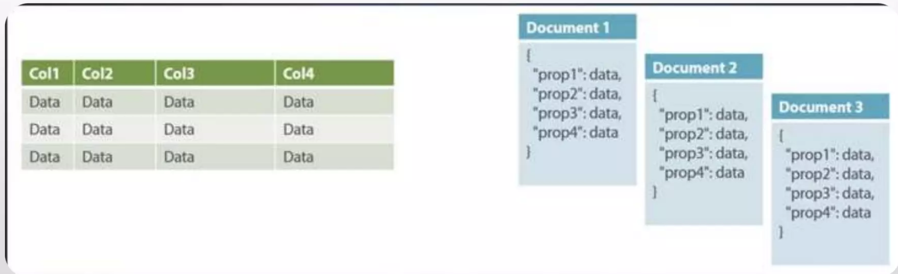
- Change components, resources.
- Expensive , Time consumption

- Add additional nodes form a cluster
- Add cluster





Relational vs Document DB



Real-time Database Limits

Data

Property	Limit	Description
Maximum depth of child nodes	32	Each path in your data tree must be less than 32 levels deep.
Length of a key	768 Bytes	Keys are UTF-8 encoded and can't contain new lines or any of the following characters: . $ # [ ] / or any ASCII control characters (0x00 - 0x1F and 0x7F)
Maximum size of a string	10 MB	Data is UTF-8 encoded.

Reads

Description	Limit	Notes
Size of a single response served by the database	256 MB	The size of data downloaded from the database at a single location should be less than 256 MB for each read operation.
Total nodes in a path with listeners or queries on it	75 million*	You can't listen to or query paths with more than 75 million nodes, cumulative. However, you can still listen to or query child nodes. Try drilling down deeper into the path or creating separate listeners or queries for more specific portions of the path. **You can't view paths with more than 30,000 total nodes from the data viewer in the Firebase console.*

Simultaneous responses sent from a single database.	~100,000/second	Responses include simultaneous broadcast and read operations sent by the server from a single database at a given time. The limit refers to the data packets that represent each individual read or broadcast operation, including push notifications, sent from the database.
Number of Cloud Functions triggered by a single write	1000	While there isn't a limit to how many read or write operations you can trigger from a single function, a single database write operation can only trigger 1000 functions per individual write operation. Cloud Functions can only be triggered by write operations, and each function can also trigger more write operations that trigger more functions (each with their own 1000-function limit).

More than that: fail and return an error reporting the limit that was hit

Our Usage with Firebase

Free

Realtime Database

Simultaneous connections	100
GB stored	1 GB
GB downloaded	10 GB/month
Multiple databases per project	✕

Virtualization Technology

- Cloud is a model not the technology itself
- Cloud computing is a model for enabling on-demand network access to a shared pool of computing resources (e.g., networks, servers, storage, applications, and services)

Disadvantage of physical server

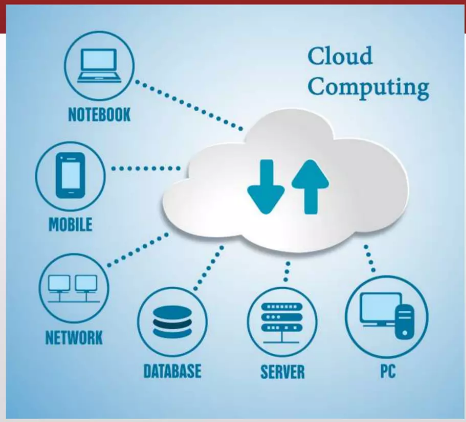
- Purchasing time (time wasting)
- Cost of ownership is high
- Cost maintaining:
  - Spare Parts
  - Energy (Electricty and cooling)
  - Wasted Hardware resources
  - Maintenance down time
- Difficult Backup and recover
- Difficult Test & Dev operations

Advantage of Cloud Computing
with just a few clicks

- Work from anywhere
- Security
- Fast Deployment, Upgrade
- Pay only for how much you consume.
- Scale up and down as required

AWS

- Secure cloud services platform
- Offers
  - Compute power
  - Database storage
  - Analytics
  - Management tools
  - Developer tools
  - Networking



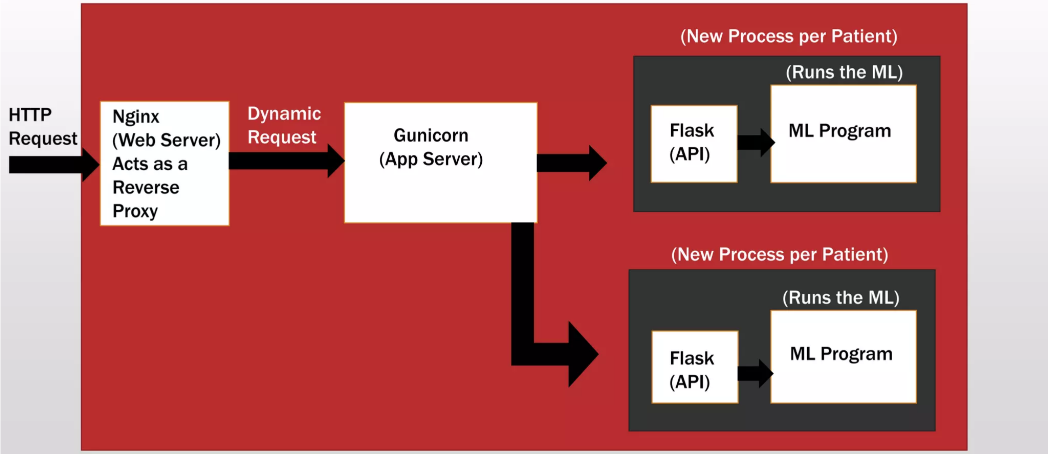
Amazon EC2 (Elastic Compute Cloud)

- Secure and resizable **compute** capacity in the cloud.
- Reduces time required to obtain and boot new server instances to minutes
- Quickly scale capacity (EC2 Auto Scaling)
- Highly reliable environment where replacement instances can be rapidly and predictably commissioned.

Our Usage to run machine learning code

- Single-Core machine
- 1 GB RAM
- Ubuntu 14.04 LTS
- Amazon Free Tier : Amazon EC2 750 Hours per month

The need for NGINX and GUNICORN



The need for NGINX and GUNICORN

- Any sort of deployment has something upstream that will handle the requests that the app should not be handling.
- NGINX handles such requests if they are static (images/css/js).
- GUNICORN handles these requests if they are dynamic.

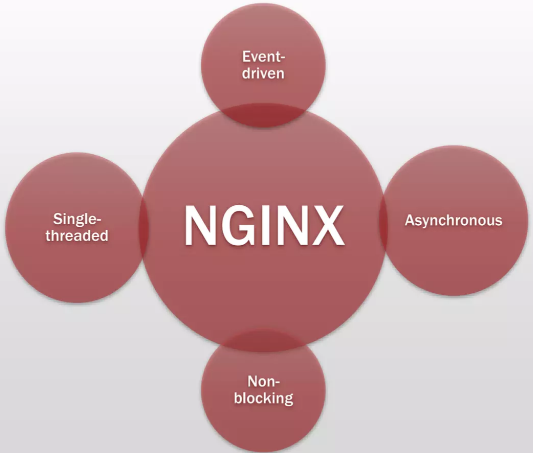
Nginx Web Server

- NGINX is a free, open-source, high-performance HTTP server.
- The most popular web server among high-traffic websites.

Nginx Web Server

Single-threaded:

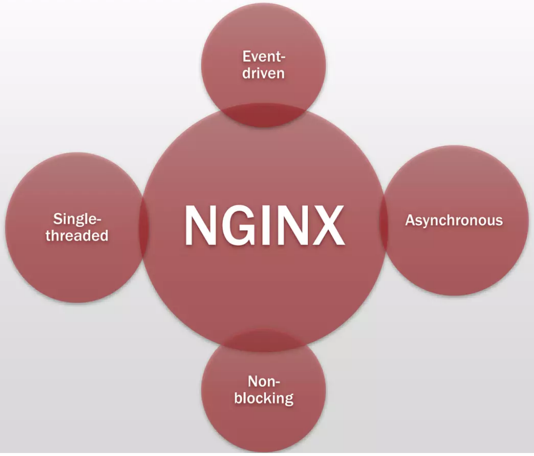
- Traditional Web servers implemented thread based models.
- It was written to address the C10K problem.



Nginx Web Server

Event-driven and non-blocking:

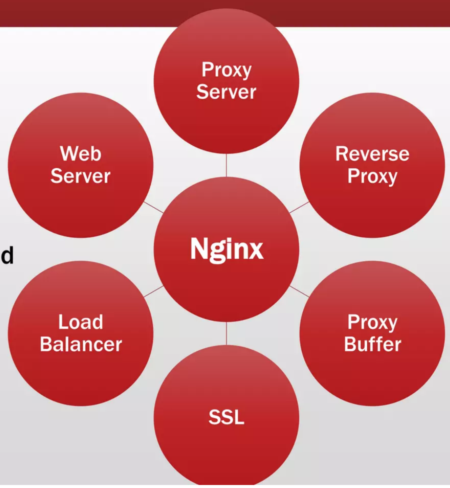
- Requests are executed concurrently without blocking.
- Has low memory usage.



Usage of Nginx

Nginx as a Reverse Proxy:

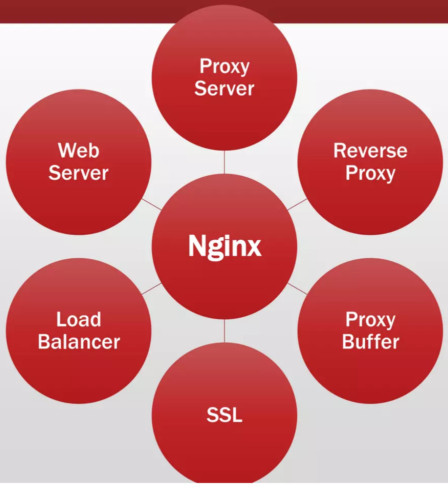
- What’s the difference between a forward proxy and a reverse proxy?
- Used to pass requests to appropriate backend server.



Usage of Nginx

Nginx as a load Balancer and a Proxy Buffer:

- It distributes the load onto other servers and manages the traffic.
- Nginx stores the responses in memory buffers.



NGINX vs Apache

NGINX	Apache
Event-driven architecture.	Process-driven architecture.
Only comes with core features.	Easier configuration and better documentation.
Less components.	More Functionality.
Doesn't create a new process/request.	Creates a new process for each request.
Low memory consumption.	High memory consumption.
Faster than Apache under same condition.	Slower under same conditions.
Its performance and scalability doesn't depend on hardware resources.	Performance and scalability depends on hardware resources like memory and CPU.

GUNICORN App Server

- It's a Python Web Server Gateway Interface HTTP server.
- Based on the worker model.
- We Used it to create multiple processes, one for each patient.

Flask Framework

- Micro web framework written in **Python.**
- Very simple, Easy documentation.
- We Used it to extract the ID of patient and pass it on to the ML program.

Conclusions

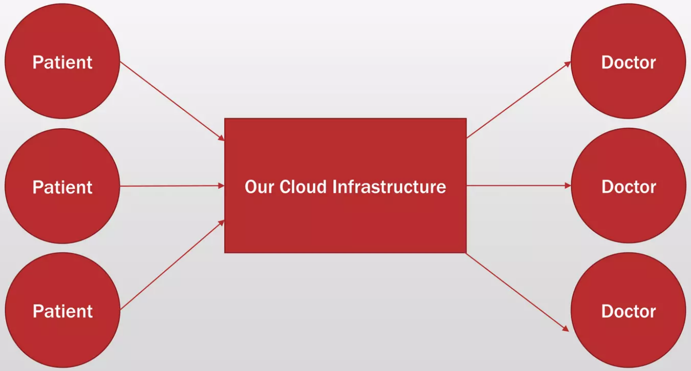
- We have created a smart healthcare system through a wearable ECG monitoring device connected to an IoT cloud using the best-fitted technologies and cost-effective options.
- The HRV analysis of the proposed healthcare system achieves high accuracy diagnosis with low computational requirements.
- The proposed IOT system including the patient's App, doctor's App, AWS, and EC2 cloud Web Service provides reliable performance in real time.
- The proposed health care system allows doctors to track in real time the status and diagnosis of their patients wherever they are.

Future Work

- The proposed ECG healthcare system can be improved by including more ECG diseases using a robust HRV approach.
- The diagnosis performance can be enhanced using advanced machine learning techniques.
- Designing and producing a cheap and small size wearable smart IoT-based ECG healthcare system.

Future Work

- Many to Many Iot system.



[Next SlideShares](#)